Glaucoma Images Classification Using Fuzzy Min-Max Neural Network Based on Data-Core

S. Sri Abirami, S.J Grace Shoba

***Abstract*: Glaucoma is the major cause of blindness in worldwide. It is an ophthalmologist disease characterized by an increase in Intraocular Pressure (IOP). The types of glaucoma are primary open angle or chronic glaucoma (POAG) and closed angle (or) acute glaucoma (CAG) which causes a slow (or) rapid rise in Intraocular Pressure (IOP). The iridocorneal angle between the iris and the cornea is the key used to differentiate OAG and CAG.**

The stratus Anterior Optical Coherence Tomography (AS-OCT) images with these diseases are detected and classified from the normal images using the proposed fuzzy min-max neural network based on Data-Core (DCFMN). Data-core fuzzy min-max neural network (DCFMN) has strong robustness and high accuracy in classification. DCFMN contains two classes of neurons: classifying neurons (CNs) and overlapping neurons (OLNs).CNs are used to classify the patterns of data. The OLN can handle all kinds of overlap in different hyper boxes. A new type of membership function considering the characteristics of data and the influence of noise is designed for CNs in the DCFMN.

The membership function of Overlapping Neurons (OLNs) deals with the relative position of data in the hyper boxes. This algorithm is performed on a batch of 39 anterior segment-Optical Coherence Tomography (AS-OCT) images obtained from the Vasan Eye Care Hospital, Chennai. The performance of the proposed system is excellent and a classification rate of 97% is achieved.

Hence using this neural network, the performance of classification of normal or abnormal (glaucoma affected images) is improved. This method also reduces the time taken for the diagnosis by the ophthalmologist.

Index Terms: Glaucoma, DCFMN, AS-OCT image.

I. INTRODUCTION

Glaucoma is an optic nerve disease resulting in a progressive, permanent visual loss or blindness glaucoma (CAG). Several techniques have been used to automate the glaucoma detection process. The shape of the ONH was modeled by a smooth two-dimensional surface with a shape described by free parameters. However, parameters were adjusted by least-squares fitting to give the best fit of the model to the image. In this parameters, plus others derived from the image using the model as a basis. It is used to discriminate between normal and abnormal images. The method that was tested by applying it to onh topography images is presented in [1].

In [2] two approaches are employed for the classification of CAG and OAG such as arc amount based approach and angle width based approach. In [3] the novel automated glaucoma detection system is employed that operates on inexpensive to acquire and widely used digital color fundus images. A different generic feature types are compressed by an appearance-based dimension reduction technique.

A probabilistic two-stage classification scheme combines these features types to extract the novel Glaucoma Risk Index (GRI) that shows a reasonable glaucoma detection performance. In [4] a new method for the detection of glaucoma using fundus image which mainly affects the optic disc by increasing the cup size is proposed. The optic cup to disc (CDR) in retinal fundus images is one of the primary physiological parameter for the diagnosis of glaucoma. After K-means clustering technique is recursively applied to extract the optic disc and optic cup region and an elliptical fitting technique is applied to find the CDR values. The ratio of area of blood vessels in the inferior superior side to area of blood vessels in the nasal-temporal side (ISNT) is combined with the CDR for the classification by using K-Nearest neighbour, Support Vector Machine and Bayes classifier of fundus image as normal or glaucoma.

Recently in [5], a method is proposed for pattern classification using Data Core based Fuzzy Min-Max Neural Network. This method for classification of glaucoma images (OAG & CAG) and normal images. The DCFMN has following features such as: 1) two kinds of neurons to handle the overlapped and containment compensations to deal with all kinds of overlap hyper boxes. It can eliminate the influence of different data values and the normalization of data. 2) A new training and classifying algorithm is designed to make pattern classification.

The rest of this paper is organized as follows method Section II elaborates the proposed method that includes pre-processing, enhancement, contrast adjustment, noise removal, segmentation. Section III provides Angle detection. Section IV demonstrates DCFMN architecture. Section V provides DCFMN algorithm. Section VI elaborates the classification of glaucoma (OAG & CAG) and normal images. Section VII shows the experimental results. Section VIII gives the conclusion.

II. PROPOSED METHOD

The proposed system deals with the Image obtained from Stratus Anterior Segment Optical Coherence Tomography (AS-OCT). All the stages are explained in detail in the following sub sections as shown in Figure (1).

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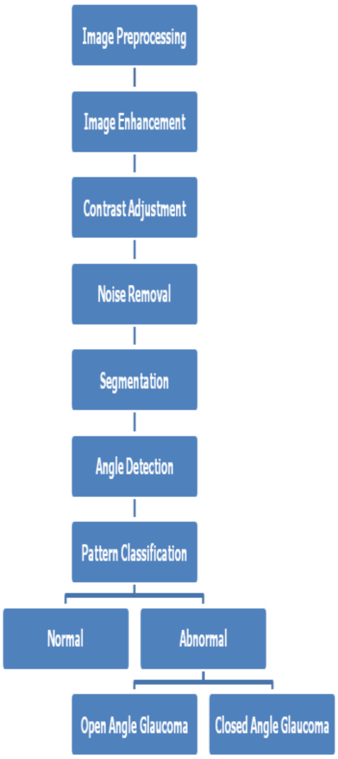


Figure.1. Block Diagram of the proposed method

A. Image Preprocessing

Pre-processing is done to the AS-OCT image which includes color conversion, resizing the image, removal of noise from the original images by using mean filter as shown in Figure (2). Image of the patient's eye obtained from OCT test will be pre processed for the removal of noise [6]. Image pre processing will be carried out 3 steps as shown in Figure 3(i), 3(ii), 3(iii).

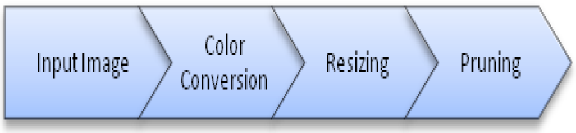
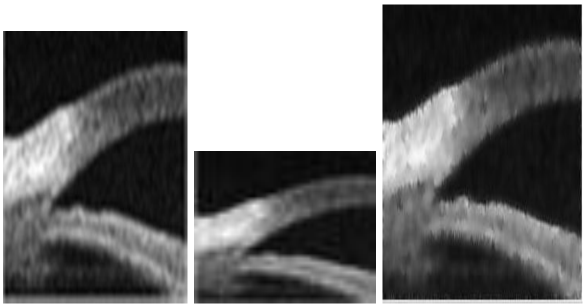


Figure.2. Block Diagram of the pre-processing technique

This process will eliminate disease independent variations from the input image. The process is aimed at removal of noise and illumination corrections. pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task presented in[7].

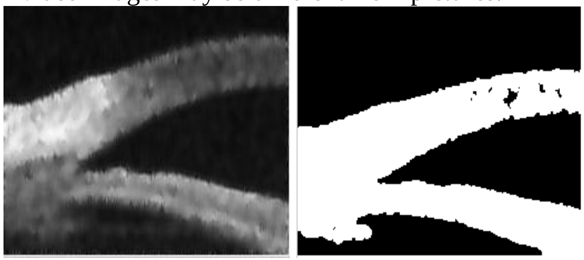


(i) (ii) (iii)

Figure.3. Image pre-processing. (i) Original image. (ii) Resize image. (iii) Filter image

B. IMAGE ENHANCEMENT

The principle objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application as shown in Figure 4(i) and 4(ii). So the specific application may determine approaches or techniques for image enhancement. (e.g.) Enhancing Ret cam video images may be different from pictures.

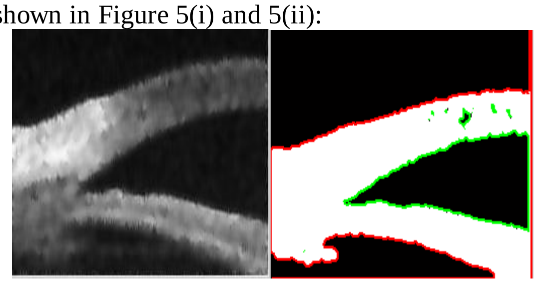


(i) (ii)

Figure.4. Enhancement process. (i) Filtered image. (ii) Enhancement image

C. Contrast Adjustment

Adjusting the brightness and contrast of an image to improve the image quality which is a little bit more complex. The first step is to calculate a contrast correction factor. The next step is to perform the actual contrast adjustment itself. There are several digital processing methods that can be used to adjust the contrast characteristics of an image. In digital radiography as well as with many of the other imaging modalities. Here using a very simple image to show how digital processing can be used to change the image contrast as shown in Figure 5(i) and 5(ii):

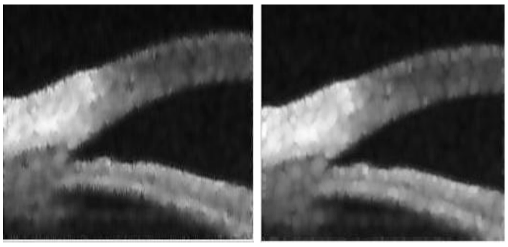


(i) (ii)

Figure.5. Contrast adjustment process. (i) Pre-processed image. (ii) Contrast adjustment

D. Noise Removal

Noise reduction is the process of removing noise from the enhanced image. One goal in image to remove the noise from the image in such a way that the "original" image is discernible. "Noise" is in the eye of the beholder removing the "noise". The key idea lies in a "min/max" speed function of the form F = min (K, 0) or F=max (K, 0), where K is the curvature and F is the speed in the normal direction as shown in Figure 6(i) and 6(ii). The min or max is controlled by a switch which depends the local average pixel value at any point. This results in an extremely strong and noise removal.



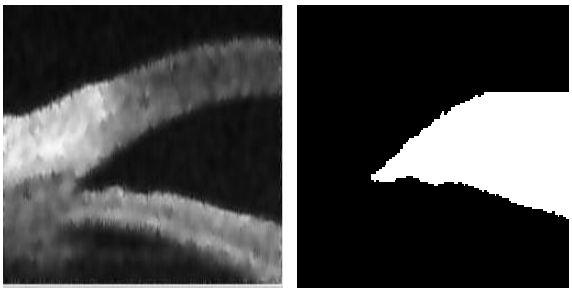
(i) (ii)

Figure.6. Noise Removal process. (i) Original image. (ii) Noise removed image.

E. SEGMENTATION

Segmentation is the process of dividing an image from the original image. This is mainly used to identify objects or other relevant information in digital images [8]. To segment the glaucoma affected part only. It can perform image segmentation in Matrix Laboratory (MATLAB). It is mainly used for the image processing toolbox and fuzzy toolbox, will provide image segmentation algorithms, and environment for data analysis. Since OCT's availability to the ophthalmic community as thickness changes [9]. In this layers are one indication of disease status. The goal of segmentation is to simplify or change the representation of an image and easier to analyze as shown in Figure 7(i) and 7(ii). The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level to turn a gray-scale image into a binary image.

Regions of interest depend of the application for scene analysis, segmentation should delimit objects for document analysis, The segmentation consists in separating text, graphics and images for image indexing, segmentation should extract uniform (colored or textured) areas presented in[10].



(i) (ii)

Figure.7.Segmentation process. (i) Pre-processed image. (ii) Segmented region

III. ANGLE DETECTION FOR SEGMENTED IMAGE

Angle Detection is done by using the DCFMN for the previously segmented images. The angle area in the arc detection, whether the angle is closed or open. Here, the propose two approaches to differentiate closed angle from open angle as shown in Figure (8).

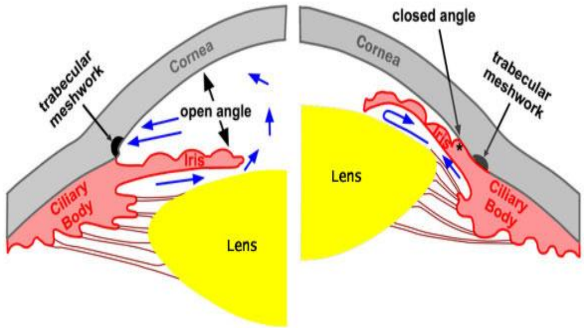


Figure.8. Structure of OAG and CAG

A. Primary Open Angle Glaucoma

There are no symptoms associated with POAG or chronic. The pressure in the eye slowly rises and the cornea adapts without swelling. If the cornea were to swell, but this disease often goes undetected presented in [11]. POAG is painless, and the patient often does not realize that is slowly losing vision until the later stages of the disease. The damage of the eye is irreversible.

B. Closed Angle Glaucoma

Unlike POAG (Primary Open-Angle Glaucoma), where the Intraocular Pressure (IOP) increases slowly but in acute angle-closure, it increases fastly. In pressure can occur within a matter of hours. If the pressure rises high enough, the pain may becomes so, intense that it can cause pupil becomes big and vomiting. IOP raises rapidly to a dangerous level not all angle-closure glaucoma sufferers will experience an acute attack presented in [12]. It is called closed angle or acute glaucoma. The iris gradually closes over the drain and no symptoms. When this occurs, scars slowly form between the iris and the drain. The IOP will not rise until there is a significant amount of scar tissue formed enough.

IV. DCFMN ARCHITECTURE

In the following, we will introduce the DCFMN. The architecture of DCFMN is shown in Figure (9). The DCFMN contains three layers. They are the input, middle, and the output layer. The input layer consists is equal to the dimension of the input data when the input data include measurement errors or noise. The middle layer represents a hyper box fuzzy set and is created during the training process [13].The output layer represents one class. In the following, we will explain membership functions, weights, and output of DCFMN, respectively.

A. Membership Functions

There are two membership functions in the middle layer.

1) CN Membership Function:

For considering the influence of noise and the density of data in the hyper box, an improved hyper box membership function of CN is defined as follows:

$$b_{j}(x_{h}) = \min_{i=1....n} \left(\min\left(f(x_{h,i} - w_{j,i} + \varepsilon, c_{j,i}) \, f(v_{j,i} + \varepsilon - x_{h,i}, c_{j,i}) \right) \right)$$

Where ε is a parameter representing noise, c is difference between the data core in the hyper box and the geometric center of the corresponding hyper box, and f is the ramp threshold function.

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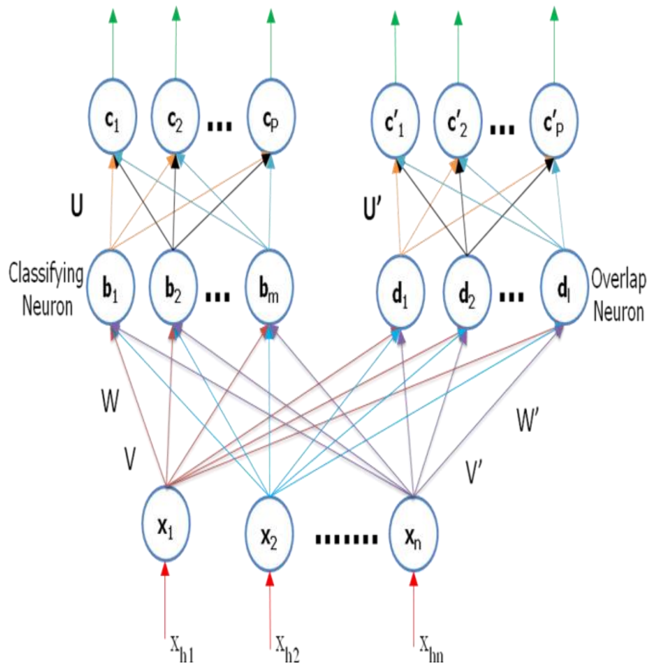

Figure.9. Architecture of DCFMN

2) OLN Membership Function:

An OLN is created when there is an overlapping area between two hyper boxes that belong to two different classes. The activation function used for OLN is given by,

$$d_{o,q}(x_h) = g(v_o', w_o', x_h, y_q) = \begin{cases} 1/n \sum_{i=1}^{n} (1 - |x_{h,i} - y_{q,i}|), & \forall\ w_{o,i} > (x_{h,i}) > v_{o,i} \\ 0, & \text{otherwise} \end{cases}$$

A. WEIGHTS

1) Weights between the Input Layer and the Middle Layer: There are two sets of connections as follows the input layer and the middle layer. The connection between the input layer and Classifying Neurons (CN) and also the connection between the input layer and Overlapping Neurons (OLN).

2) Weights between the Middle Layer and the Output Layer: The connections between CN and the output layer are binary valued and stored in u. The values from b_j to the output layer node c_i as follows:

$$u_{ji} = \begin{cases} 1, & \text{if } bj \in c_i \\ 0, & \text{otherwise} \end{cases}$$

C. OUTPUT

The output of DCFMN for class *r* is given as:

$$O_r = \begin{cases} \underset{r=1}{\overset{p}{\text{Max}}}\ (cr'), & \underset{i=1\ldots.l}{\exists}\ d_i \neq 0 \\ \underset{r=1}{\overset{p}{\text{Max}}}\ (cr), & \text{otherwise} \end{cases}$$

The index o_r is the final result of classification.

V. DCFMN ALGORITHM

The architecture of DCFMN and we will give the learning and classification algorithms of DCFMN.

A. LEARNING ALGORITHM:

The DCFMN learning methodology includes three procedures: expansion, overlapping test, and adding OLN if needed as shown in Figure 8.

1) Expansion: Identify the expandable hyper boxes and expand them. For the hyper box to be expanded, the following constraint is given by,

$$\forall\ (\max(w_{j,i}, x_{h,i}) - \min(v_{j,i}, x_{h,i})) \leq \theta$$

$i = 1\ldots., n,$

$j = 1\ldots.., m$

2) Overlapping Test: Determine whether any overlapping hyper box from different classes exists.

Case 1 : $v_{j,i} < v_{k,i} < w_{j,i} < w_{k,i}$ $\alpha^{new} = \min(w_{j,i} - v_{k,i}, \alpha^{old})$.

Case 2 : $v_{k,i} < v_{j,i} < w_{k,i} < w_{j,i}$ $\alpha^{new} = \min(w_{k,i} - v_{j,i}, \alpha^{old})$.

3) Adding OLN: If an overlap between hyper boxes of different classes exists, the process of adding OLN is as follows.

Case 1 : $v_{j,i} < v_{k,i} < w_{j,i} < w_{k,i}$ $v_{m'+o,i} = v_{k,i}$, $w_{m'+o,i} = w_{j,i}$.

Case 2 : $v_{k,i} < v_{j,i} < w_{k,i} < w_{j,i}$ $v_{m'+o,i} = v_{j,i}$, $w_{m'+o,i} = w_{k,i}$.

B. Classification Algorithm

The flowcharts of classification algorithm only use OLN to classify the test data as shown in Figure (10). Because the membership functions of OLN is zero when test data do not belong to any overlapped area as shown in Figure (11) and also results for the classification as shown in Figure (12).

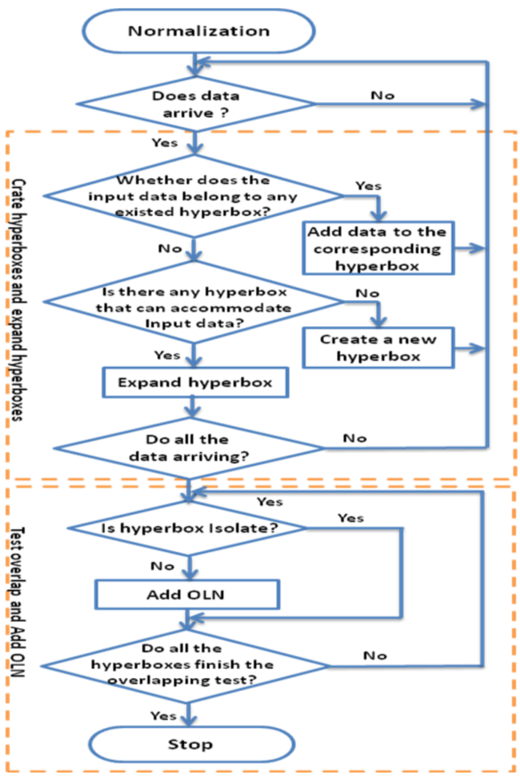

Figure.10. Flow chart of the DCFMN learning algorithm

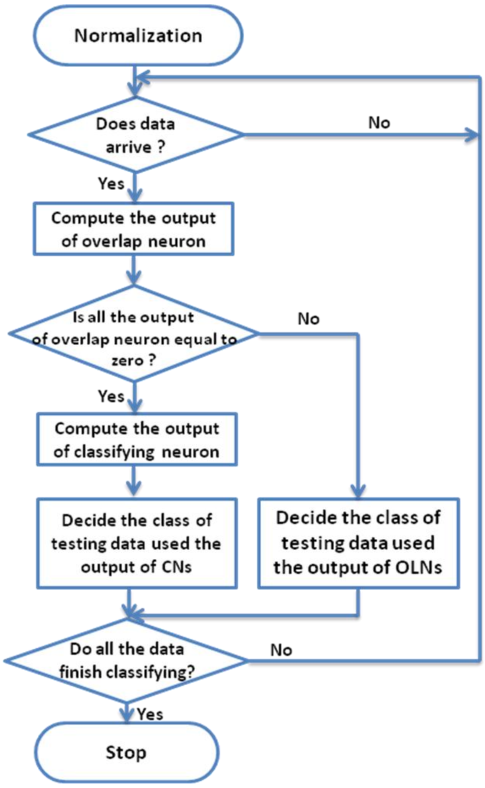

Figure.11. Flow chart of the DCFMN classifying algorithm.

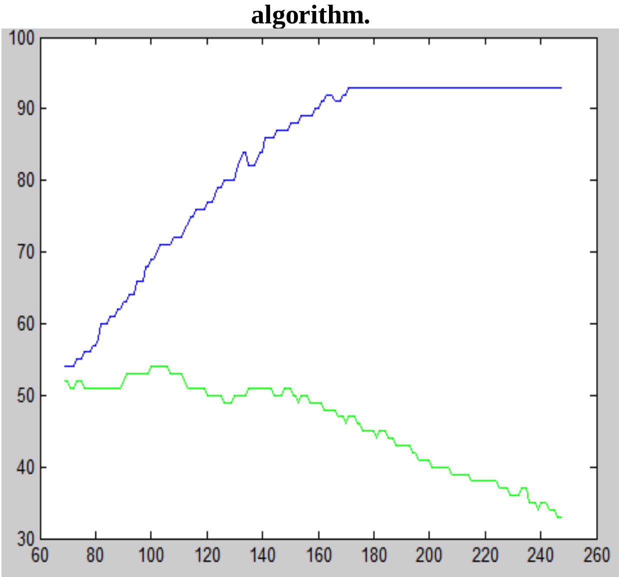

Figure.12. Fuzzy Neural network training process for angle detection

VI. PATTERN CLASSIFICATION OF RETINAL IMAGES USING DCFMN

The AS-OCT is a new technology that offers an alternative method of anterior chamber imaging. It is the greater quality and high resolution than the most common technology

Principles and simulation

This technology uses low-coherence interferometer to produce in cross-sectional images of tissue structure and reflections returning from the tissue are analyzed to obtain depth information presented in [14]. More recently, AS-OCT has been reported to demonstrate better detail of non-transparent tissues due to its increased penetration, while allowing sufficient illumination power to be used to enable high-speed imaging.

In this process of simulation, used retinal fundus images presented [15]. The RET CAM video device was used to collect the data for pattern classification. The running status of retinal fundus image was divided into two types: 1) Normal status 2) abnormal status. For the purpose of testing the accuracy of DCFMN, we initiated the two running status of the retinal fundus image. In this process, retinal images with these diseases are detected and classified from the original images. The performance of the proposed system is measured as the range of test set images classified into the correct feature class. Hyper plane: let a_1, a2... a_n be scalars not all equal to 0. The set S consisting of all vectors X = [x_1, x2... xn] in R^n such that $a_1x_1 + a_2x_2 + ... + a_nx_n = 0$ is a subspace of R^n called a hyperplane. The minimum, maximum and mean are the most popular choices for A. Any function A: [0, 1] L→ [0, 1] can be used. The classification stage is shown in Figure (13).

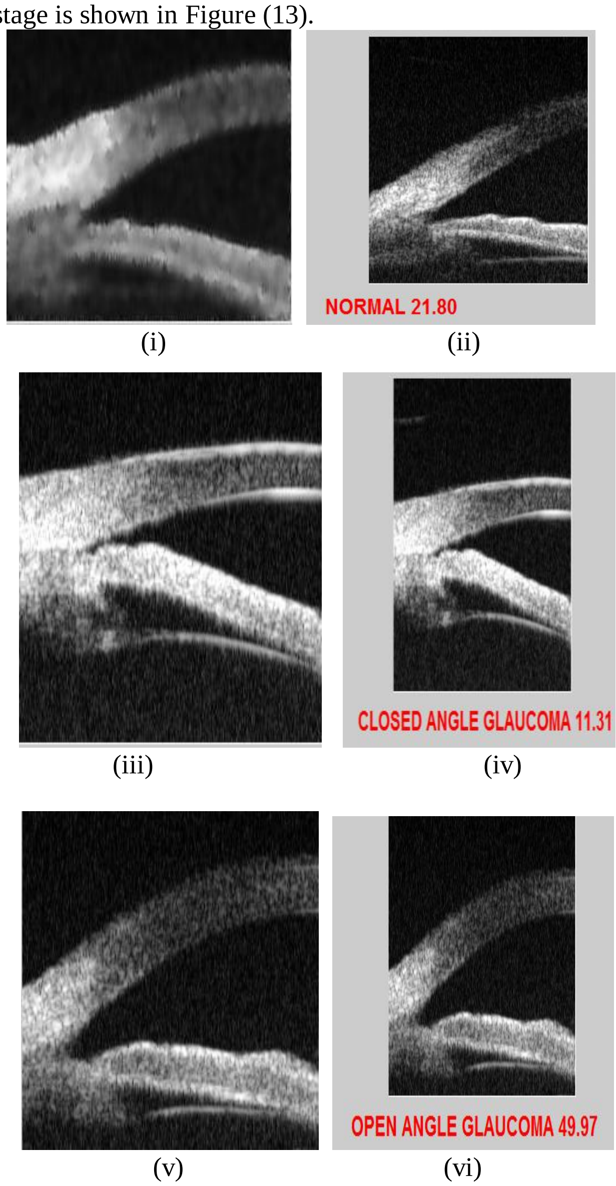

Figure.13. Classification results using DCFMN. (i, iii, v) Original images and (ii, iv, vi) classified images

Types of retinal images	Angle Range
Normal	20-40

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Closed Angle Glaucoma	<20
Open Angle Glaucoma	>40

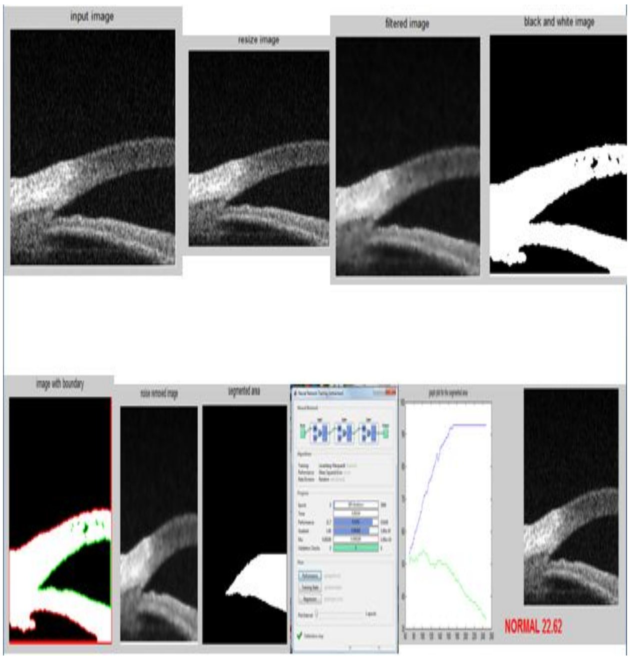
Table 1 Tabulation of Classification values

VII. EXPERIMENTAL RESULTS

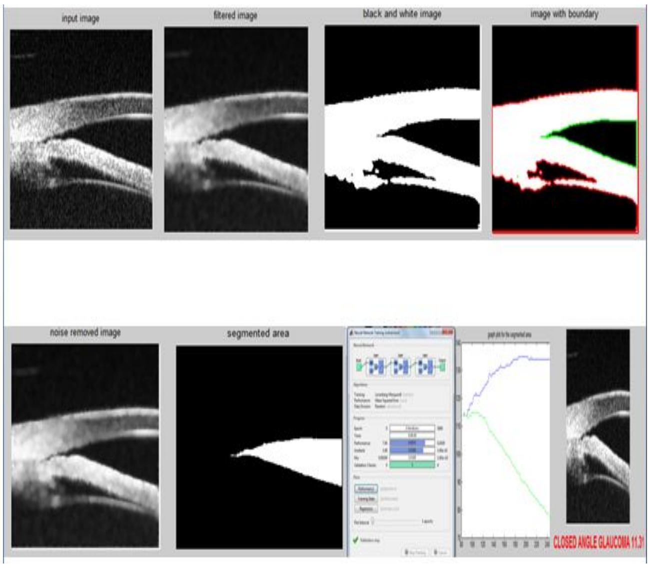
The proposed algorithm is tested on 15 normal fundus images and 24 fundus images obtained from the hospital. Pattern Classifier is used to analyze the performance of the proposed system. In pattern classifier is the organization of patterns into groups of patterns sharing the same set of properties and tabulation of classification values from the Table1. The number of training set and testing set as shown in Table 2. From the table, totally 12 fundus images are used to train the classifier as shown in Figure (14).

Category	No. Of Training Set	No. Of Testing Set
Normal	5	15
Abnormal	7	24

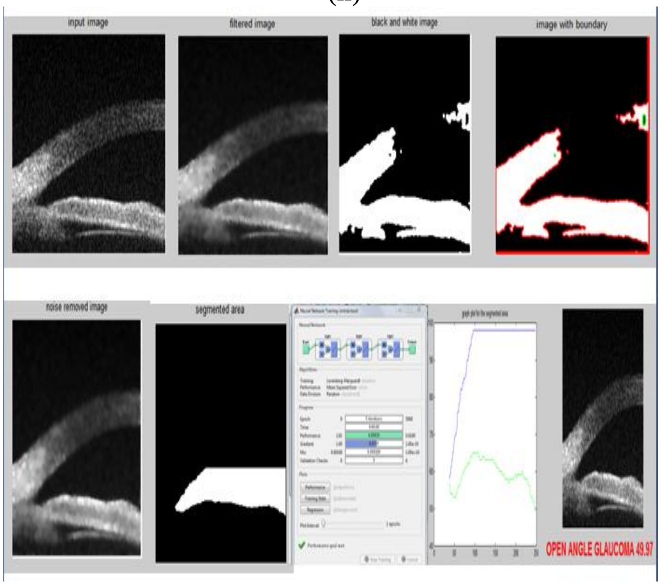
Table 2 Tabulation for Number of training set and testing set retinal fundus images.



(i)



(ii)



(iii)

Figure.14.Results of AS-OCT images using DCFMN (i) Normal result. (ii) Closed angle glaucoma result. (iii) Open angle glaucoma result.

VIII. CONCLUSION

In this paper, a new approach has been proposed to classify normal and glaucoma affected images using Fuzzy min-max Neural Network based on Data Core (DCFMN). DCFMN has strong robustness and high accuracy in classification taking into account the effect of Data Core and noise. The OCT images are preprocessed which includes color conversion, resizing and pruning before it is given as input for classification. This classification techniques using Fuzzy min-max neural network algorithm will be implemented on the retinal fundus images. The algorithm was tested on images obtained from Vasan Eye Care Hospital, Chennai. Experimental results show that the maximum classification rate of 97% is achieved. The detection and classification results obtained using this DCFMN algorithm is verified with the findings of the ophthalmologist which results in the same performance.

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