# "GLAUCOMA DIAGNOSIS USING HYBRID NEURO-FUZZY MODEL"

*A dissertation report submitted in partial fulfillment of the requirements for the award of degree*

**of**

**Master of Technology**

**in**

**Computer Science & Engineering**

**with specialization in**

**Artificial Intelligence and Artificial Neural Networks**

**By**



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**April – 2014**

# CERTIFICATE

This is to certify that the project work entitled "**Glaucoma Diagnosis using Hybrid Neuro-Fuzzy Model**" done by **Roohi Sille, R102212006,** for partial fulfillment of the requirements for the award of the Degree of Masters of Technology in Computer Science & Engineering With Specialization in Artificial Intelligence and Neural Networks, to Centre For Information Technology, University of Petroleum & Energy Studies is a bonafide report of the work carried by them under our guidance and supervision.

To my best of knowledge, the literature embodied in this project work has not been submitted to any other University/Institute for the award of any degree or diploma.

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# CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in this thesis entitled **'GLAUCOMA DIAGNOSIS USING HYBRID NEURO-FUZZY MODEL'** in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Computer Science & Engineering With Specialization in Artificial Intelligence and Neural Networks and submitted in the Department of Centre of Information Technology, University of Petroleum & Energy Studies, Dehradun, is an authentic record of my own work carried out during a period from January 2014 to April 2014, under the supervision of Dr. Hanumat Sastry G. name of guide and Desig, Department Assistant Professor, Centre of Information Technology, Affiliation University of Petroleum & Energy Studies, Dehradun.

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# ABSTRACT

Glaucoma is a group of ocular disorders characterized by elevated intraocular pressure, visual field sensitivity, decrease in retinal nerve fiber layer, effect on papillary, damage in optic nerve head and decreased cup-disc ratio. Glaucoma diagnosis at its early stage is very essential so that it can control the percentage of blindness in the total population. In medical field, glaucoma is diagnosed with the help of following tests: tonometry, ophthalmoscopy, perimetry, optical coherence tomography (OCT), pachymetery, gonioscopy, and heidel retina tomography (HRT). Glaucoma is the only disease which can be cured at its early stage after it has been detected. If the glaucoma is detected earlier in an individual, then the individual can be prevented from being blind.

Automated diagnosis has proven to be an efficient method of diagnosing glaucoma at an early stage. A number of clinical, statistical and automated diagnosing techniques have been developed for glaucoma diagnosis. However, all techniques have not been successful in early prediction of glaucoma at its early stage.

The main objective of this thesis is to improve the existing techniques and develop a hybrid neuro-fuzzy model for the early prediction of glaucoma at its initial stage. The thesis focusses on the disadvantages of the existing techniques and also compares the artificial neural network model with the developed hybrid neuro-fuzzy model.

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# CHAPTER 1
# INTRODUCTION

- Glaucoma
- Artificial Neural Network
- Fuzzy Inference System
- Hybrid Neuro-Fuzzy System

# 1. INTRODUCTION

## 1.1 GLAUCOMA:

Glaucoma is one of the leading causes of blindness. Glaucoma has never before seen such an advance in research and therapies coming forward in to the clinical workplace. Glaucoma refers to a group of conditions characterized by typical changes to the retinal nerve fibre layer and optic nerve head resulting in reduced visual field sensitivity [1]. Glaucoma has been called "silent thief of sight" because loss of vision often occurs gradually over a long period of time and symptoms occur when disease is advanced. It has been responsible for 20% blindness in the world. In USA and Great Britain, glaucoma accounts for 8% of cases related to legal blindness and the same in African countries; it varies from 8% to 20%. For Asian countries, it is just 0.5% to 36.3%; out of which India leads to lowest percentage [2]. Glaucoma has affected 61 million of the whole population so it is necessary to diagnose it as early as possible [3].

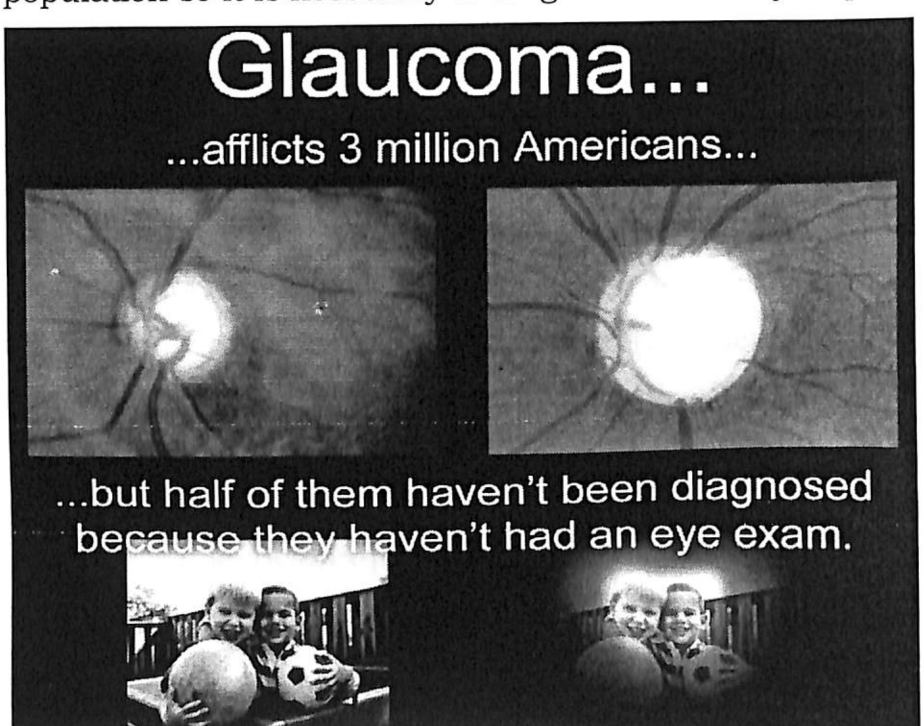


Figure 1.1: Glaucoma affecting America's population [Courtesy Source: http://www.insightseyecare.net/disorders.html]

Glaucoma is a term describing a group of ocular disorders (related to eyes) with multi factorial etiology united by a clinically characteristic intraocular pressure associated optic neuropathy. The main symptom of glaucoma is the progressive deterioration of the visual field. It is also associated with increased fluid pressure in eye (aqueous humor). Management of glaucoma involves careful monitoring of the progress of disease with regular visual field tests. Accurate identification and early intervention can potentially prevent advanced vision loss. Raised IOP (above 21mmHg or 2.8 kPa) is the only modifiable factor. Ocular hypertension occurs due to increased intra ocular pressure. Normal/Low tension occurs when optic nerve is damaged and associated visual field loss but normal or low intra ocular pressure. Nerve damage is due to the loss of retinal ganglion cells. Management of glaucoma involves careful monitoring of the progress of disease with regular visual field tests. Accurate identification and early intervention can potentially prevent advanced vision loss.

Primary Open Angle Glaucoma (POAG) comprises the most frequent type of glaucoma afflicting the visual function of individuals and is the third leading cause of blindness worldwide. It is a progressive condition characterized by damage of the retinal nerve fibre layer and optic nerve head and resulting in visual field defects. Main clinical signs of POAG are alterations of the optic nerve head topography and structural defects of retinal nerve fibre layer, visual field defects corresponding to the anatomical organization of the retinal nerve fibre layer.

Glaucoma is basically of two types: open angled glaucoma and close angled glaucoma. Open angle glaucoma progress at slower rate whereas closed angle glaucoma appear suddenly. Open angled glaucoma is not painful whereas close angled glaucoma is painful. Signs of open angled glaucoma are gradually progressive visual field loss and optic nerve changes (increase cup to disc ratio). Signs of close angled glaucoma are sudden ocular pain, red eye, very high IOP (>30mmHg), nausea, vomiting, suddenly decreased vision and a fixed mid dilated pupil.

Glaucoma is caused mainly of two reasons; firstly caffeine increases IOP of glaucoma patients and secondly prolonged use of steroids.

Glaucoma is the only disease which can be cured at its early stage after it has been detected. If the glaucoma is detected earlier in an individual, then the individual can be prevented from being blind. It requires long term drug therapy, strict patient compliance, periodical monitoring of ocular parameters and a reliable follow up. But the drug therapy is not economic, as these drugs are not available for free.

### 1.1.1 VARIOUS RISK FACTORS:

1) Trans-cribrosal and CSF pressure: The lamina cribrosa provides structural and nutritional support to retinal ganglion cells (RGC). When the glaucoma advances, the lamina cribrosa displays marked posterior bowing in the direction of a pressure difference created between IOP and the CSF [trans-cribrosal pressure differential (TCPD)] [4][5]. CSF pressure may be a risk factor for primary open angle glaucoma (POAG).

2) Low BMI is also one of the risk factors for glaucoma. CSF pressure increases proportionate to body mass index (BMI) [6]. Individuals with a BMI of 35 $kg/m_2$ have mean CSF pressure 32.4 per cent higher than individuals with BMI of 18 $kg/m_2$. Higher intraocular pressure is also caused by high BMI.

3) One of the risk factors of POAG is low CSF pressures ($9.1 \pm 0.77$ mmHg).

4) Fluctuation of intraocular pressure helps in extending glaucoma to an advanced state. Maintaining the IOP is useful in controlling the progressive glaucoma at earlier stages which can avoid blindness in individuals. IOP has now become one of the most cured risk factor.

### 1.1.2 CLINICAL DIAGNOSIS:

As mentioned earlier, elevated intraocular pressure, visual field loss and optic nerve head damages are the three common denominators leading to blindness in glaucoma. They provide the basis for our understanding of glaucoma and represent the focus of clinicians' efforts to diagnose the disease.

#### 1.1.2.1 Intraocular Pressure

The IOP has a Gaussian distribution in the general population and is usually in the range of 10 - 20 mm Hg. The pressure can be recorded by a few different methods: indentation tonometry, applanation tonometry and non-contact tonometry. The common instrument used is the tonometer; the tonometer measures the IOP using a relation between the deformation of the eye's globe and the force responsible for the deformation. The Schiotz tonometer indents the cornea, whereas the Goldmann applanation tonometer flattens a standard area of the cornea measuring the force required. Another type of tonometer, the Maklakov-type measures the area flattened using a standard force. More modern instruments, such as pneumatic tonometers electronically record the pressure. Non-contact tonometers use a puff of air as a standard force and automatically record the time required or the deformation of the cornea.

There are many factors which influence the IOP, some cause long term changes and some only short term fluctuations. The long term influences on pressure are genetics, age, gender, refractive error, and race. The fluctuations in eye pressure are due to body position: movement of the eye and eyelid; physical exertion; the time of the day; ocular and systematic conditions; foods and drugs. The variability of the pressure measurement is high due to the influence of the above factors. Tonometer is neither sufficiently sensitive nor specific enough to be used alone as a screening test.

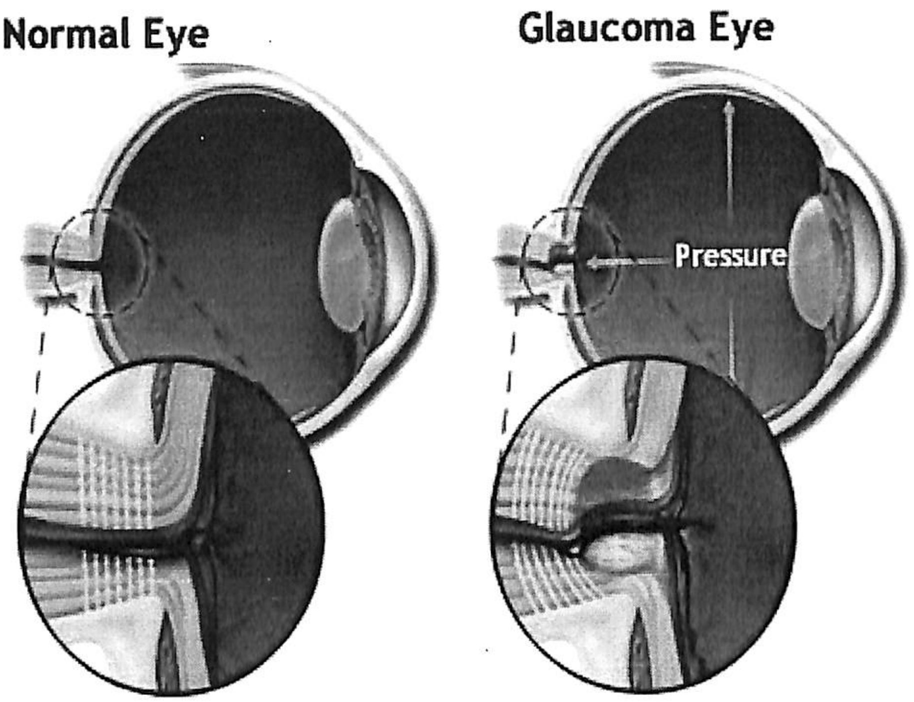


Figure 1.2: Elevation in IOP [Courtesy Source: http://www.northcincinnatieyecare.com/34801/34822.html]

**1.1.2.2 Visual Field Testing**

The normal visual field may be depicted as a three-dimensional surface, representing areas of relative retinal sensitivity and characterized by a peak at the point of fixation, an absolute depression corresponding to the optic nerve head and a sloping of the remaining areas to the boundaries of the field. Early glaucomatous damage may produce a generalized depression of this surface which can be demonstrated with several psychophysical tests. However, the specific visual field changes of glaucoma are localized defects that correspond to the loss of retinal nerve fiber bundles.

Perimeters are the instruments used to measure the field of vision, may have static and/or kinetic targets. The targets are presented against a background screen; the advancement from the flat screen of the campimeter to the arc or bowl perimeter increases the reliability of the measurements. The targets are either controlled manually or automatically; the change from manually moved test objects to a projected or screen displayed light source make easier the control of test environment.

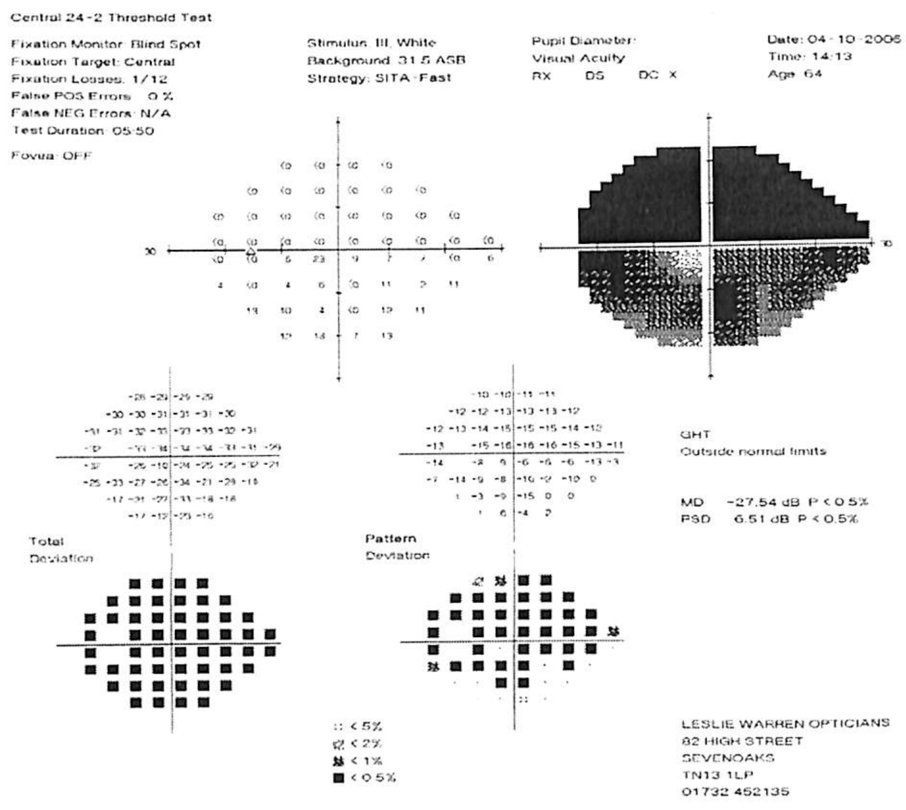

Figure 1.3: Visual Field in Glaucoma [Courtsey Source: http://www.revophth.com/content/d/glaucoma_management/c/30967/]

### 1.1.2.3 Optic Nerve Head Examination

Clinical examination of the ONH started with the introduction of the ophthalmoscope in 1850 and its use to observe the optic disc by von Graefe in 1854. The success of human fundus photography in 1886 combined with the extensive fundus drawings available, such as von Jaeger's atlas of 1869, paved the way for diagnosis of ocular diseases. In 1966, stereo-photogrammetry was used to measure the optic disc cup. In 1980, scanning laser ophthalmoscope began to be used in ophthalmology and was combined with confocal imaging after five years. The result was that topographic digital images of the ONH were collected from the measurements recorded using a laser beam. These scanned images could then be analyzed using computer algorithms.

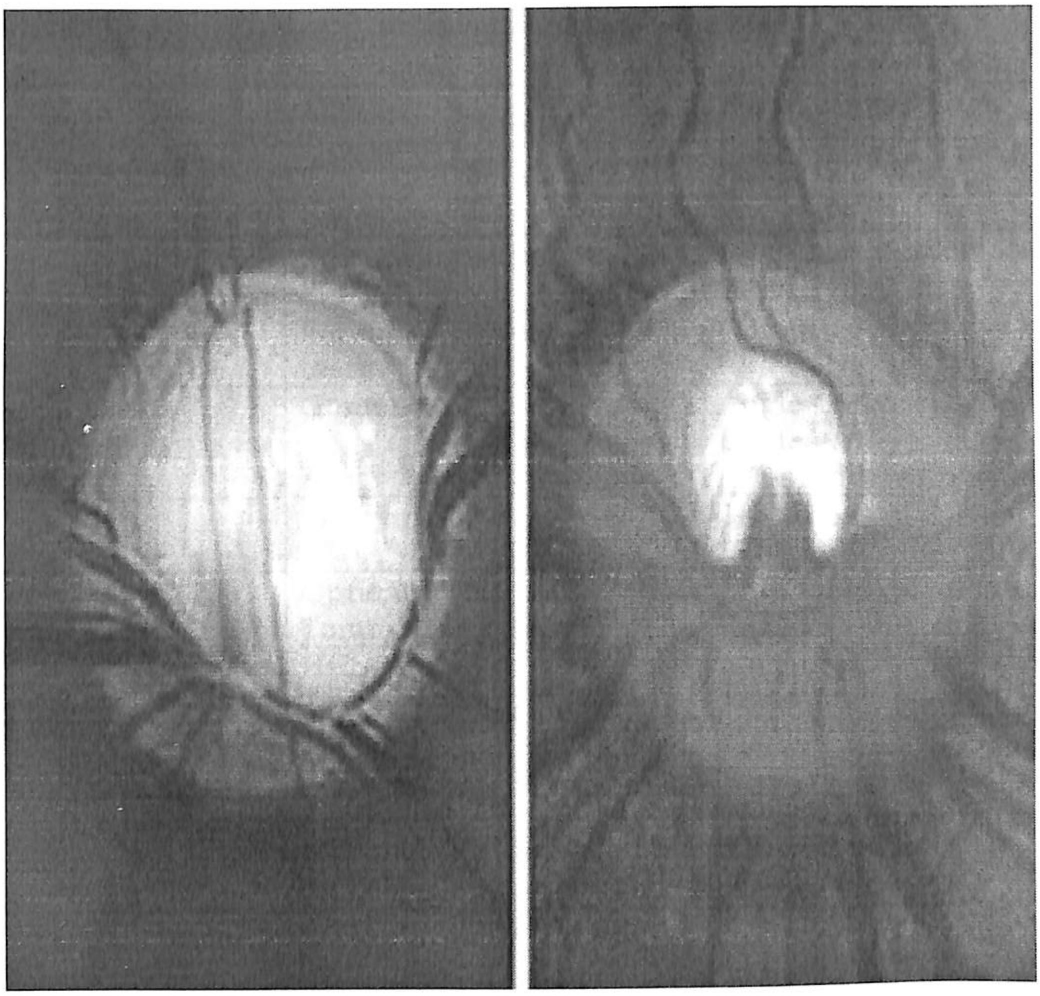

Figure 1.4: Glaucomatous Optic Nerve Head [Courtesy Source: http://tennantinstitute.us/healing-eye-diseases/glaucoma.html]

**Table 1.1: Different Clinical Diagnostic Tests**

| SNO | TEST | What it examines |
|---|---|---|
| 1) | Tonometry | Inner eye pressure (10-21 mmHg for normal) |
| 2) | Ophthalmoscopy | Shape and color of optic nerve |
| 3) | Perimetry (Visual Field test) | Complete Field Vision |
| 4) | Gonioscopy | Angle between iris and cornea (40-45 degree normal) |
| 5) | Pachymetery | Thickness of cornea (540nm for normal) |
| 6) | Optical Coherence Tomography (OCT) | Thickness of nerve fibre layer |
| 7) | Heidelberg Retina Tomography (HRT) | Measures the retinal nerve fibre layers |

## 1.2 ARTIFICIAL NEURAL NETWORK

ANN classifiers can be used to perform three different tasks: 1) identify which class best represents an input pattern; 2) simulate associative memory; 3) vector quantify or cluster N inputs into M clusters. The type of ANN chosen, its structure and method of training will define the task it will perform. In medicine and biology, pattern classes are often not known and examples of clusters are required to enable the classifier to generalize going beyond just memorization. There are many examples of ANN classifiers which used supervised learning for medical and biological classification problems. ANN is also used for computerized analysis of medical images.

In ophthalmology applications of ANN have been used for the interpretation of the visual field for recognition and evaluation of the cell population of corneal endothelium [7] and recognition of retinographs and angiofluorescent graphs in diabetic retinopathy [8].

Antón et al. (1997) used the ANN for the interpretation of the incipient perimetric lesions produced in glaucoma and conclude that both the networks and the logistic regression are capable of differentiating between the incipient perimetric lesions produced by the glaucoma and those produced by other illnesses with important precision [9]. They add that if these methods were applied to the PALOC, or another perimetric test, more sensitive to glaucomatous functional lesions than conventional perimetry, it would be a great aid for the identification and interpretation of the defects produced by this neuropathy. Brigatti et al. (1996) also use the ANN to classify patients into normal or glaucomatous [10]. They include automated data of the visual field, such as average defects, variances of corrected losses and fluctuation in the short term, and structural data such as radius of excavation, volume of disc and thickness of the nerve fiber layer. On including the data for the visual field and the structural data the results are better than when the data are used separately. The sensitivity with the data together was 90% and the specificity 84%. Only with the structural data a sensitivity of 87% and specificity of 56% were achieved and the results were 84% and 86% respectively if only the functional data were trained.

Artificial neural networks have been trained on different optic nerve head imaging analyzer parameters to classify eyes as glaucomatous or healthy in accordance with confocal scanning laser ophthalmoscopy [10][11]. Using this method, the neural network classifier is trained to detect a relationship between input (parameters of structural study) and a predefined gold-standard diagnosis by comparing its prediction with the labeled diagnosis and by learning from its mistakes.

Different types of neural networks used for glaucoma diagnosis are as follows:

### 1.2.1 Multilayer Perceptron Networks

A neural network is defined in mathematical terms as a graph with the following properties: (1) each node i, called neuron, is associated with a state variable $x_i$ storing its current output; (2) each junction between two neurons i and k, called synapse or link, is associated with a real weight $\omega_{ik}$; (3) a real threshold $\theta_i$ , called activation threshold, is associated with each neuron i; (4) a transfer function fi [$n_k, \omega_{ik}$, $\theta_i$ , (k $\neq$ i)] is defined for each neuron, and determines the activation degree of the neuron as a function of its threshold, the weights of the input junctions and the outputs $n_k$ of the neurons connected to its input synapses. In our case, the transfer function has the form f ($\sum k\ \omega_{nk} - \theta_i$), where f (x) is a sigmoidal function, defined by $f(x) = 1/(1 + e^{(v-x)})$, which corresponds to the continuous and derivable generalization of the step function [12][13][14]. Multilayer perceptrons are networks with one or more layers of nodes between the layer of input units and the layer of output nodes; Fig. 1.5 shows a three-layer perceptron. These layers contain hidden units or nodes which obtain their input from the previous layer and output their results to the next layer, to both of which they are fully-connected. Nodes within each layer are not connected and have the same transfer function. The strength of the multilayer perceptron originates from the use of non-linear sigmoidal functions in the nodes. If the nodes were linear elements, then monolayer networks with appropriately selected weights could repeat the calculations carried out by a multilayer network [15]. A multilayer perceptron with a non-linear step function and a hidden layer can solve problems in which the decision regions are open or closed convex regions. In the case of perceptrons with one hidden layer, problems with arbitrary decision regions can be solved, but more complex regions will need a greater number of nodes in the network [16][17].

Fundamental characteristics of a multilayer perceptron network are: (i) it is an adaptive method which permits the carrying out of non-linear statistics; (ii) fitting is made by a gradient method using the training data; (iii) a multilayer perceptron with three layers with step transference functions can solve any problem with arbitrary decision regions; (iv) noise in the patterns, the same as in the statistical fitting, does not impede their classification; (v) training of the connection weights must be very great; (vi) back-propagation algorithm usually finds the global minimum of the error function.

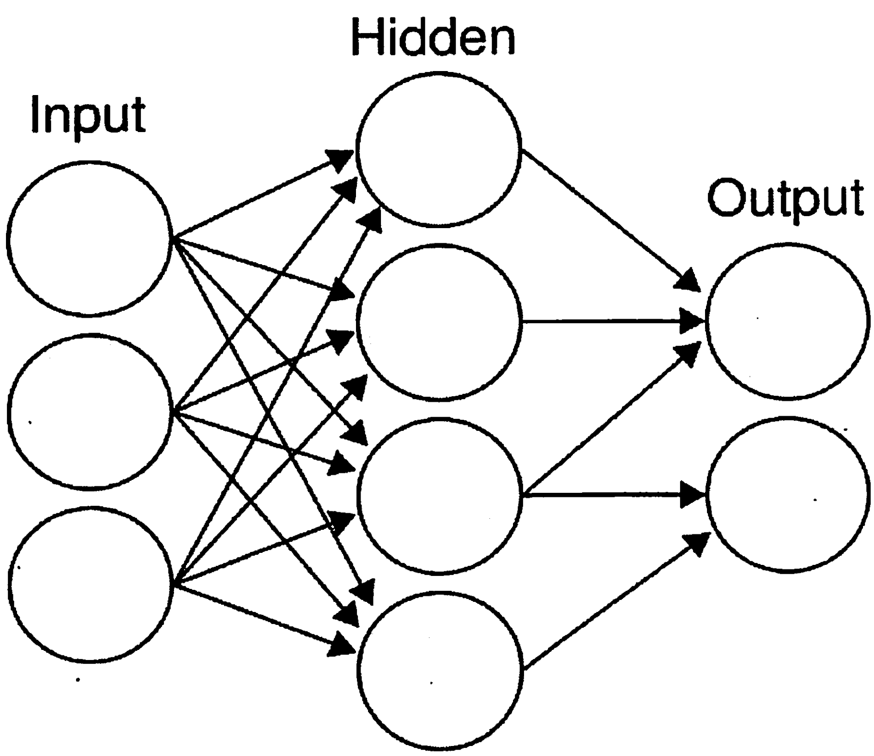


**Figure 1.5: Three layer perceptron**

### 1.2.2 Back-propagation Algorithm

The accuracy of the multilayer perceptron depends basically on the correct weights between nodes. The backpropagation training algorithm is an algorithm for adjusting those weights which uses a gradient descent method to minimize the mean quadratic error between the actual outputs of the perceptron and the desired outputs.

Let $x_{ij}^k$ and $y_{ij}^k$ be the input and output, respectively, for the i pattern of node j of layer k. Let $\omega_{ij}^k$ be the weight of the connection of neuron j of layer k with neuron i of the previous layer. By definition of the perceptron by layers, the following relationships are fulfilled

$$x_{ij}^{k} = \sum_{l=0} \omega_{lj}^{k} y_{il}^{k} ; \; y_{ij}^{k} = f(x_{ij}^{k})$$

The mean quadratic error function between the real output of the perceptron and the desired output, for a particular pattern i, is defined as $E_i = \frac{1}{2}(\sum_{jk}(y_{ij}^{k} - d_{ij}^{k}))$ , where $d_{ij}^{k}$ is the desired output for pattern i of node j of layer k. In order to minimize the error function we use the descending gradient function, considering the error function Ep and the weight sequence $\omega_{ij}^{k}(t)$, started randomly at time t = 0, and adapted to successive discrete time intervals. We then have $\omega_{ij}^{k}(t+1) = \omega_{ij}^{k}(t) - \eta \, \partial E1/\partial \omega_{ij}^{k}(t)$, where $\eta$ is the so-called learning rate constant.

We can conclude that $\omega_{ij}(t+1) = \omega_{ij}(t) + \eta \partial_j x_i'$ , where $x_i'$ is the output of neuron i, and $\partial_j$ is an error term for node j. For output neurons, it must be $\partial_j = y_j(1 - y_j)(d_j - y_j)$. For a hidden layer j,$\partial_j = x_j'(1 - x_j') \sum_k \partial_k \omega_{jk}$, where k ranges over all neurons in the layers above neuron j. Internal node thresholds are adapted in a similar manner.

The high performance usually achieved with this backpropagation algorithm is rather surprising if we take into account the fact that the gradient method, of which the backpropagation training algorithm is a generalization, can find a local minimum of the error function instead of the desired global minimum. Some ideas for improving performance and reducing the appearance of local minimums are, for example, the addition of new nodes in the hidden layers, the lowering of the gain term used for the adaptation of weights and, above all, the initial training with a different set of random weights.

### 1.3 FUZZY INFERENCE SYSTEM:

Fuzzy systems propose a mathematic calculus to translate the subjective human knowledge of the real processes. This is a way to implement practical knowledge with some level of uncertainty. The fuzzy sets theory was initiated by Lofti Zadeh, in 1965. The behavior of fuzzy systems is described through a fuzzy rule set, like: IF <premise> THEN <consequent> that uses linguistics variables with symbolic terms. Each term represents a fuzzy set. The terms of the input space (typically 5-7 for each linguistic variable) compose the fuzzy partition. The fuzzy inference mechanism consists of three stages: in the first stage, the values of the numerical inputs are mapped by a function according to a degree of compatibility of the respective fuzzy sets; this operation can be called fuzzyfication. In the second stage, the fuzzy system processes the rules in accordance with the firing strengths of the inputs. In the third stage, the resultant fuzzy values are transformed again into numerical values; this operation can be called de-fuzzyfication. The advantages of the fuzzy systems are: capacity to represent inherent uncertainties of the human knowledge with linguistic variables; simple interaction of the expert of the domain with the engineer designer of the system; easy interpretation of the results, because of the natural rules representation; easy extension of the base of knowledge through the addition of new rules; robustness in relation of the possible disturbances in the system. And its disadvantages are: incapable to generalize, or either, it only answers to what is written in its rule base; not robust in relation the topological changes of the system, such changes would demand alterations in the rule base; depends on the existence of an expert to determine the inference logical rules.

### 1.4 Neuro fuzzy systems

The community perceived that the development of a fuzzy system with good performance is not an easy task. The problem of finding membership functions and appropriate rules is frequently a tiring process of attempt and error. This leads to the idea of applying learning algorithms to the fuzzy systems. The neural networks, that have efficient learning algorithms, had been presented as an alternative to automate or to support the development of tuning fuzzy systems. A neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory. The (heuristically) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system.

A neuro-fuzzy system can be viewed as a 3-layer feed forward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables. Fuzzy sets are encoded as (fuzzy) connection weights. It is not necessary to represent a fuzzy system like this to apply a learning algorithm to it. However, it can be convenient, because it represents the data flow of input processing and learning within the model. Its application spread for all the areas of the knowledge like, data analysis, data classification, imperfections detection and support to decision-making, etc. Neural networks and fuzzy systems can be combined to join its advantages and to cure its individual illness. Neural networks introduce its computational characteristics of learning in the fuzzy systems and receive from them the interpretation and clarity of systems representation. Thus, the disadvantages of the fuzzy systems are compensated by the capacities of the neural networks. These techniques are complementary, which justifies its use together.

# CHAPTER 2
# LITERATURE REVIEW

# 2. LITERATURE REVIEW

Automatic diagnosis is proven a wide source of research in medical field. Automatic diagnosis is required to study the voluminous medical data with less time and more accuracy. This automatic diagnosis includes the various machine learning classifiers. The various soft computing/machine learning techniques used for glaucoma diagnosis are as follows:

- Artificial Neural Networks
- Fuzzy Inference Systems
- Image Processing Systems
- Support Vector Machines
- Hybrid Models

**Artificial neural network** is one of the machine learning classifiers. The use of artificial neural networks is a recently developed cross disciplinary field that integrates neuroscience, information science and computer sciences. It is suitable for the processing of diverse and variable medical data to solve complex issues in the field of medical diagnosis, such as feature extraction. It can eliminate subjective human factors and provide an accurate and objective diagnosis. One domain where such applications have found significant utility is the analysis of medical data sets. In ophthalmology applications, ANNs have been used for the interpretation of the visual field for recognition and evaluation of the cell population of corneal endothelium and recognition of retinographs and angiofluorescent graphs in diabetic retinopathy. ANN models are capable of treating qualitative and quantitative variables and perform with asymmetric variables of distribution or that are much distanced from a normal distribution. ANN have a great potential to become a useful clinical tool in the diagnosis of glaucomatous visual field loss, and may be of value in the study of the performance of a range of types of data inputs with different machine classifiers. Contributions from the various authors and publications have been reviewed here.

**Table 2.1: Analytical Review of Various Methods**

| Author Name | Input parameters | Neural Network | Sensitivity at Specificity |
|---|---|---|---|
| 1) C. Bowd [18] | Heidel retina tomograph parameters | Multi-layer perceptron and Support vector machines (Gaussian & linear) | SVM Gaussian 91% |
| 2) K.Chan [19] | Standard Automated Perimetry parameters | Machine learning Classifiers (MLP,MOG, SVM, MGG) | 0.833, 0.923, 0.914, 0.902 (area under ROC curves) |
| 3)F.S Mikelberg [20] | Topographic Images of patient's optic nerve heads | Feed forward network with error back-propagation | 84.4% |
| 4) K. R. Sung [21] | Imaging of retinal nerve fibre layer | Spectral Domain Optical Coherence Tomography Technique | |
| 5) Goldbaum MH [22] | IOP and appearance of optic nerve | Two layered network with back-propagation learning | 67% |
| 6) L. Boquete [23] | Multi-Focal Electroretinography | Radial basis Function Network with Learning Machine algorithm | 0.8 (area under ROC curves) |
| 7) G. Santos-Garcia [24] | Standard Perimetry & Scanning Laser Polarimetry | Multi-Layer Perceptron with Levenberg Marquardt & Backpropogation | 100% |
| 8) Grewal [25] | Optic Disc Examination and perimetry (IOP,optic nerve head and retinal nerve fibre layer) | Easy NN simulator | 71.4% |
| 9) M Aranzazu Simon [26] | Perimetry | Hybrid Visual Field Classifier System | 97% |
| 10)K.Chiranjeevi [27] | Ultrasound images of eye | Segmentation and signal processing | 97% |

| | | | |
|---|---|---|---|
| | | techniques along with Multi-scale algorithm | |
| 11) Jorg Meier [28] | Image features from fundus images | Principal Component Analysis (PCA) method & Support Vector Machine | 81% |
| 12)D C Hoffman [29] | To detect visual field progression in eye images | Fuzzy logic neural network | 75% |
| 13)W.K Wong [30] | To detect cup disc ratio from fundus images | Level set techniques | 96% |
| 14) Jiang Liu [31] | Patient personal data, retinal images and quality controlled genome data | Automatic glaucoma diagnosis through medical imaging informatics (AGLAIA-MII) | 0.866 under curve value |
| 15) P. A. Sample [32] | Visual field parameters with ocular hypersensitive eyes with SAP (stereo-photographs) | STATPAC-like methods and machine learning classifiers [support vector machine (SVM), a mixture of Gaussian (MoG) classifier, a constrained MoG, and a mixture of generalized Gaussian (MGG)] | Machine learning classifiers predicted confirmed abnormality. |
| 16)Mei-liu Hang et. al. [33] | Data reports of Stratus OCT | Adaptive neuro fuzzy inference system | ROC area was increased to 0.925. |
| 17) S. Sri abirami [34] | Anterior Stratus OCT images | Data Core Fuzzy min-max neural network | 97% accuracy |
| 18) K. narasimhan [35] | Fundus images | K-means clustering with SVM classifier | 95% accuracy |

**Fuzzy Inference Systems** are the rule based system based on unertainity. These systems mainly uses if then rules that uses linguistics variables with symbolic terms. This system consists of basic three mechanisms that are fuzzification (assigning membership function to each input), firing of if-then rules and de-fuzzification. These are useful for making predictions.

**Image Processing Systems** are the systems mainly used for analyzing of medical images such as glaucomatous eye's images. Some of the image processing systems are medical imaging informatics (AGLAIA-MII) and Spectral Domain Optical Coherence Tomography Techniques.

**Support Vector Machines** are kernel based methods that can be trained to recognize patterns in data and adapt their decision boundary to the training data. Unlike ANN's, these algorithms perform classification by using kernels to map the input data in a space of higher dimensionality and with the help of constructed support vector machines (from part of training data), they create hyperplanes that maximize the separation between the classes while minimizing the generalization error.

**Hybrid Models** are models developed by the combination of two or more methods. These models are more efficient than other machine learning techniques. Some of the hybrid models are neuro-fuzzy model that is combination of neural network with fuzzy inference systems; combination of neural network with genetic algorithm; combination of neural network and support vector machines.

# CHAPTER 3
# DRAWBACKS OF EXISTING TECHNIQUES

## 3. DRAWBACKS OF EXISTING TECHNIQUES

Many statistical and machine learning/soft computing techniques have been used in the field of medical diagnosis. Linear discriminant functions and principal component analysis are some of the statistical techniques used for glaucoma diagnosis. Artificial Neural Networks and Fuzzy Inference Systems are some of the machine learning techniques. But there are several disadvantages of using these techniques in medical diagnosis. These disadvantages are discussed below:

- Artificial Neural Networks are unable to make predictions.
- Fuzzy Systems are incapable to incapable to generalize, or either, it only answers to what is written in its rule base.
- Fuzzy systems are not robust in relation the topological changes of the system, such changes would demand alterations in the rule base.
- Fuzzy systems depend on the existence of an expert to determine the inference logical rules.
- Statistical techniques require the restrictive assumptions about the relationship between independent and dependent variables.
- Statistical techniques are not appropriate in a non-linear environment.
- Clinical techniques have the major disadvantage is that: to study and pinpoint anomalies in voluminous data collected over several hours are strenuous and time consuming.
- Bio-signals are non-stationary signals. The statistical techniques such as time series techniques can produce poor predictions.
- These depend heavily on key assumptions about the model or underlying relationship between the output of the series and its patterns.
- The data are not in common units so scaling problems may arise in statistical techniques.
- Data sources need to be weighted according to their reliability but most of the statistical methods do not have such mechanism.

- These techniques are not flexible with the noisy data such as HRT parameters.
- LDF analysis assumes that data representing different groups are linearly separable. If this assumption is not well met, the classifier's performance is degraded.

# CHAPTER 4
# PROPOSED METHODOLOGY

# 4. PROPOSED METHODOLOGY

In my previous work, a pattern recognition feed forward neural network was proposed for the classification of different stages of glaucoma. The stages defined include stage 0, which corresponds to normal eyes; stage 1, for ocular hypertension; 2, for early Glaucoma; 3, for established Glaucoma; 4, for advanced Glaucoma and 5, for terminal Glaucoma. The input layer consists of 4 input neurons and receives the value of 4 input variables and the output layer consists of 6 output neurons and obtains the value of the output variable that corresponds with the stage of the Glaucoma for each eye. The four variables were chamber depth, mean, mean thickness and intra-ocular pressure. The ANN model was training using levenberg-marquardt algorithm.

Since the accuracy of the neural network model was not that much accurate so in this thesis we propose a hybrid model combining neural networks and the fuzzy inference systems.

The output of the artificial neural network is fed as input to the fuzzy inference system in the form of if-then rules. The output of the fuzzy inference system will classify whether the patient is glaucomatous or non-glaucomatous.

The proposed framework for the diagnosis used in this thesis is shown in the following figure:

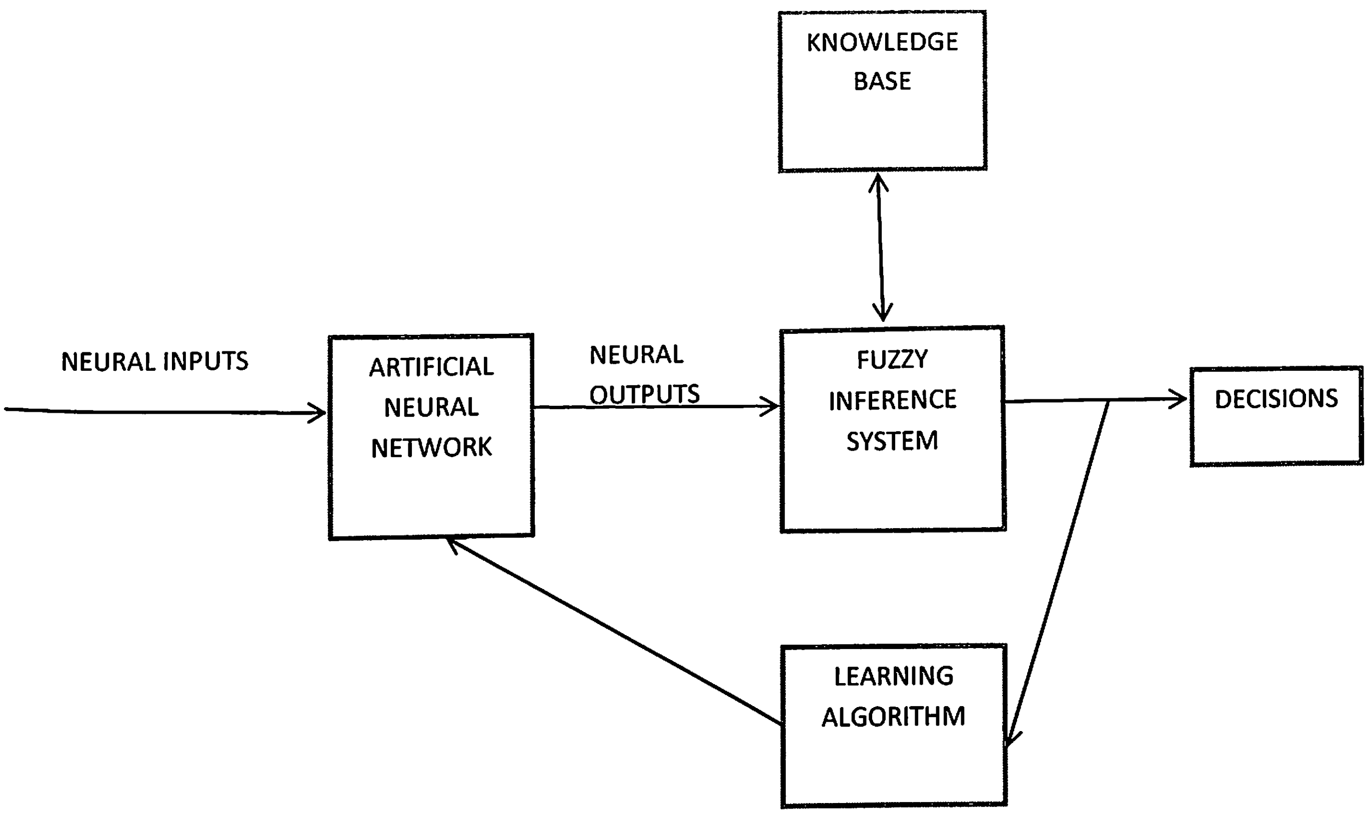


Figure 4.1 Hybrid Neuro Fuzzy Model

In this hybrid neuro fuzzy model, the outputs from the neural network are fed as the inputs to the fuzzy inference system. Within the fuzzy inference system, the fuzzy system inputs are assigned with membership functions. This process is called fuzzification. After this each input is matched with the fuzzy rules that are stored within the knowledge base. According to the rules comparison, decision is made whether the patient is glaucomatous or non-glaucomatous. After this, defuzzification is done and decisions are made.

# CHAPTER 5
# DESIGN AND IMPLEMENTATION

# 5. DESIGN AND IMPLEMENTATION

The designed hybrid neuro-fuzzy model consists of 4 input variables I, C, M and T. The training data is characterized by two classes N and G. Each input is represented by two linguistic terms, thus we have 16 rules. The figure below represents the hybrid neuro-fuzzy model

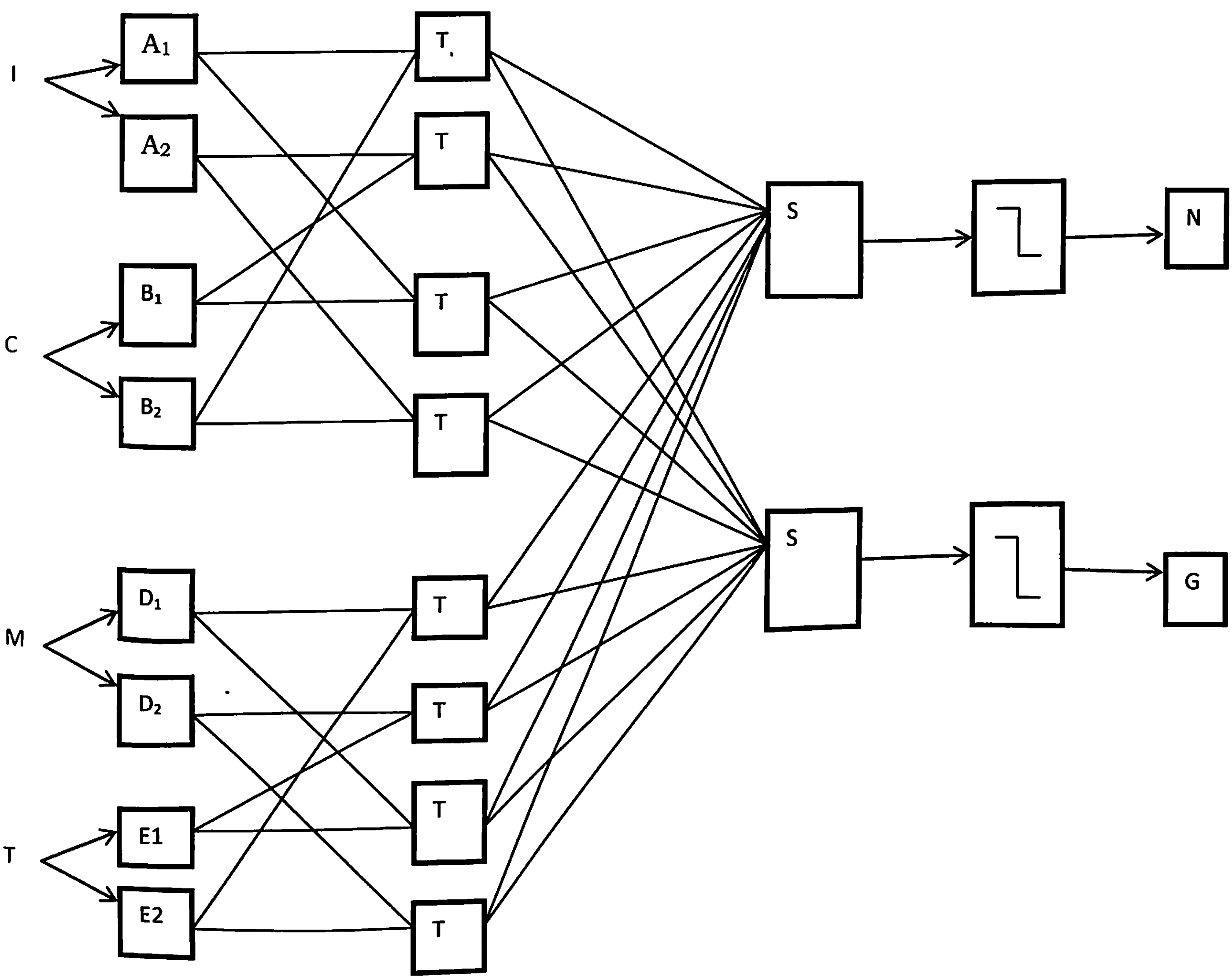


Figure 5.1: Flow of Hybrid Neuro Fuzzy Model

- **Layer 1** The output of the node is the degree to which the given input satisfies the linguistic label associated to this node. Usually, we choose bell-shaped membership functions

$$\exp\,[-\frac{1}{2}(\frac{u-a_{i1}}{b_{i1}})^2]$$

$$\exp\,[-\frac{1}{2}(\frac{v-a_{i2}}{b_{i2}})^2$$

to represent the linguistic terms, where *{ai1, ai2, bi1, bi2},* is the *parameter set.* As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic labels *Ai* and *Bi.*
- **Layer 2** Each node generates a signal corresponding to the conjunctive combination of individual degrees of match. The output signal is the firing strength of a fuzzy rule with respect to an object to be categorized.

In most pattern classification and query retrieval systems, the conjunction operator plays an important role and its interpretation context-dependent.
Since does not exist a single operator that is suitable for all applications, we can use parameterized t-norms to cope with this dynamic property of classifier design. All nodes in this layer are labeled by *T,* because we can choose any t-norm for modeling the logical *and* operator. The nodes of this layer are called *rule nodes.*
We take the linear combination of the firing strengths of the rules at *Layer 3* and apply a sigmoidal function at *Layer 4* to calculate the degree of belonging to a certain class.
If we are given the training set
$\{(x_k, y_k), k = 1, \ldots, K\}$
where $x_k$ refers to the $k$-th input pattern and

$yk =$

$\{(1, 0)T$ if $x_k$ belongs to Class 1

$(0, 1)T$ if $x_k$ belongs to Class 2$\}$

then the parameters of the hybrid neural net (which determine the shape of the membership functions of the premises) can be learned by descent-type methods. The error function for pattern $k$ can be defined by

$$E_k = \frac{1}{2}\left[\left(o_1^k - y_1^k\right)^2 + \left(o_2^k - y_2^k\right)^2\right]^2$$

where $y_k$ is the desired output and $ok$ is the computed output by the hybrid neural net.

Following are the rules implemented in designed fuzzy block:

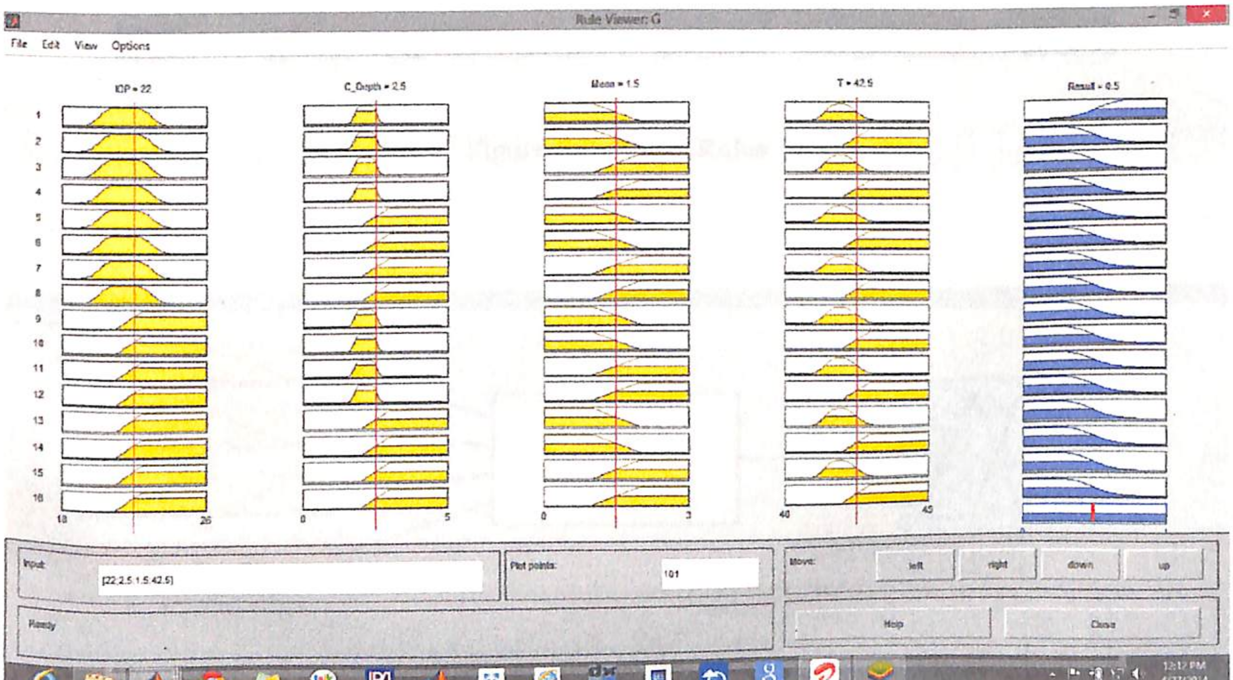


Figure 5.2: Designed Fuzzy Inference System

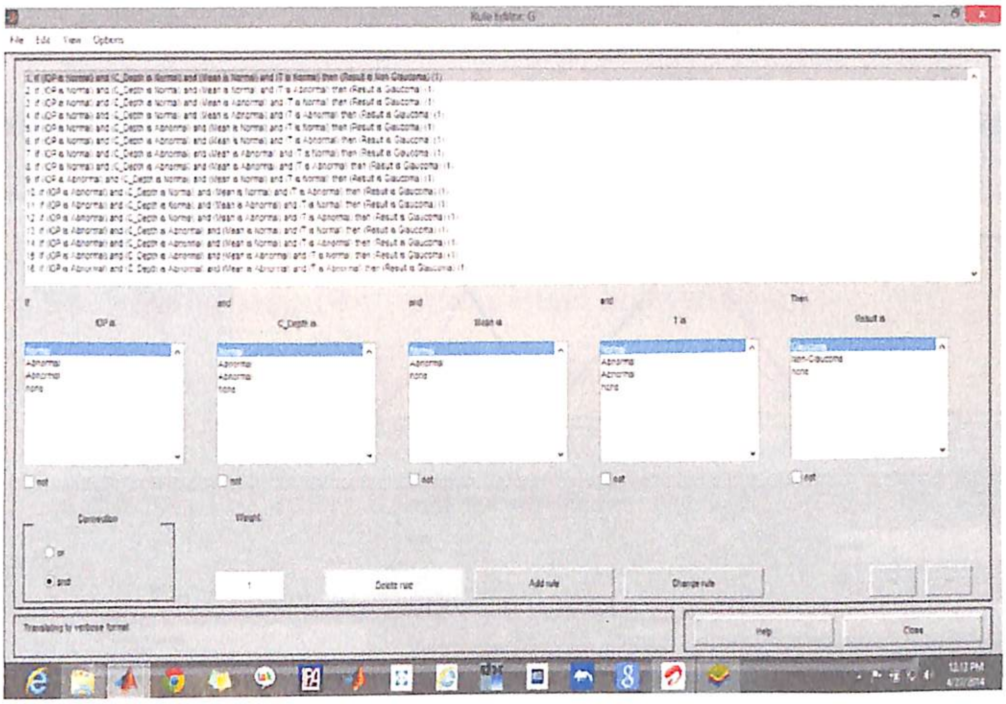

Figure 5.3: Fuzzy Rules

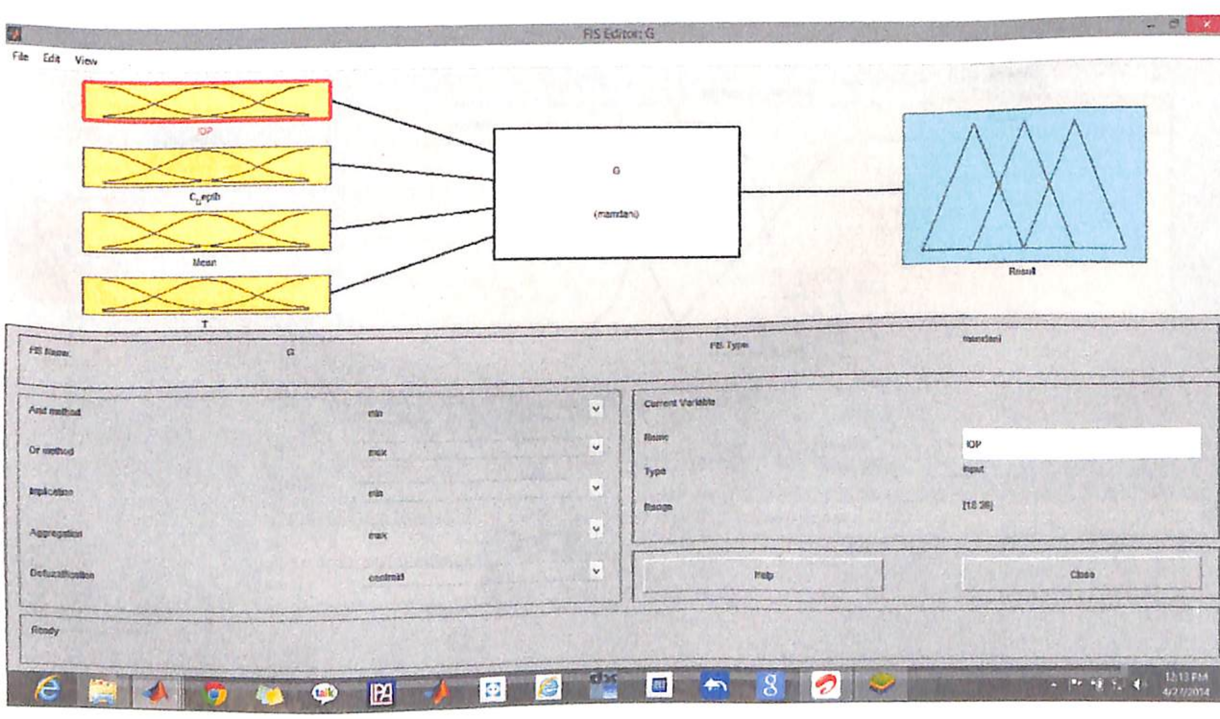


Figure 5.4: Fuzzy Block Diagram

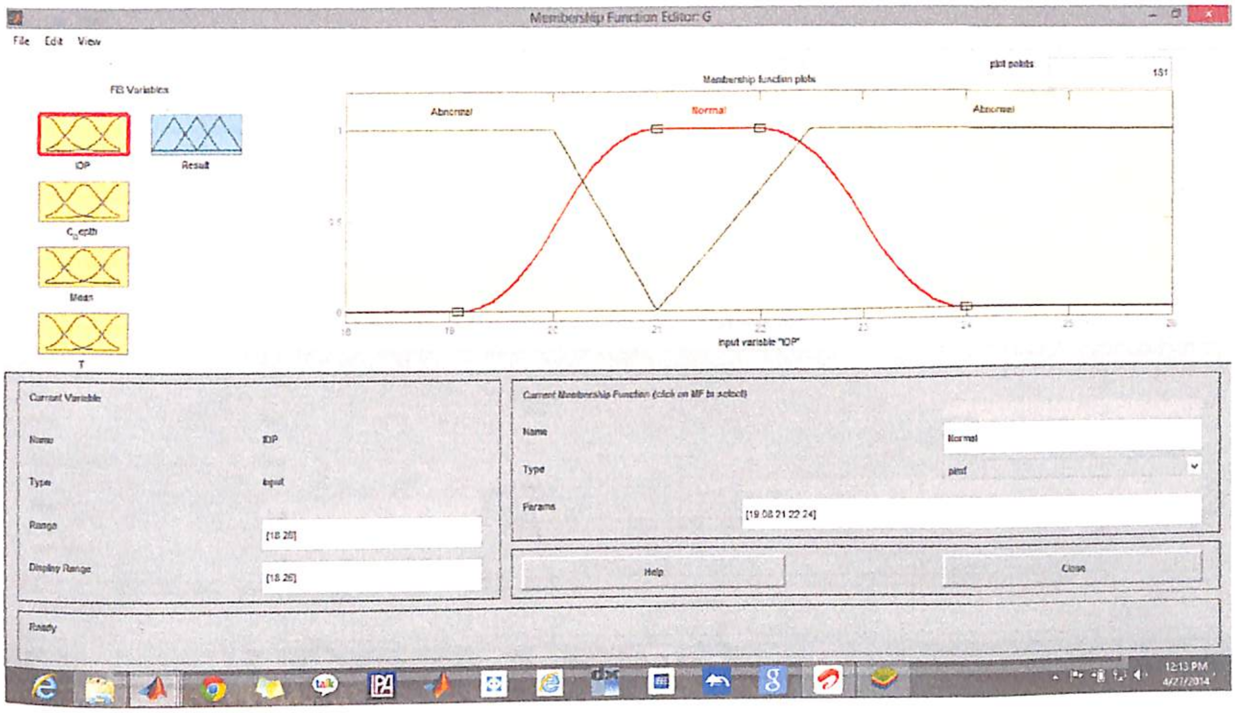

Figure 5.5: Membership Functions Plot (IOP)

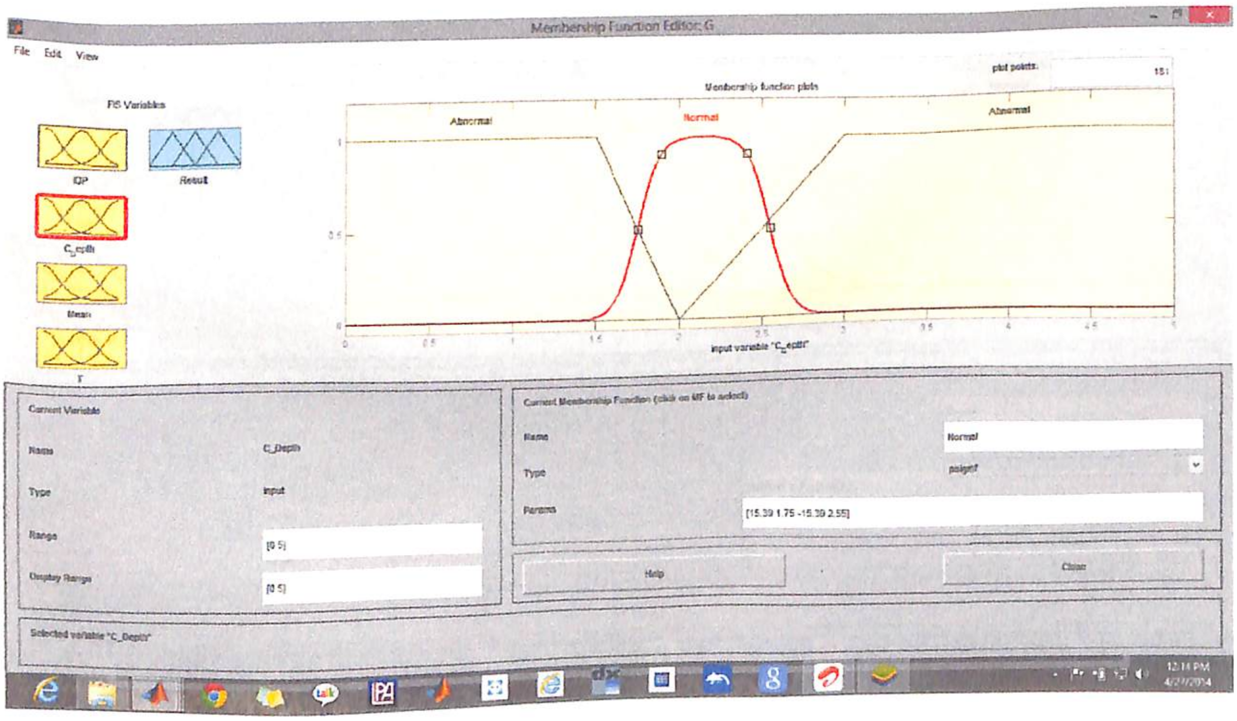

Figure 5.6: Membership Function Plot (Chamber Depth)

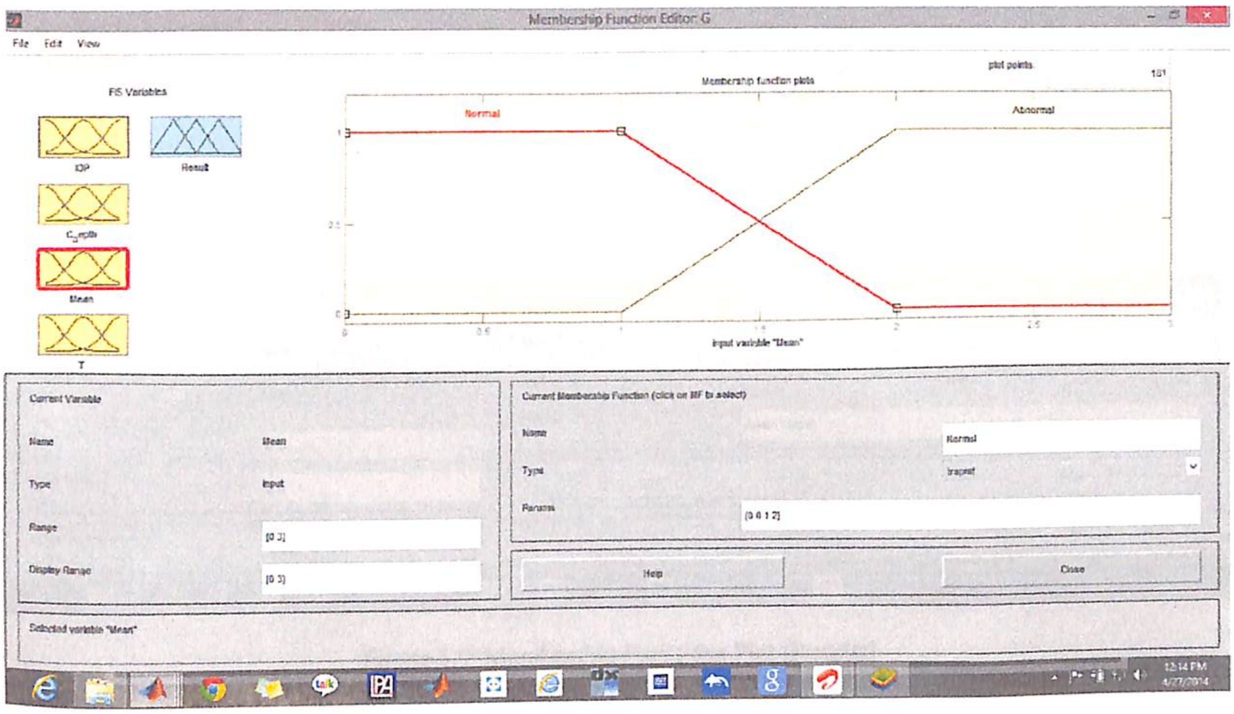


Figure 5.7: Membership Function Plot (Mean)

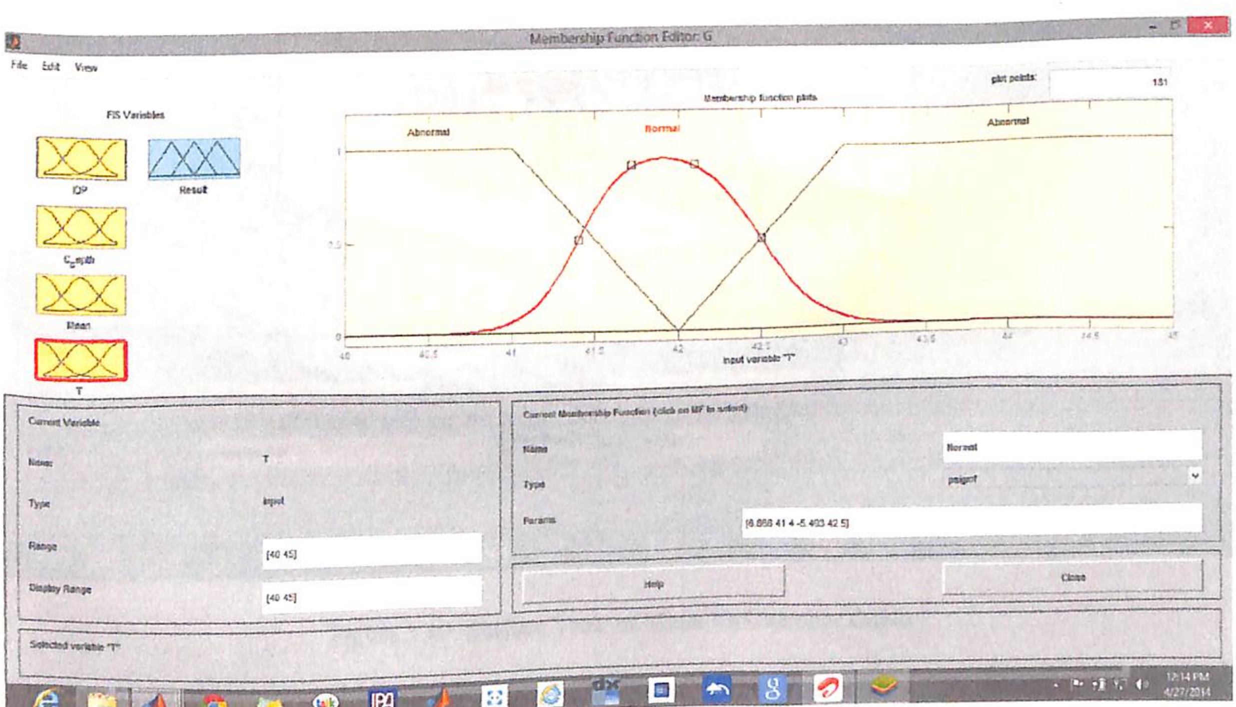


Figure 5.8: Membership Functions Plot (Mean Thickness)

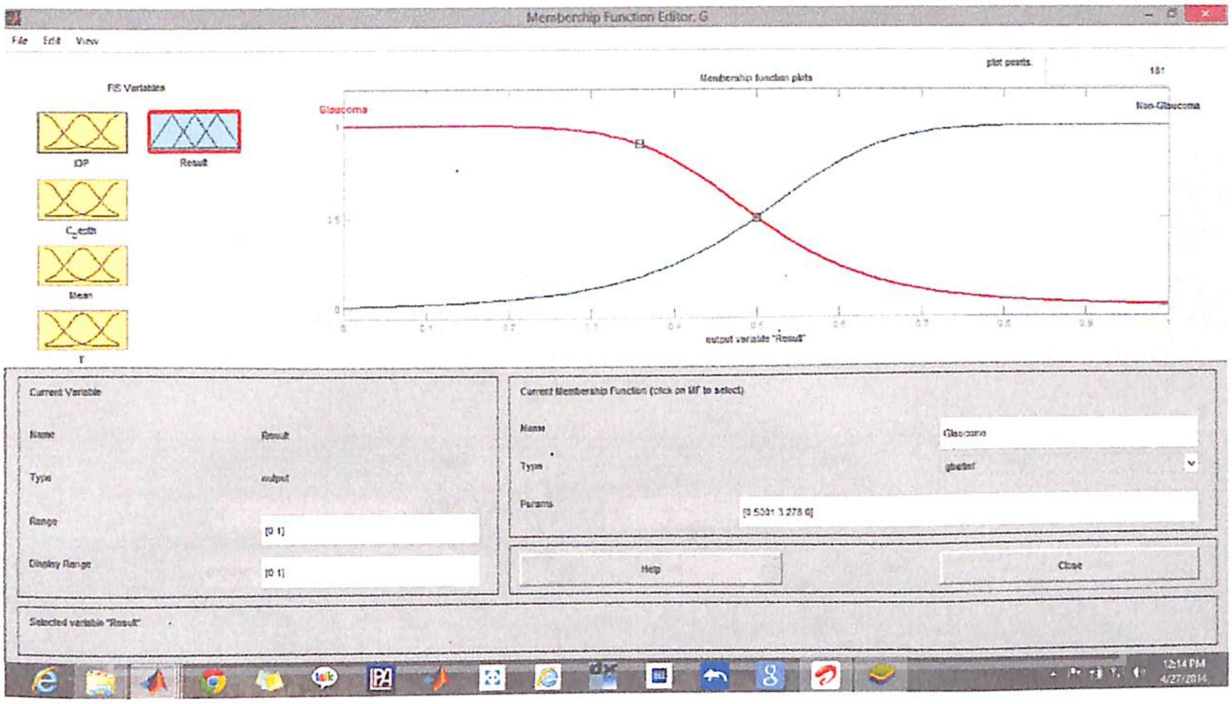

Figure 5.9: Membership Functions Plot (Results)

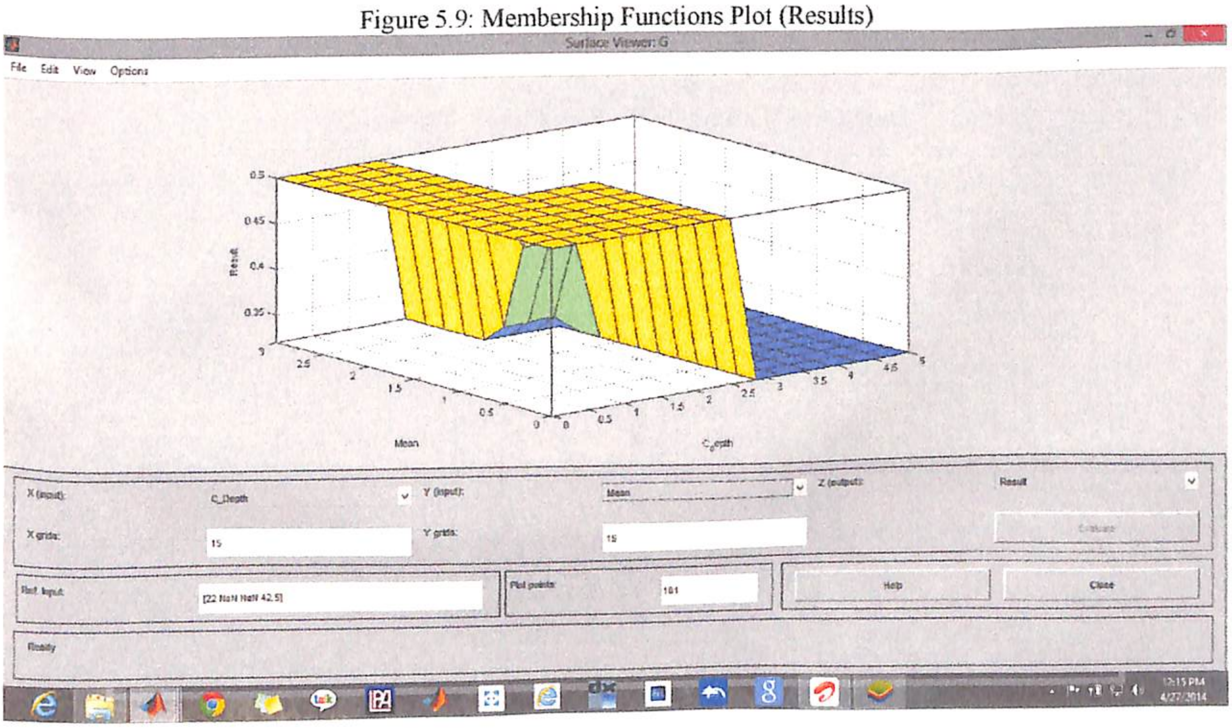

Figure 5.10: Surface View of Mean Vs Chamber Depth

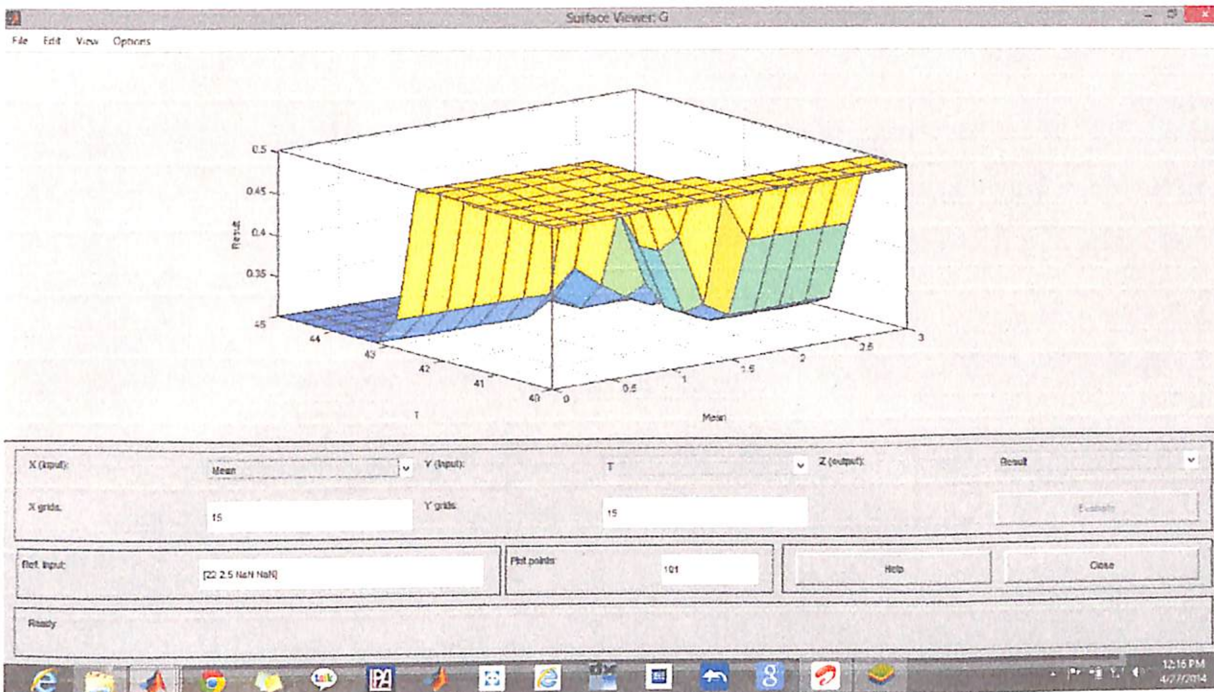


Figure 5.11: Surface View of Thickness Vs Mean

# CHAPTER 6
# COMPARISON OF ANN AND HYBRID MODEL

# 6. COMPARISON OF ANN AND HYBRID MODEL

The previously proposed artificial neural network was unable to make predictions about the early glaucoma diagnosis. As analyzed from the literature survey that artificial neural networks and fuzzy systems have the own drawbacks.

The artificial neural network has following disadvantages:

- Impossible interpretation of the functionality.
- Difficulty in determining the number of layers and number of neurons.
- Unable to make predictions.

The fuzzy system has following disadvantages:

- Incapable to generalize, or either, it only answers to what is written in its rule base.
- Not robust in relation the topological changes of the system, such changes would demand alterations in the rule base.
- Depends on the existence of an expert to determine the inference logical rules.

By analyzing the drawbacks of previously proposed neural network model, we come to the hybrid neuro-fuzzy model. Since the neural network as well as the fuzzy system has many drawbacks so we tried to combine the advantages of both the neural network as well as fuzzy system. The problem of finding membership functions and appropriate rules is frequently a tiring process of attempt and error. This led to the idea of applying learning algorithm to the fuzzy systems. The neural networks, that have efficient learning algorithms, had been presented as an alternative to automate or to support the development of tuning fuzzy systems.

**ADVANTAGES OF HYBRID NEURO-FUZZY MODEL:**

- Easy interpretation of system's functionality.
- Fast learning through patterns.
- On-line adaptability.
- Small computational complexity.
- Self-adjusting with the aim of obtaining the small global error possible.
- These are universal approximators with the ability to solicit interpretable IF-THEN rules.
- Strong robustness and high accuracy.
- Neural networks are used to tune membership functions of fuzzy systems that are employed as decision-making systems for controlling equipment.

# CHAPTER 7
# CONCLUSION

# 7. CONCLUSION

Glaucoma is an optic neuropathy characterized by group of ocular disorders. Elevated intraocular pressure is one of the risk factors that can lead to glaucoma. But in case of low tension glaucoma, IOP remains the same. Therefore, it cannot be considered as the only parameter that leads to glaucoma.

Since, the diagnosis of glaucoma cannot be relied on one single parameter. Therefore other parameters such as retinal nerve fibre layer, optic nerve head, cup disc ratio, visual field defects and many other parameters are taken into consideration. Some of the parameters such as cup disc ratio as well as the effect on papilla are proven to be the most valid parameters to discriminate between glaucomatous and non-glaucomatous eyes.

In our proposed work, Hybrid neuro-fuzzy model was developed for the glaucoma diagnosis. For our model we took only four parameters that are chamber depth, intraocular pressure, effect on papilla thickness and mean of all isopters (15, 20, 25 ad 30 degrees) of visual fields. Some fuzzy rules were created based on the above mentioned parameters. Based on these rules, fuzzy inference system was created.

The following are the list of direction which could be taken:

- The number of parameters could be increased at the input layer.
- Some learning algorithm such as genetic algorithm can be introduced to make the model more predictive.
- Some new parameters such as optic nerve head parameters could be introduced to make are model more reliable.
- Increase the dataset size to further define the model and investigate other analysis methods for early prediction.

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