A

DISSERTATION REPORT

On

Neuro-Fuzzy System for the Diagnosis of EMG Based Diseases

Submitted to

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In partial fulfillment of the requirements for the award of degree of

MASTER OF PHILOSOPHY (M.Phil)

IN

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CERTIFICATE OF THE SUPERVISOR

This is to certify that the work entitled "Neuro-Fuzzy System for the Diagnosis of EMG Based Diseases" is a piece of research work done by Ms. Heena under my guidance and supervision for the degree of Master of Philosophy in Computer Science of Lovely Professional University, Phagwara, Punjab, India. To the best of my knowledge, the present work is the result of her original investigation and study. No part of the project report has ever been submitted for any other degree or diploma.

The dissertation is fit for the submission for the partial fulfillment of the conditions for the award of M.Phil n computer science.

Date: 25April2014

Signature of supervisor

Dr. Babita Pandey

DECLARATION BY THE CANDIDATE

I hereby declare that the dissertation titled ”Neuro-Fuzzy System for the Diagnosis of EMG Based Diseases” is an authentic record of my own work carried out as requirement for the award of degree of M.Phil(Computer Application) at Lovely Professional University, Phagwara, Punjab, India. The matter presented in the dissertation has not been submitted in part or full to any other university or institute for the award of any degree.

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Abstract

This thesis include Electromyography (EMG) based diseases and their diagnosis. EMG is a procedure to record electrical activity from the muscles. These diseases are progressive in nature therefore their early diagnosis is very difficult. Therefore, we need a diagnostic method that accurately diagnoses the neuro muscular disease (NMD) in their early stage. Neuro-fuzzy system is developed for the diagnosis of EMG based diseases at second level because the integration of fuzzy logic and neural network reduces the rules, decreases computational time, and consumes the less memory. For diagnosis EMG based diseases at second level, using psychological, cognitive and muscular as well as EMG parameters will produce more accurate results. The results were satisfactory and were shown in the form of sensitivity and specificity.

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Lastly and most importantly, I wish to thanks to all those who were directly and indirectly involved in the completion of this work thereby making it a total success.

Signature of Candidate

Ms. Heena

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ANN…….Artificial neural networks

AN……..anxiety

AM…….....amplitude

BMD……..Becker muscular dystrophy

CBR ……..case base reasoning

CMD…….Congenital muscular dystrophy

Cog……....Cognitive symptoms

CRD……..complex repetitive discharge

CS……..**.....**climbing stairs

DE…….depression

DM……..…..Data mining

DMD…….Duchenne muscular dystrophy

DU……....duration

EDMD……..**....**Emery–Dreifussmuscular dystrophy

EMG…….Electromyography

EM…….Endocrine myopathy

FA……Fasciculation

FI……...Fibrillations

FNN……...Fuzzy Neural Network

FR……...frustration

FSH……..Facioscapulohumeral muscular dystrophy

FT…… fatigue

H…….....high

HD……...hearing disability

Int lig……...internal ligual parameters

IS…….....isolation

LD…….learning disability

L…….....Low

LGMD…….Limb-girdle muscular dystrophy

LH……...lifting above the head or shoulder

M …….....Medium

MA…….motor activity

MD…….Muscular dystrophy

MDI…….....mytonic discharge

MG……..myasthenia gravis

MIMO…….multiple inputs and Multiple outputs

MI……..muscle inflammation

MM…….Metabolic myopathy

MMD…….myotonic muscular dystrophy

Mot…….....motor symptoms

MP……...Muscle pain

M phy……..muscular physiology

MS……...muscle stiffness

Mus…….Muscular

Mus Psy……..muscular psychological symptoms

MUAP…….Motor unit action potential duration

N…….Neuropathy

NFS…….Neuro-Fuzzy System

NMD……..neuromuscular disorder/ neuromuscular diseases

NVC…….....nerve conduction velocity

OPMD……...Oculopharyngeal muscular dystrophy

PH…….....phase

PHY…….....physiological symptoms

PL……poliomyelitis

PO……ploymyositis

PP……physio-psycho

PSW…….....positive sharp wave

Psy…….....psychological symptoms

QEMG……..Qualitative Electromyography

R…….……...running

RBR ……..……rule base reasoning

RC…….rising above the chair

ROC…….….Receiver operating characteristics

SD……..speech disability

SPO…….....Spontaneous activity

TC……..touch disability

VB……..….Visual Basic

VD…….....visual disability

VH…….....very high

VL…….....very low

W……...walking

Chapter-1

Introduction

EMG (Electromyography) is procedure to record an electrical activity from the muscle. The qualitative and quantitative assessment of EMG signal is used for the diagnosis of Neuro muscular disease. Qualitative assessment of EMG (QEMG) is subjective and based on skilled and experienced clinician and prone to higher error whereas quantitative assessment of EMG is objective. The clinicians use the feature of EMG for the diagnosis of neuromuscular disorder (NMD). The EMG recorded from muscle affected by NMD is changes depending upon the extent to which muscle is affected. Therefore QEMG is an important method to diagnosis NMD. Several QEMG methods such as inference pattern analysis, frequency domain analysis and time domain analysis are already used for the diagnosis of NMD. But they have certain limitations.

Neuromuscular disease (NMD) is caused by muscular abnormality. These diseases are progressive in nature therefore their early diagnosis is very difficult. Some of the NMD are also not curable in the final stage. Therefore, we need a diagnostic method that accurately diagnoses the NMD in their early stage. Although a number of conventional and intelligent methods such as: heuristic methods, artificial neural networks (ANN), data mining (DM), case base reasoning (CBR), rule base reasoning (RBR) [2,3,19] are available for the diagnosis of NMD but they have their own limitations. The disadvantages of one type of intelligent technique can be reduced by integrating two or more intelligent techniques. The integration of RBR with CBR improves knowledge acquisition, modularity [2]. The integration of fuzzy and neural network reduces the rules, decreases computational time, consumes the less memory and improves learning [19].

In this work we have combined fuzzy with neural network for accurate results diagnosis EMG based diseases at second level, using psychological, cognitive and muscular as well as EMG parameters will produce more accurate results. For classification of EMG based diseases at second level using Neuro-fuzzy system, eight muscular dystrophy diseases are used and these diseases are duchenne muscular dystrophy (DMD), Becker muscular dystrophy (BMD), congenital muscular dystrophy (CMD), Emery–Dreifussmuscular dystrophy (EDMD), Facioscapulohumeral muscular dystrophy (FSH), Limb-girdle muscular dystrophy (LGMD), myotonic muscular dystrophy (MMD) and Oculopharyngeal muscular dystrophy (OPMD).

1.1Objective:

As discussed in above section, psychological, cognitive, muscular symptoms play very important role in the diagnosis of NMD.

The central hypothesis of this thesis is:

Integration of Neural network and fuzzy logic will produce more accurate results for the diagnosis of NMD at second level when psychological, cognitive, and muscular as well as EMG parameters are used.

AIM 1: To identify psychological, cognitive and muscular symptoms is depicted in second level NMD.

AIM 2: To develop Neuro-fuzzy system for the diagnosis of second level Neuromuscular disorder.

1.2. Basic Concepts:

EMG: EMG is a technique used to record electrical activities of muscles from the body. Figure 1.1 shows EMG signals.

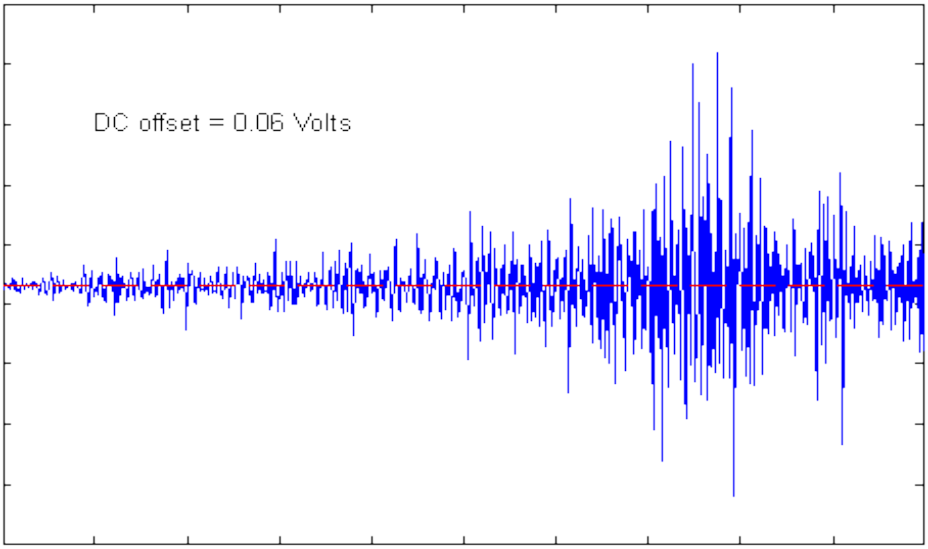


Figure 1.1: EMG signals [21]

- **EMG signal parameters:** EMG signal parameters are divided into two groups: pattern characteristic such as: positive sharp wave, complex repetitive discharge and mytonic discharge and MUAP (motor unit action potential)parameters such as: amplitude, duration, and phase.

  - **Positive sharp wave:** positive sharp waves are unstructured firing action potentials stimulated by needle movement of an injured muscle fiber.

  - **Complex repetitive discharge:** Complex repetitive discharge is an high frequency discharges that are action potentials originating from a principle innovator, initiate a group of single muscle fibers.

  - **Mytonic discharge:** Mytonic discharge is single muscle fiber action potentials trigger by needle movement, striking, or controlled reduction.

  - **Duration:** Duration is a time measurement which exit.

  - **Amplitude:** Amplitude is an electronic communication which uses transmits information via radio waves**.**

- **Phase:** It encodes the information carried from signals processing of a wave.

- **Physio-psycho parameters:** It is a behavioral science that studied the brains activities. Physio-psycho parameters are further divided into muscular parameter which is further divided into two parts: Muscular (MUS) parameters such as fibrillations (FI), fasciculation (Fa), muscle pain (MP), muscle inflammation (MI) and muscle stiffness (MS); and motor (MOT) parameters such as: difficulty in climbing stairs (CS),difficulty in walking (W), difficulty in running (R), difficulty in lifting above the head or shoulder.

- **Cognitive Parameters:** cognitive parameters are mental processing in which consideration of working memory is used. Cognitive parameters are visual disability (VD), touch disability (TC), speech disability (SD), hearing disability (HD) and learning disability (LD).

- **Psychological parameters:** psychological has immediate goal of understanding the concepts or entities. Psychological parameters are: fatigue (FT), anxiety (AN), depression (DE), isolation (IS) and frustration (FR).

- **Muscular psychological parameters:** Muscular psychological has immediate goal to understanding the entities related to muscles**.** These are fatigue (FT), anxiety (AN), depression (DP), isolation (IS).

- **Internal ligual parameters:** Internal ligual parameters are lung problem (LP), Cardiac arrhythmia (CA), congestive heart failure (CHF), chest pain (CP), heart muscle disease (HMD).

1.2.1 EMG Diseases:

Different types of muscular disease are muscular dystrophy, endocrine myopathy, neuropathy etc. these neuromuscular diseases are further classified at second level such as muscular dystrophy is further classified in following sub types:

➢ 1.2.1.1 EMG diseases at First Level:

Muscular dystrophy (MD): Muscular dystrophy is a group of inherited disorders that involve muscle weakness and loss of muscle tissue, which get worse over time. Figure 1.2 shows hierarchical representation of symptoms of Muscular dystrophy.

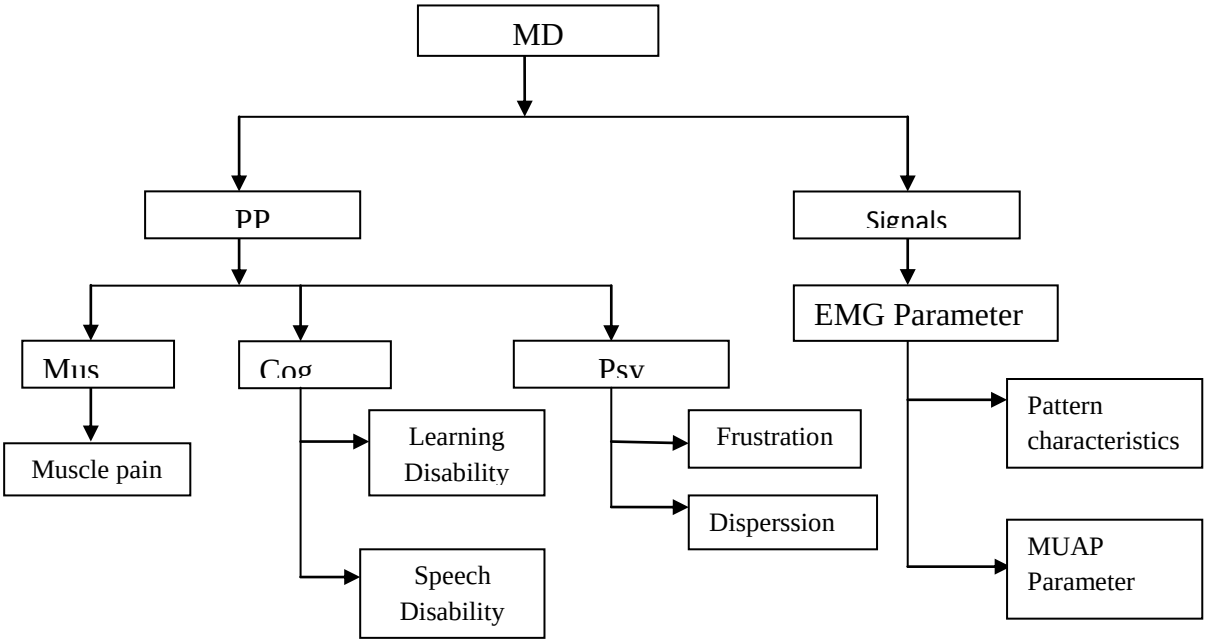


Figure 1.2: Hierarchical representation of symptoms of Muscular dystrophy

Polymyositis (PO): polymyositis is inflammatory disease from myopathies group of muscle disease associated with muscles and tissues. Figure 1.3 shows hierarchical representation of symptoms of polymyositis.

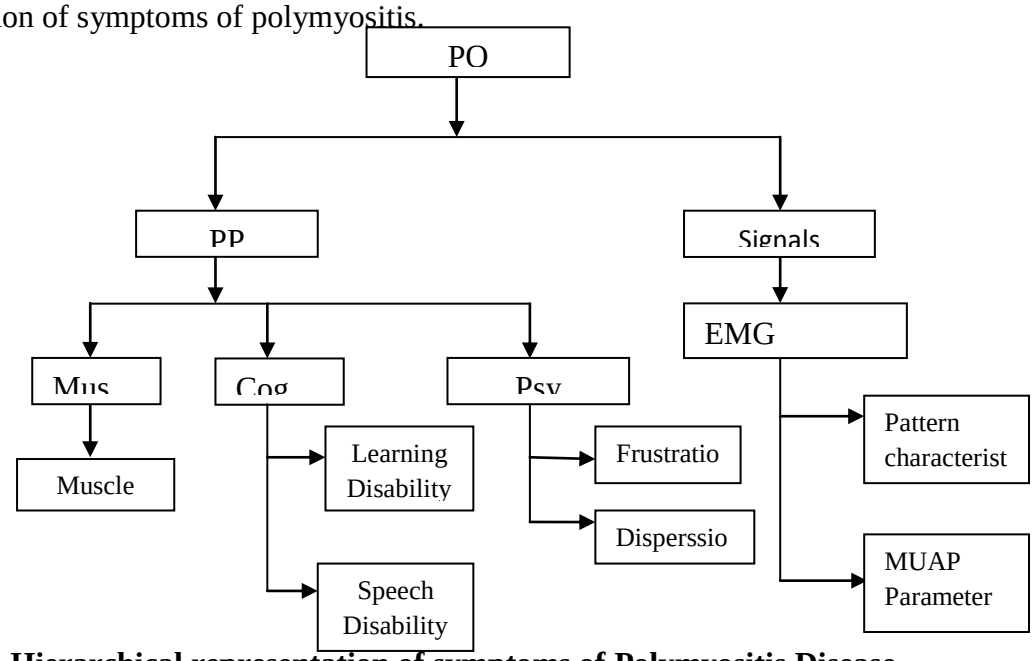


Figure 1.3: Hierarchical representation of symptoms of Polymyositis Disease

Endocrine myopathy (EM): It is an abnormal state of striated muscle. It occurs when gland produces very much or very small amount of hormones. Figure 1.4 shows hierarchical representation of symptoms of Endocrine myopathy.

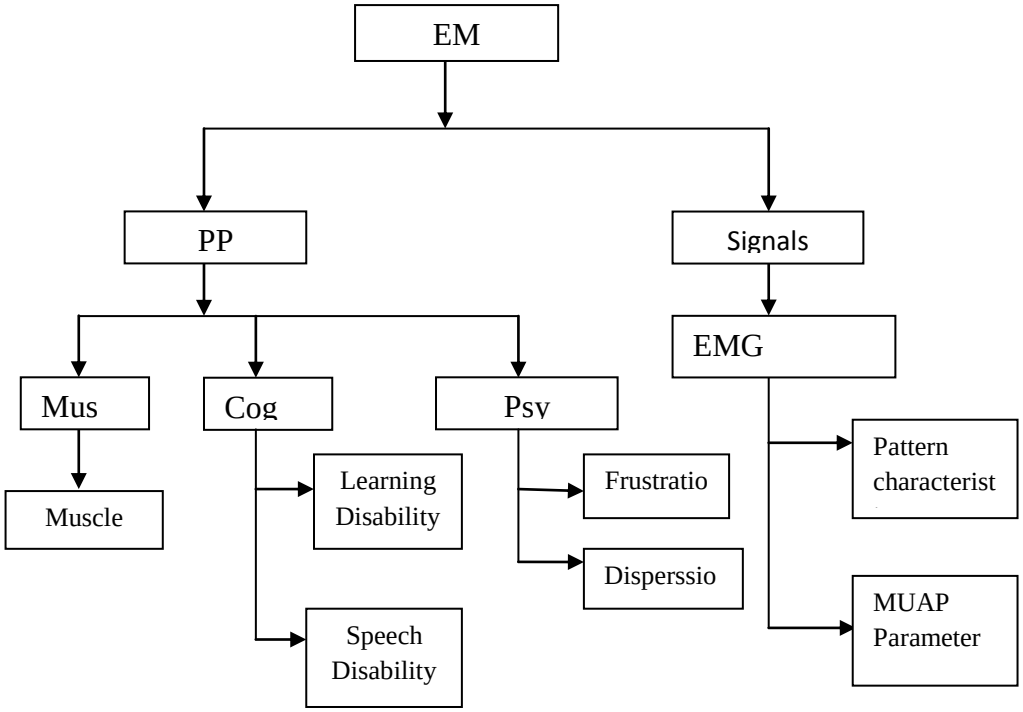


Figure 1.4: Hierarchical representation of symptoms of Endocrine myopathy

Metabolic myopathy (MM): it is a genetic disease, caused by defective genes. Figure 1.5 shows hierarchical representation of symptoms of Metabolic myopathy.

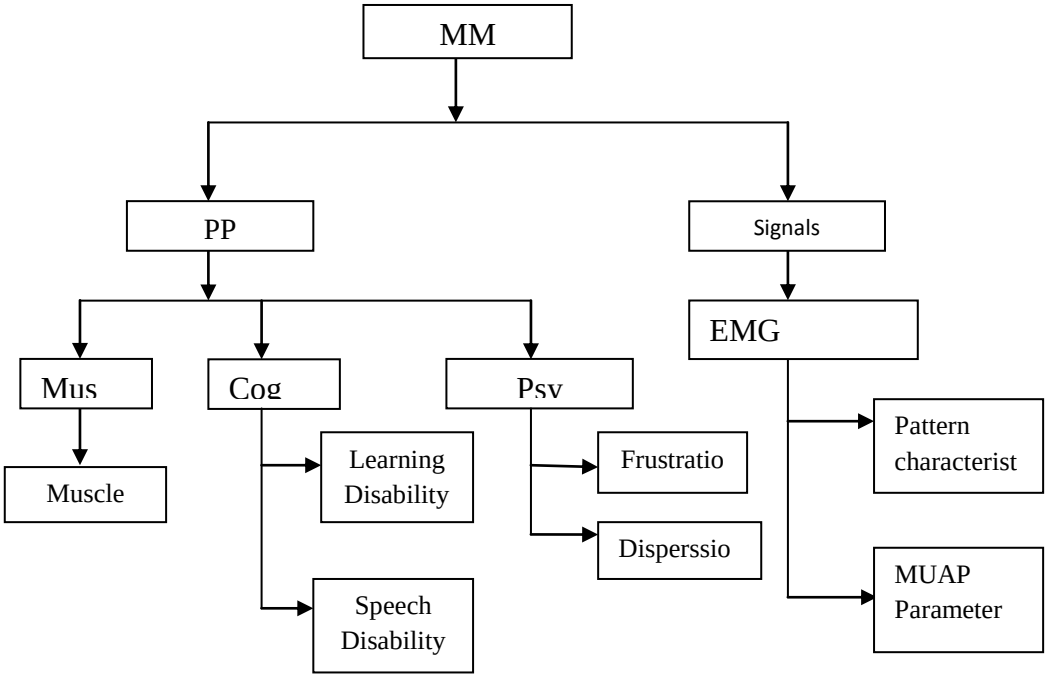


Figure 1.5: Hierarchical representation of symptoms of metabolic myopathy

Myopathy: myopathic disorder is caused by muscle fibretrophy, splitting. Amplitude of myopathy is similar to healthy patient, so it is difficult to analysis. Figure 1.6 shows hierarchical representation of symptoms of myopathy.

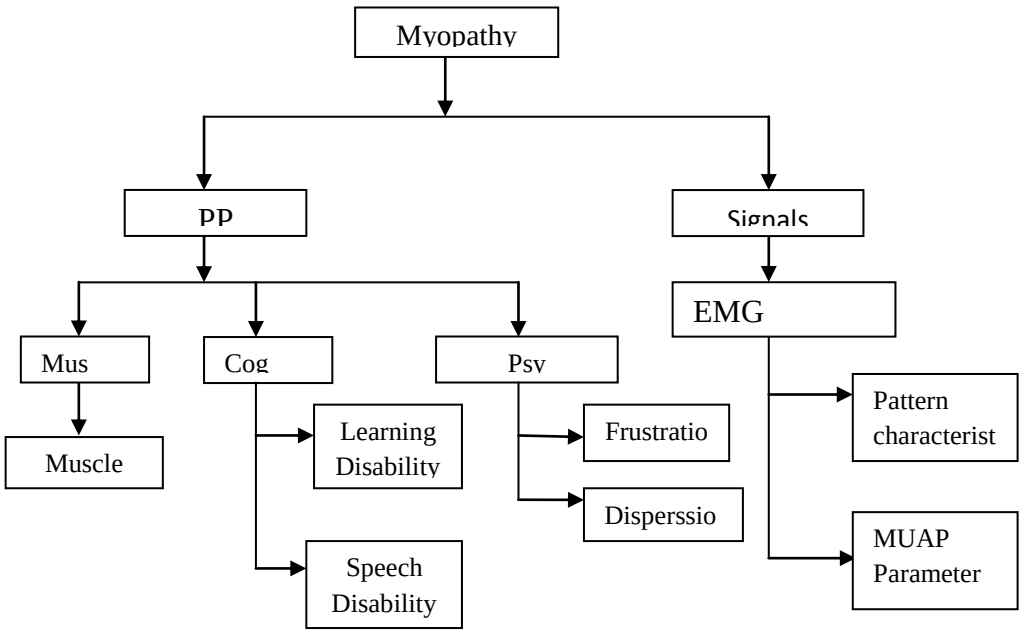


Figure 1.6: Hierarchical representation of symptoms of myopathy

Neuropathy: neuropathy is also known as peripheral neuropathy. It means damage in nerves and it also affects nerves outside of the brain and spinal cord. Figure 1.7 shows hierarchical representation of symptoms of neuropathy.

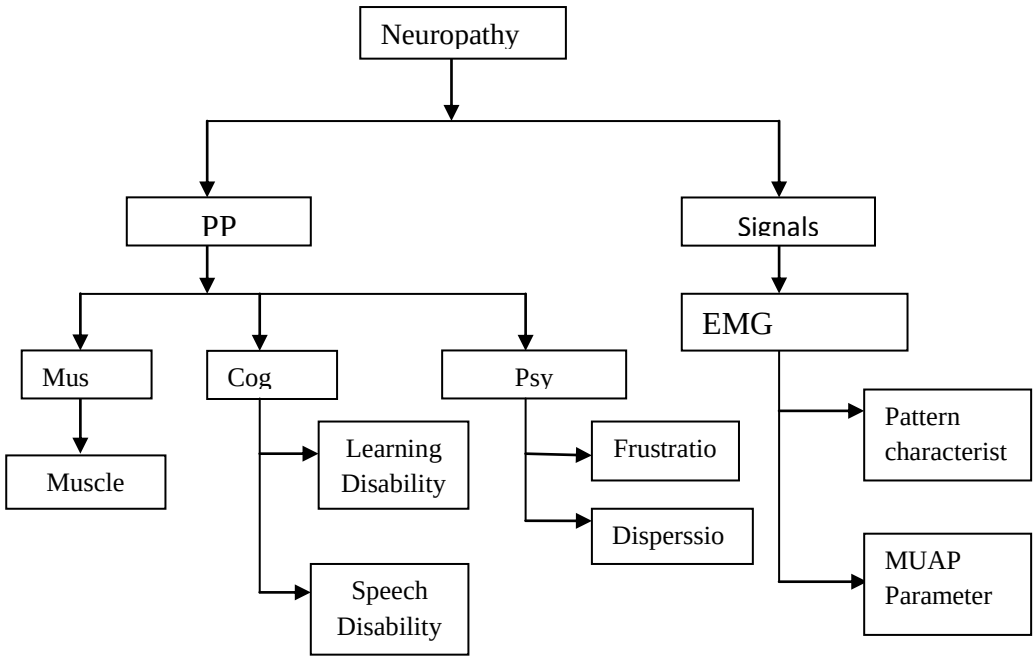


Figure 1.7: Hierarchical representation of symptoms of neuropathy

Myasthenia gravis (MG): It is a neuromuscular disorder. Neuromuscular disorders involve the muscles and the nerves that control them. Figure 1.8 shows hierarchical representation of symptoms of myasthenia gravis.

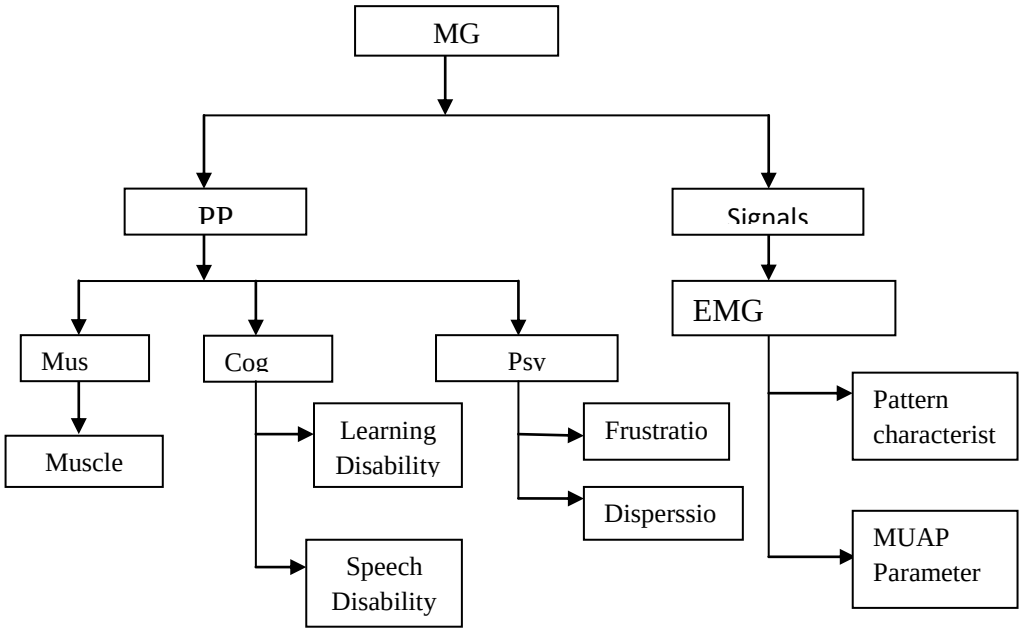


Figure 1.7: Hierarchical representation of symptoms of Myasthenia gravis

➢ 1.2.1.1 EMG diseases at Second Level:

Duchenne muscular dystrophy (DMD): It is a genetic disorder that involves muscle weakness and become worst very quickly. Figure 1.9 shows hierarchical representation of symptoms of DMD.

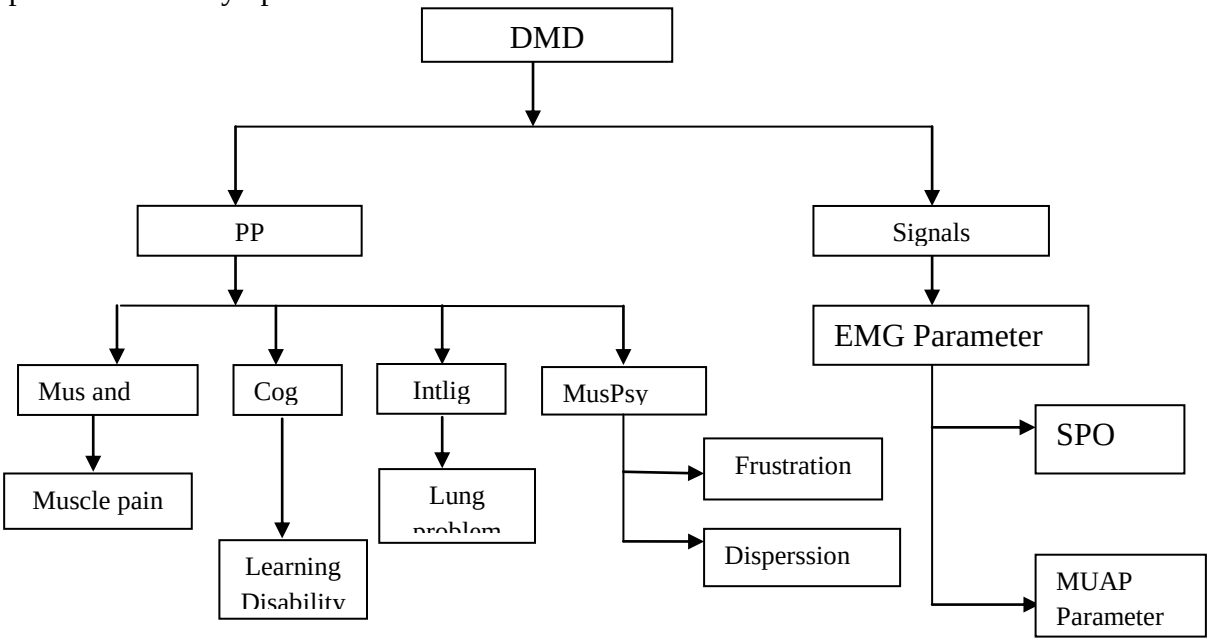


Figure 1.9: Hierarchical representation of symptoms of DMD

Becker muscular dystrophy (BMD): It is inherited diseases which progressive slowly and makes legs muscles weak. Figure 1.10 shows hierarchical representation of symptoms of BMD.

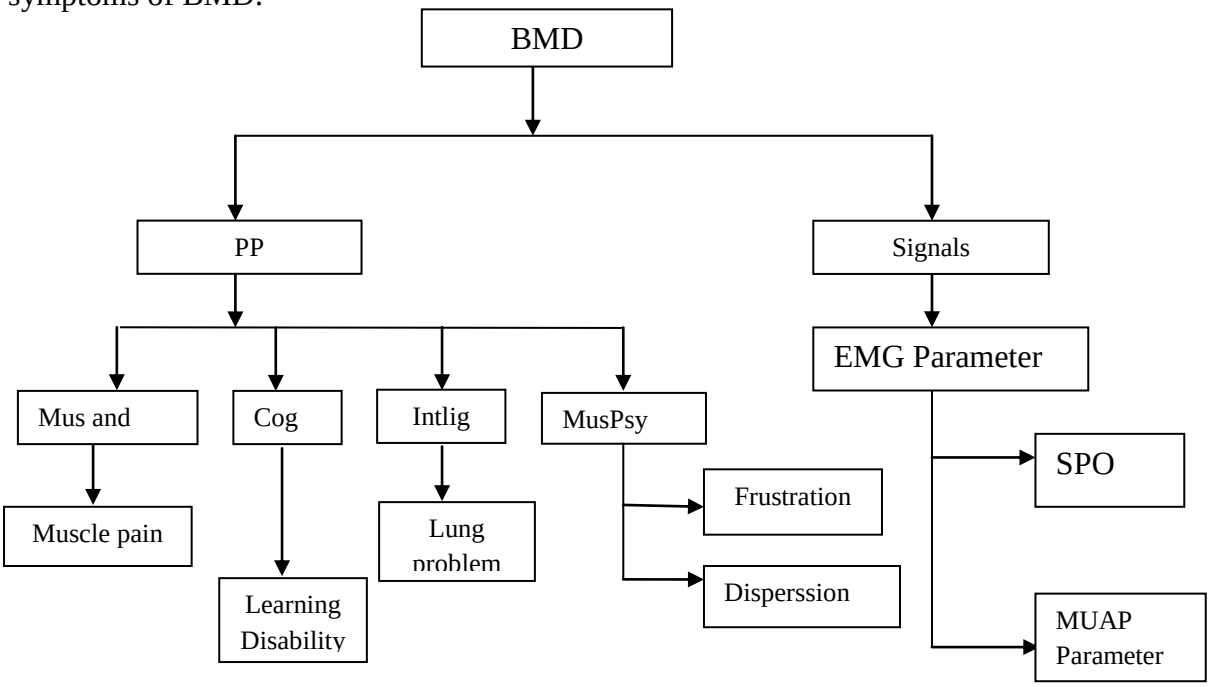


Figure 1.10: Hierarchical representation of symptoms of BMD

Congenital muscular dystrophy (CMD): It is a muscle weakness present in body by birth. Figure 1.11 shows hierarchical representation of symptoms of CMD.

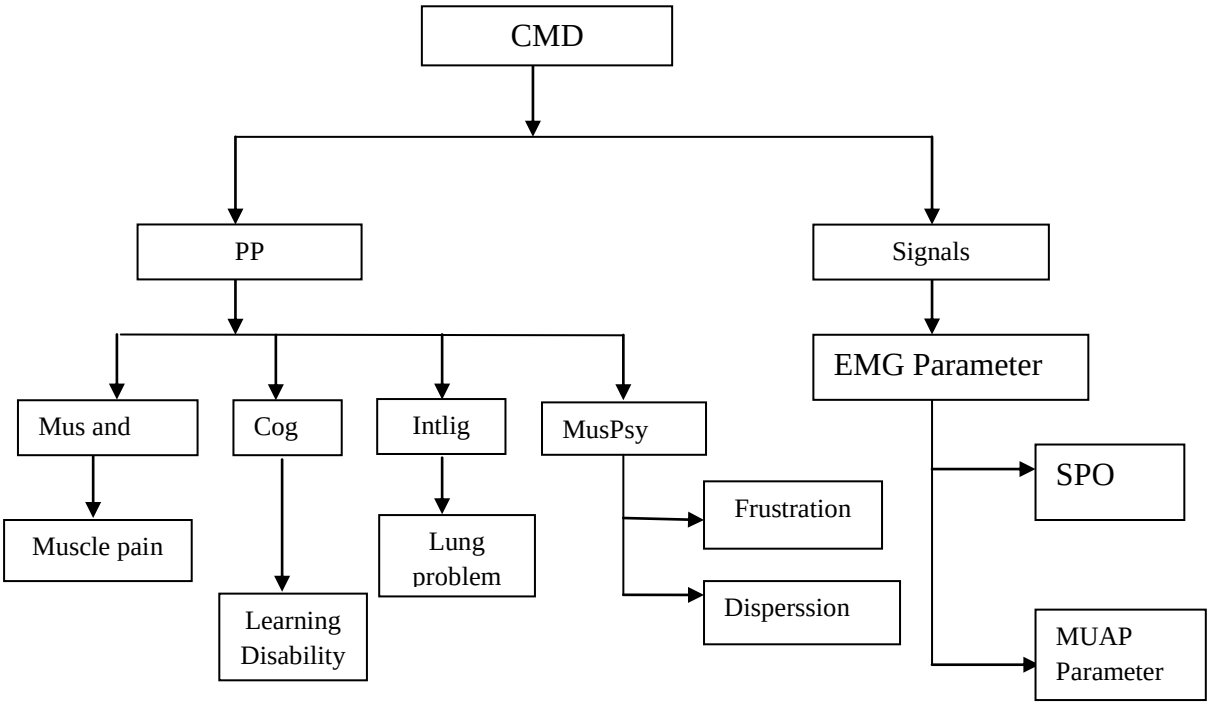


Figure 1.11: Hierarchical representation of symptoms of CMD

Emery–Dreifussmuscular dystrophy (EDMD): It affects the heart and movement muscles of body. Figure 1.12 shows hierarchical representation of symptoms of EDMD.

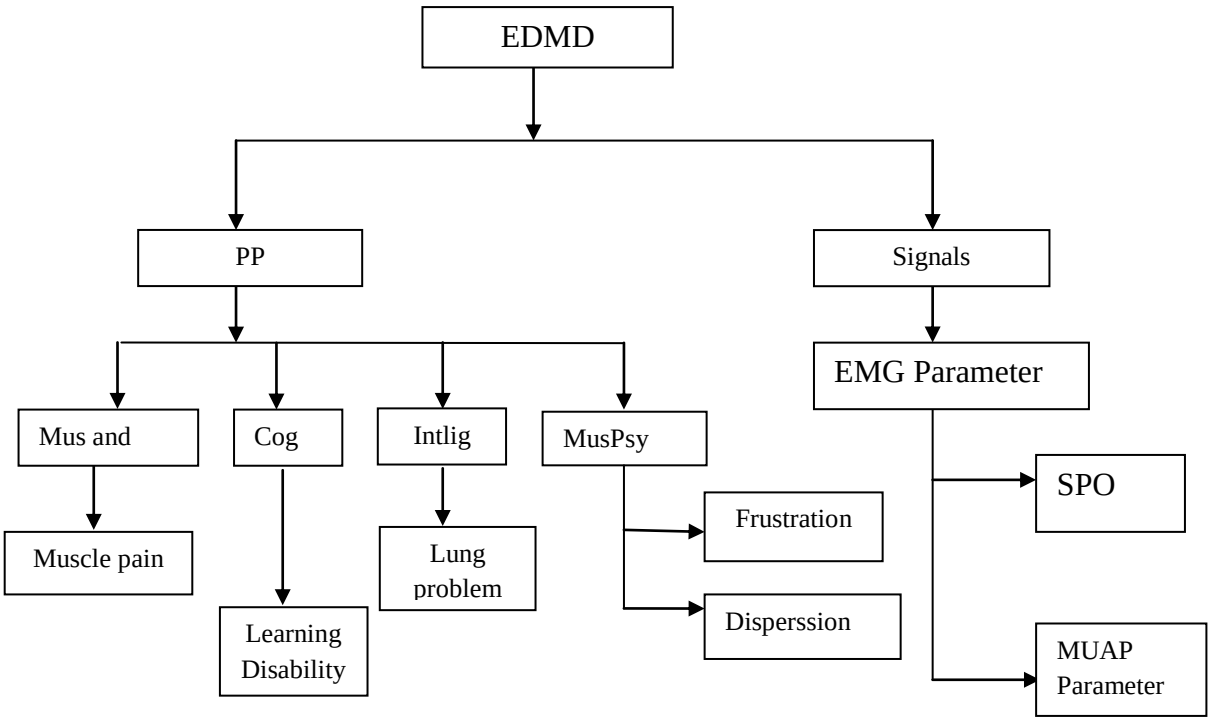


Figure 1.12: Hierarchical representation of symptoms of EDMD

Facioscapulohumeral muscular dystrophy (FSH): It affects the upper body muscles, its symptoms can be developed in childhood. Figure 1.13 shows hierarchical representation of symptoms of FSH..

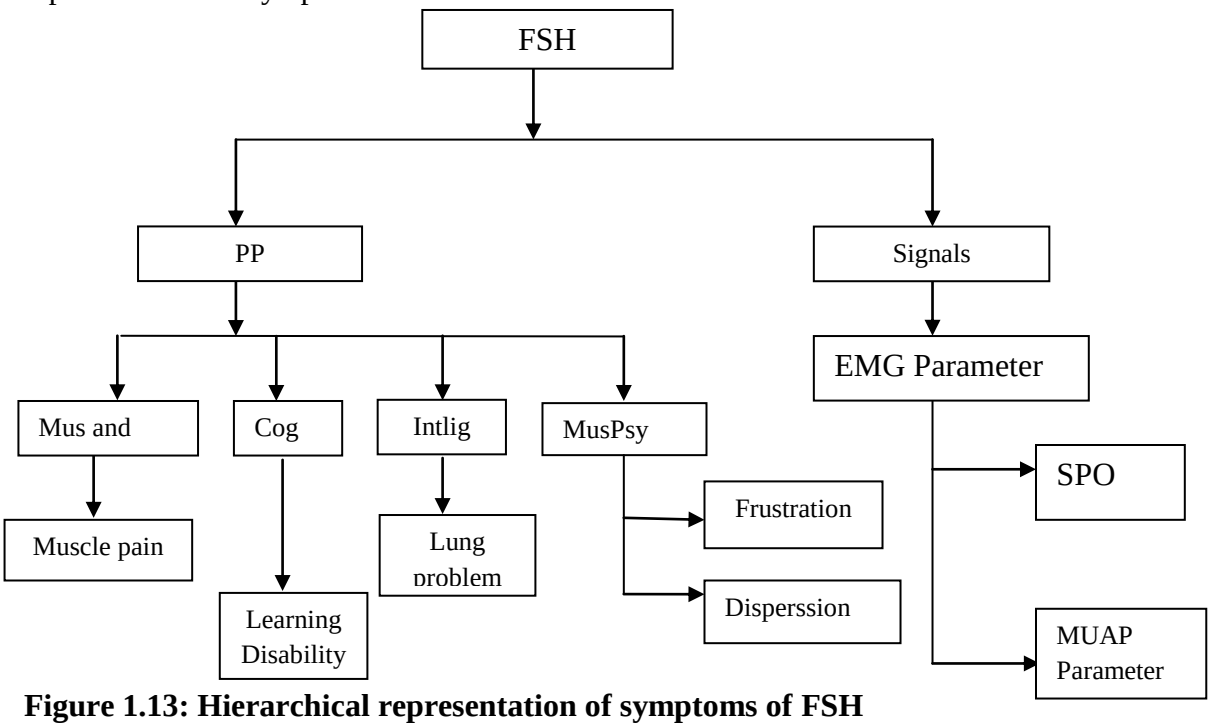


Figure 1.13: Hierarchical representation of symptoms of FSH

Myotonic muscular dystrophy (MMD): It is common disorder which occurs in adulthood. It can be Myotonic dystrophy type1 or Myotonic dystrophy type2. Figure 1.14 shows hierarchical representation of symptoms of MMD.

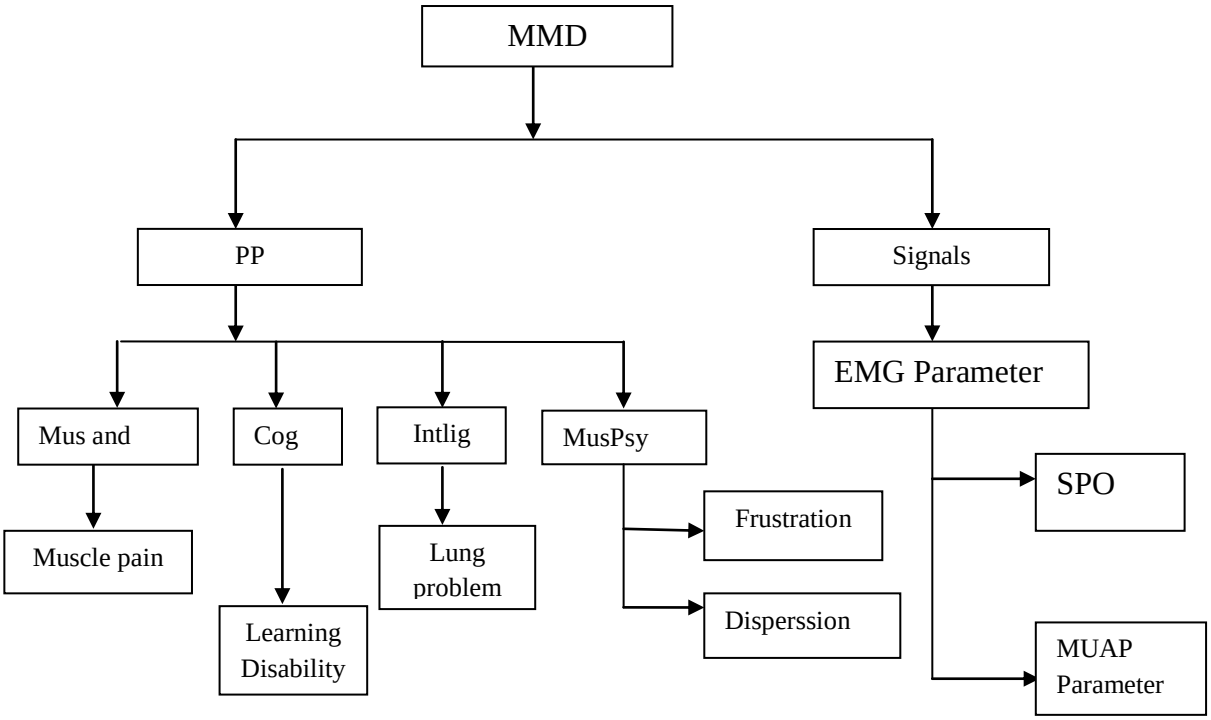


Figure 1.14: Hierarchical representation of symptoms of MMD

1.2.2 Neuro-Fuzzy System:

Neuro-fuzzy is combination of two techniques by combining human like reasoning like fuzzy systems and the learning structure of neural networks. Neuro-fuzzy system incorporates the human-like reasoning of fuzzy systems through the use of a linguistic model consisting of a set of IF-THEN fuzzy rules.[16]The main advantage of Neuro-fuzzy systems is that, they have the ability to apply IF-THEN rules.

1.2.2.1Neural Network (ANN):

Neural network is an information processing system or model that is inspired by the nervous system like Brain. Neural network is composed of large no of interconnected processing elements like “neurons” working in a unit to find solution for particular problem [16]. It requires less statistical training, and has ability to detect complex

relationship between the variables. Different neural network architecture is used like feed forward network and feedback network.[16]

The structure of neural network is produced with three layers and these are input layer, hidden layer and output layer.

1. Input Layer: input layer pass the input to the network for the processing.
2. Hidden Layer: The activity of hidden layer is depends on the activities of the input layer. Data is processed in this layer and produce output according to the input.
3. Output Layer: The action of output layer is based on the activity of the hidden layer. Data process and transfer result to the neuron in the next layer that is output layer.

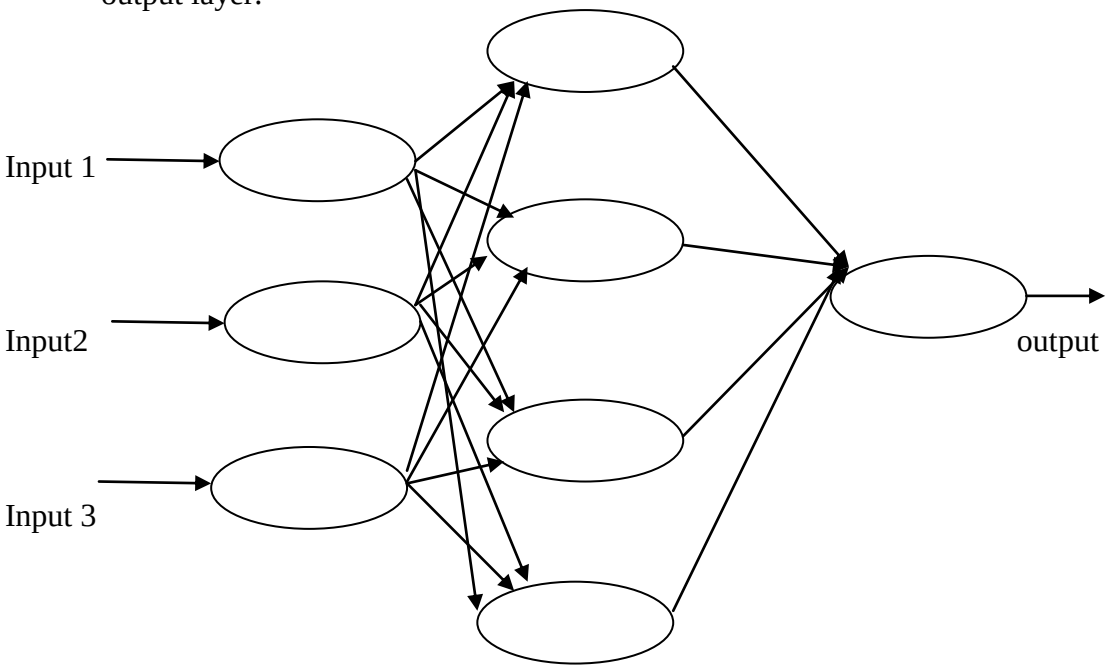


Figure 1.15: Layers of neural network

1.2.2.2 Fuzzy Logic:

Fuzzy logic is developed by Lotfi A. Zadeh in1965**.** Fuzzy logic can be defined into two senses, in narrow sense; it refers to a logical system that generalizes multivalve logic for reasoning under uncertainty and in broad sense, fuzzy logic refers to all theories and technologies that use fuzzy sets with unsharp boundaries in which membership is a matter of degree[11]. Fuzzy logic is designed to solve problems as

humans do by considering all presented data and process it to make best result. Fuzzy logic can be defined as mapping of input data into output. Fuzzy logic consists of four basic concepts and these are fuzzy sets, linguistic variables, possibility distributions and if-then rules.

1.3. Literature Review

Shaw and Bagha [12] deployed principal component analysis (PCA) and probabilistic neural network for the diagnosis of neuromuscular diseases. In their work, principal component analysis (PCA) is combined for features extraction and probabilistic neural network (PNN) technique is used to classify to the EMG signal.

Emanetal [5], deployed hidden markov model of surface electromyography (EMG) and ANN for the diagnosis of NMD. In their work, hidden markov model algorithm facilitates automatic SEMG feature extraction. EMG findings are used to detect and describe disease processes affecting the motor unit of the muscle.

Gerberet al [1], proposed a method for analyzing EMG signals, which estimate and detect potentials caused by active motor units in human, are described. His work is consisting of three phases, one is learning phase, second is decomposition phase and three is presentation of results.

Pino et al. [13], proposed in this paper, analysis of EMG signals data muscles are often characterized as normal or affected by a neuromuscular disorder. Motor unit potential (MUP) being detected from a muscle of each of the following types: myopathic, normal and neuropathic. Using EMG signals, the objective of this was to evaluate the correlation between the muscle characterization measures produced by different MUP characterization methods and the level of involvement of disorder.

Moreno et al. [15], proposed in the paper, DMD is a recessive X-linked form of muscular dystrophy and it is most prevalent genetic disorder of the childhood. Purpose was to define a core signature of gene expression related to DMD via

integrative analysis of mouse and human datasets. It tells us which group of body affects the expression of signature genes.

Huang et al. [7], deployed neural network model for the assessment of neuromuscular disorders. They used a hybrid decision support system based on fusion multiple neural network outputs. Back propagation (BP) neural network are work as a single system in every feature set. Multiple neural network outputs are combined by fuzzy integral.

Bodruzzamanet al [14], deployed neural network based technique for the online processing of neuromuscular disease. They collect EMG signals with the help of microcomputer-based real-time data acquisition system. Data was collected from three different groups. They deployed number of signal processing techniques such as autoregressive modeling (AR); short time. Signal processing features extracted from one of these methods was used to train a neural networking using back propagation method.

Arasu et al. [6], deployed to demonstrate the concept of Neuro-fuzzy agent (NFA) programming. NFA analyses the signals that can be EEG, EMG etc, of different patients and communicate with each other to make decision.

Christodoulou et al. [4], deployed an artificial neural network (ANN) technique based on unsupervised learning, using self-organizing feature maps (SOFM) algorithm used to the classify the EMG signals.

Chong and Sundaraj [23], proposed a classifying EMG signal pattern using back-propagation and basis neural networks. Signals may different depend on the activity of the muscle movement. Classification of EMG signals are divided into two parts: training and testing. Result: BPNN has advantages on PNN. For real time applications, BPNN is better option because it performs faster.

Kouchakiet al. [19], proposed method for decomposed EMG signals by empirical mode decomposition (EMD) to its natural subspaces. It introduced an effective

combinational feature to enhance the classification rate in control group and with neuropathy and myopathy diseases.

Abbas and Chizeck [9], deployed two stage neural networks that combination of adaptive feed forward and feedback control techniques. It was developed for the control of cyclic movement in functional neuromuscular stimulation (FNS) system. It over comes from three major problems of FNS control system: customization of control system parameters for a particular individual , adaptation during operation to account for changes in musculoskeletal system and attaining resistance to mechanical disturbances.

Kanoun and Ali [18], proposed new technique for accurate estimation of motor unit action potential (MUAP).When new technique compared with traditional estimation techniques it proved smoothest baselines and an acceptable factor.

XIE et al.[8], describes Support vector machines (SVMs) based on mutli-class classifier for the identification of normal and patients suffering from motor neuron disease (MND) and myopathies (MYO).SVM ‘s performance is compared with back-propagation(BP) neural networks. Recognition accuracy indicates the SVM technique is better in clinical neuromuscular disorder evaluation.

Fang et al. [10], Deployed technique to identify single motor unit (SMU) and decompose overlapped EMG signals into constituent SMU potentials. It is one-channel EMG recordings and is easy to implement for clinical EMG tests.

Gamarnik et al. [21], Proposed MEMS technology for the possibility of robust motion capture in uncontrolled environments. MEMS-sensor based system evaluates a motion capture in the NMD patient. It led to significant progress the implementation a new device, which is accurate, affordable and clinically relevant.

Table 1.1: Literature review

Author's Name	Techniques	Benefits
Shaw and Bagha[12]	principal component analysis (PCA) and probabilistic neural network	classify to the EMG signal using features extraction
Emanetal[5]	hidden markov model	Detect and describe disease processes affecting the motor unit of the muscle.
Gerberet[1]	Segmentation and nearest-neighbours clustering algorithm.	It Consisting of three phases, one is learning phase, second is decomposition phase and three is presentation of results.
Pino[12]	Pattern discovery	MUP being detected from a muscle and evaluate the correlation between the muscle characterization measures produced by different MUP.
Moreno[15]	core signature of gene expression via integrative analysis of mouse and human datasets	It tells us which group of body affects the expression of signature genes.
Huang[7]	Back-propagation neural network model	single method uses time domain measures, autoregressive coeffidents,
Bodruzzamanet[14]	Neural network based	It converts data into three

	technique for the online processing of neuromuscular disease.	groups: normal, neuropathy, and myopathy, use it for testing and training using neural network.
Arasu[6]	Neuro-fuzzy agent	It analyses the signals that can be EEG, EMG etc.
Christodoulou[4]	Artificial neural network based on unsupervised learning, using self-organizing feature maps.	It identifies MUAP s EMG signals and classifies the similar type of MUAP parameter.
Chong and Sundaraj[23]	back-propagation and basis neural networks	Classification of EMG signals are divided into two parts: training and testing.
Kouchakiet[19]	empirical mode decomposition	Effective combinational feature to enhance the classification rate in control group and with neuropathy and myopathy diseases.
Abbas and Chizeck[9]	neural networks that combination of adaptive feed forward and feedback control techniques	It over come from the following problems exist in other methods are: customization of control system parameters for a particular individual , adaptation during operation to account for changes in musculoskeletal system .

Kanoun[18]	Interference rejection Algorithm	New technique compared with traditional estimation techniques it proved smoothest baselines and an acceptable factor.
XIE[8]	Support vector machines based on mutli-class classifier. Its performance is compared with back-propagation (BP) neural networks.	Recognition accuracy indicates the SVM technique is better in clinical neuromuscular disorder evaluation.
Fang[10]	One-channel EMG recording	Deployed technique to identify single motor unit (SMU) and decompose overlapped EMG signals and it is one-channel EMG recordings and is easy to implement for clinical EMG tests
Gamarnik[21]	MEMS-sensor based system	It led to significant progress the implementation a new device, which is accurate, affordable and clinically relevant

4. Plan of Thesis:

- In chapter1, discuss about EMG based diseases and their types and also I describe objective of my thesis and literature review related to my topic.
- In chapter 2, discuss about my first research paper that is "**Classification of EMG based Diseases using Fuzzy".**

- In chapter 3, discuss about another research paper that is **"Classification of EMG based Diseases using Fuzzy at second level".**
- In chapter 4, describes Neuro-fuzzy system for diagnosis of EMG based diseases at second level.
- Chapter 5, describes the results.
- Chapter 6, explain Conclusion.

Chapter -2

Classification of EMG Based Diseases using Fuzzy Logic at First Level

This chapter describes the diagnosis of EMG based diseases using fuzzy logic at first level. Fuzzy logic based system is developed for the classification of seven types of neuromuscular diseases (NMD) at first level: duchenne muscular dystrophy (DMD), ploymyositis (PO), endocrine myopathy (EM), metabolic myopathy (MM), neuropathy (N), poliomyelitis (PL) and myasthenia gravis (MG) using clinical parameters such as: physiological (muscle pain etc), cognitive (learning disability, hearing disability etc), motor parameters (difficulty in walking etc), psychological parameters (fatigue, anxiety etc.) and EMG parameters such as: amplitude, duration, phase etc.

2.1. Neuromuscular diseases: sign and symptoms

Table 2.1 describes NMD diseases with their two important parameters: physio-psycho (PP) parameters and EMG signal characteristics (EMG). Physio-psycho parameter is further divided into three parts: is further divided into three parts: muscular physiology (M Phy)consisting of muscular (M) parameters such as: fibrillations(FI),fasciculation (Fa), muscle pain (MP), muscle inflammation (MI)and muscle stiffness(MS) (see columns 2–6 in Table 2.1); and motor activity (MA) parameters such as: difficulty in climbing stairs (CS),difficulty in walking (W), difficulty in running (R), difficulty in lifting above the head or shoulder (LH) and difficulty in rising above the chair(RC) [5] (see columns7–11 in Table 2.1), cognitive (Cog) and psychological (Phy) parameters. The cognitive parameters are visual disability (VD), touch disability (TC), speech disability (SD), hearing disability (HD) and learning disability (LD) (see columns 12–16 in Table 2.1). The psychological parameters are: fatigue (FT), anxiety (AN),

depression (DE), isolation (IS) and frustration (FR) (see columns 17–21 in Table 2.1) . The signal characteristics also divided into two parts: pattern characteristics such as: positive sharp wave (PSW), complex repetitive discharge (CRD) and mytonic discharge (MDI) (see columns 22–24 in Table 2.1) and MUAP (motor unit action potential)parameters such as: amplitude (AM), duration (DU), phase (PH)and nerve conduction velocity (NVC) (see columns 25–28 in Table2.1). In Table 2.1 first column contain the disease and columns 2–28contains the symptoms of the diseases. The columns 2–21 contain ‘‘Y” if the respective symptom is present in the disease shown in the respective row. For example, Muscular Dystrophy (MD) has muscular symptoms such as: muscle pain, muscle in Flammarion and fibrillation. Therefore, the columns 2, 4 and 5contain ‘‘Y” as in Table 2.1.The other column of the Table 2.1 such as 22, 23 and 24 of a particular row contains ‘‘Y” or ‘‘N” depending upon the characteristics of MUAP of the disease. The columns 25–27 contains” Y” if amplitude is less than 270 lm, duration is greater than10.2 ms and phase is greater than or equal to 5, respectively ,and ‘‘N” if amplitude is less than 160 lm, duration is less than9.8 ms and phase is less than 5, respectively. The column 28 contains ‘‘Y” if there is normal decrease in nerve conduction velocity.

Table2.1: Sign and Symptoms of NMD diseases at first level

Diseases	Physio-Psycho Parameters																				EMG signal Parameters						
	Physiological					Motor action					Cognitive Parameters					Psychological Parameters					Pattern Characteristics			MUAP Parameters			
	FI	FA	MP	MI	MS	CS	W	R	LH	RC	VD	TD	SD	HD	LD	FT	AN	DE	IS	FR	PSW	CRD	MD	AM	DU	PH	NCV
MD	Y	N	Y	Y	N	Y	Y	Y	N	N	N	N	Y	N	Y	Y	Y	Y	Y	N	Y	Y	N	N	Y	Y	Y
PO	Y	N	Y	Y	N	Y	Y	N	Y	Y	Y	N	N	N	N	Y	N	Y	N	N	Y	Y	N	N	N	Y	N
EM	N	Y	Y	N	Y	Y	Y	Y	N	N	Y	N	N	N	N	Y	Y	Y	N	N	N	N	Y	N	N	Y	Y
MM	Y	N	Y	N	N	Y	N	Y	Y	N	Y	N	N	N	N	Y	N	N	N	N	N	Y	Y	N	N	Y	N
N	Y	Y	N	N	Y	Y	Y	Y	N	N	N	Y	N	N	N	Y	Y	N	Y	Y	Y	Y	N	Y	Y	Y	N
PL	Y	Y	Y	N	N	Y	Y	Y	N	N	N	N	N	N	N	N	Y	Y	N	N	N	Y	Y	Y	Y	Y	Y
MG	Y	Y	N	N	N	Y	N	N	Y	Y	Y	N	Y	Y	N	Y	Y	N	N	N	Y	N	N	N	N	Y	Y

2.2. Fuzzy Logic

The fuzzy model was elaborated based on experience and knowledge of neuromuscular diseases experts and literatures. These experts and literatures considered following inputs as important variables: physiological symptoms (Phy), motor symptoms (Mot), Cognitive symptoms (Cog), psychological symptoms (psy) as well as on EMG test variables such as: Spontaneous activity (SPO) and MUAP parameters (MUAP).

Fuzzy rule base system consists of four major components: (1) fuzzification module which translates crisp inputs into fuzzy values through linguistic variables, (2) fuzzy rule base; (3) fuzzy inference method; (4) defuzzification.

2.2.1 Fuzzification

In fuzzification step, numerical inputs and output variables are converted into linguistic terms or adjectives (such as low, high, big, small, etc.), and the corresponding degrees of the one or more

Several membership functions are determined. The fuzzification is done in following steps:

2.2.1.1Compute the domain interval of each input

The domain interval of variable means that most probability the variables lie in their domain intervals. It is computed as follow:

a. Represent the six parameters Phy, Mot, Cog, Psy, SPO and MUAP given in table 1, into binary strings. Where number of bits are equivalent to number of sub parameters taken under particular parameters. For example, phychological parameter is represented by 5 bits.
b. Take the minimum and maximum decimal value represented by binary string. For example, using five bits the minimum and maximum decimal numbers represented by string are 0 and 31. Therefore the domain interval for phy is [0, 31].

Similarly, the domain interval for Mot, Cog and Psy, SPO and MUAP are computed. The domain interval for Mot, Cog and Psy are [0, 31], for SPO is [0, 7] and for MUAP is [0, 15].

2.2.1.2Divide each domain interval into regions

The next step in divide each domain interval into regions. The Physiological, Motor, Cognitive and Psychological symptom (Phy) are divided into five regions: very high (VH), high (H), medium (M), low (L), very low (VL). The SPO and MUAP activities are divided into three regions: high (H), medium (M), low (L). The corresponding fuzzy membership functions for input variables are shown in Figure 2.1. First column, in Table 2.1 contains the input parameters, 2nd and 3rd column contains the fuzzy set and their ranges. The 4th column contains the fuzzy membership expression for the corresponding input parameter in 1st column.

The domain interval of output is computed as follow:

1. Determine the degree of given inputs Phy, Mot, Cog, Psy, SPO and MUAP in different regions. For this first convert the signs and symptoms given in Table 1, to its binary equivalent where Y is converted to '1' and N is converted to '0'. For example, the binary string equivalent to phy in MD is '10110' as shown in second cell of column 2 in Table 3. Then convert the binary string to equivalent decimal number. The equivalent decimal to '10110' is 22 as shown in the right of equal sign in second cell of column 2 in Table2.2. This is called, score of phy for MD. Similarly, the score of each input for each disease is calculated and shown in right side of equal to sign in Table 2.2. This score of Phy in MD as from the Figure 2.1 has degree less than 0.5 in VH, degree greater than 0.5 in H and zero degree in all other regions.
2. Assign a given inputs Phy, Mot, Cog, Psy, SPO and MUAP to maximum degree. For example, in case of MD, Phy be in H set as shown in 2nd cell of row headed by R1. For example, in case of MD, Phy be in H set. Similarly, other is computed. Different levels are given to different set. The level of VH is 5, H is 4, M is 3, L is 2 and VL is 1.
3. Then, different weights are given to different inputs depending upon the number of bits used to represent the particular input. For example, the weight

assigned to Phy (W_{phy}) is 5 as 5 bit string is used to represent it. Similarly, the weight assigned to mot (W_{mot}), cog (W_{cog}), psy (W_{psy}), spo (W_{spo}), and MUAP (W_{muap}), are 5, 5, 5, 5, 3 and 4.

4. Next step is to calculate the score of diseases as follows:

Score of MD = W_{phy}* Level of Phy in MD + W_{mot} * Level of Mot in MD + W_{cog} + Level of Cog in MD + W_{psy}* Level of Psy in MD + W_{spo} * Level of SPO in MD +W_{muap} + Level of MUAP in MD

= 5 * 4 + 5 * 5 + 5 * 1 + 5 * 5 + 3 * 3 + 4 * 3

= 96

Similarly, score of other diseases are calculated. The score of PO, EM, MM, N, PL and MG are 97, 98, 77, 110, 95 and 108 respectively in last column of Table 2.2 the value given. These score of diseases decide the boundaries of output. The boundaries of output are [77, 110]. The member ship functions used for input are trapezoidal and triangular functions. The membership function of output variable is shown in Figure 2.1.

Table 2.2: Computation of score of diseases at first level

Diseases	Phy	Mot	Cog	Psy	SPO	MUAP	Score
MD	10110=22	11100=28	00101=3	11110=30	110=6	0111=7	96
PO	10110=22	11011=27	10000=16	10100=20	110=6	0010=2	97
EM	01101=13	11100=28	10000=16	11100=28	001=1	0011=3	98
MM	10100=6	10110=22	10000=16	10000=16	011=3	0010=2	77
N	11001=25	11100=28	01000=8	11011=27	110=6	1110=14	110
PL	11100=28	11100=28	00000=0	01100=12	011=3	1111=15	95
MG	11000=24	10011=19	10110=22	11000=24	000=0	0011=3	108

2.2.2Rule base

The defined fuzzy rule base is formed by 7 rules (Table 4) and therefore is not complete because with six input features the number of combinations that can be made is greater than seven. That doesn't mean that the model is poorly representative though because many feature combinations don't necessarily represent a real case or class. These rules were generated by some computation as mentioned in 2.2.1.1 and 2.2.1.2 and verified with the help of a NMD expert.

Table 2.3: Fuzzy Rule Base

Rule	Phy	Mot	Cog	Psy	SPO	MUAP	Diagnosis
R1	H	VH	VL	VH	M	M	DMD
R2	H	VH	M	H	M	L	PO
R3	M	VH	M	VH	L	M	EM
R4	L	H	M	M	M	L	MM
R5	VH	VH	L	VH	M	H	N
R6	VH	VH	VL	M	M	H	PL
R7	VH	H	H	VH	L	M	MG

2.2.3Fuzzy Inference and Defuzzification

Designed system uses inference mechanism Mamdoni approach. The programming environment MATLAB 6.1 along with the FUZZY LOGIC TOOLBOX was used for the implementation of the fuzzy model and the classification algorithm. For defuzzification process, designed system uses "Centroid" method**.** On the basis of above-mentioned fuzzy steps, a detailed schematic of the MIMO (multiple inputs and Multiple outputs) fuzzy system applied in this study is depicted in Fig.2.1.

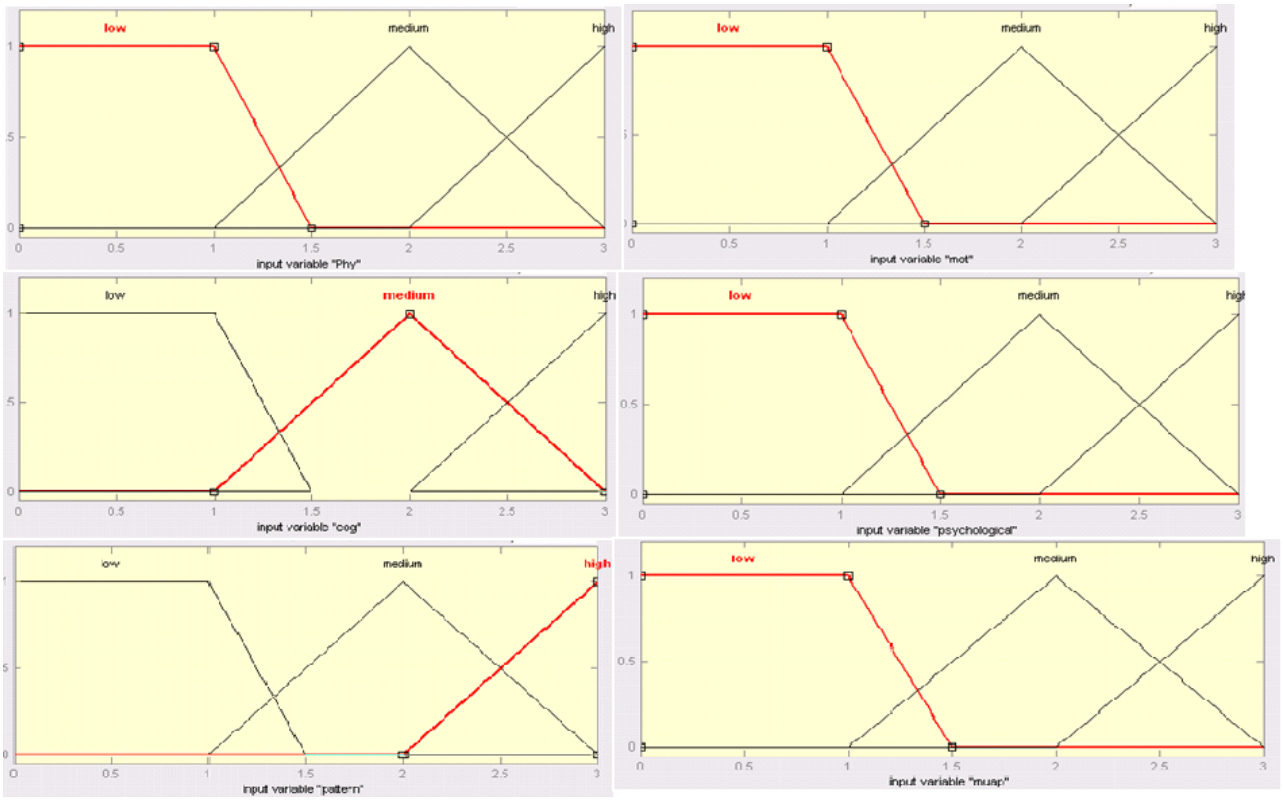


Figure2.1: Membership function of input variables at First level

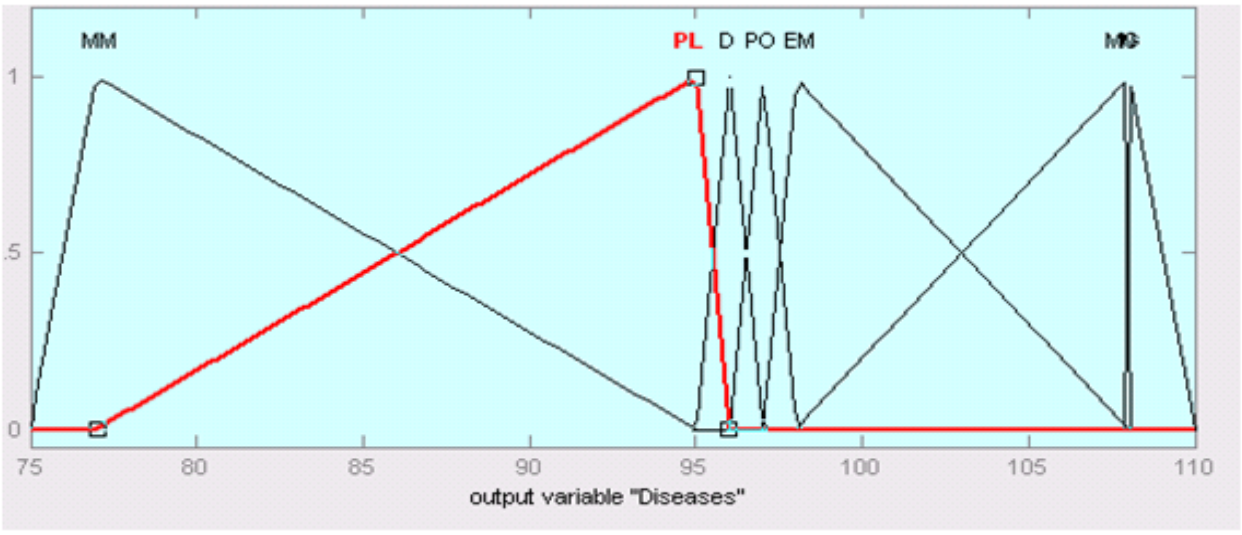


Figure 2.2: Membership function of output variables at first level.

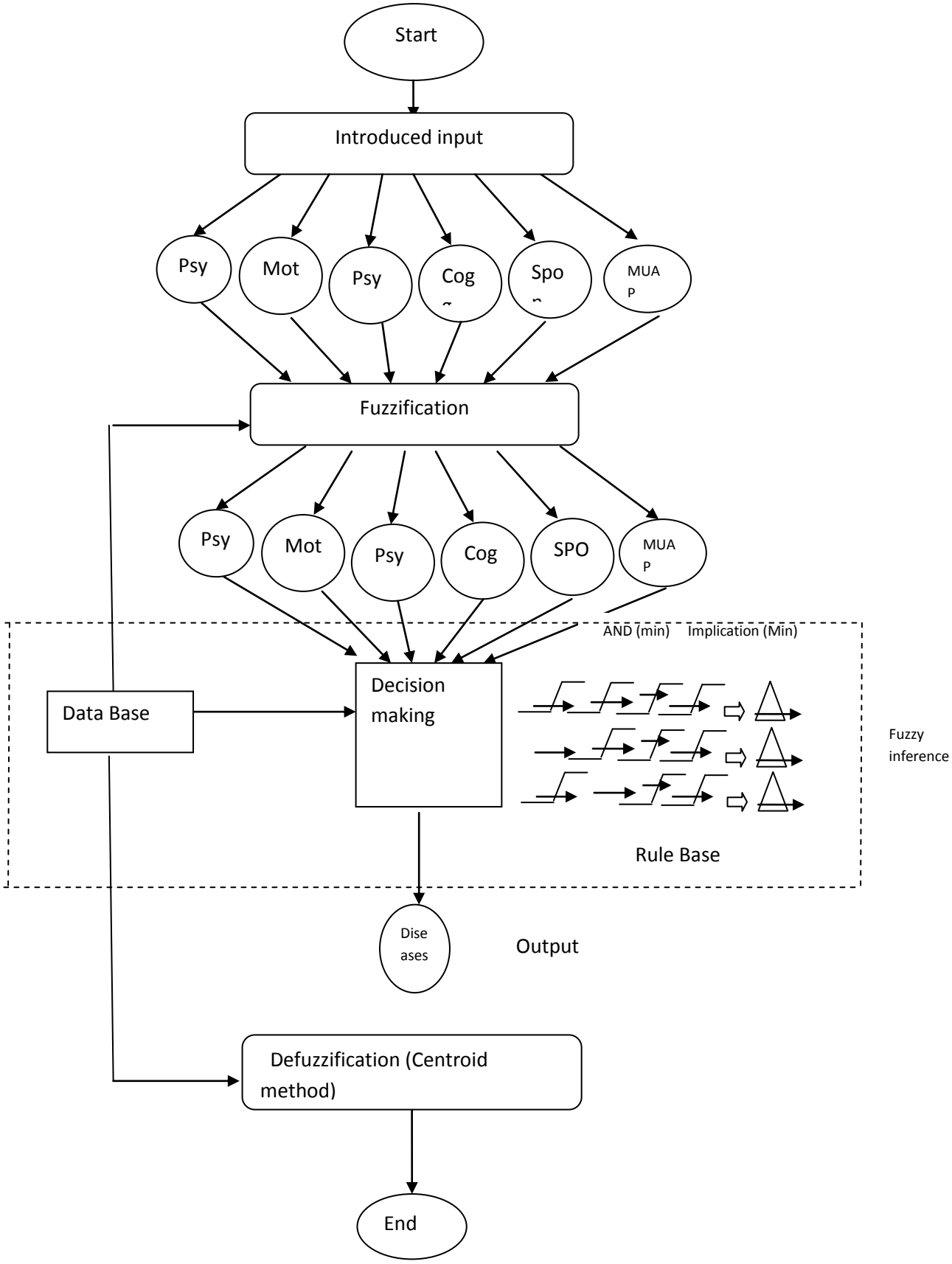


Figure 2.3: A detailed schematic of the MIMO fuzzy system applied in this study.

2.3. Result

The test data consist of 61 cases. It was created from expert opinion and literature survey. It consists of 10 DMD cases, 20 PO cases, 5 EM cases, 6 MM cases, 5 N cases, 5 PL cases and 10 MG cases. The accuracy of a classifier can be computed using sensitivity and specificity. For the given seven classes, we consider in terms of positive tuples (diagnosis =any specific disease like DMD) versus negative tuples (eg., diagnosis = not that specific disease like not DMD). True positives refer to the positive tuples that were correctly labeled by the classifier, while true negatives are the negative tuples that were correctly labeled by the classifier. False positives are the negative tuples that were incorrectly labeled by the classifier, while false negatives are the positive tuples that were incorrectly labeled by the classifier. These measures are defined as

Sensitivity = tpos /pos

tpos is the number of true positives (i.e. samples that were correctly classified suffering with a specific disease) and pos is the number of positive (i.e. sample that are actually suffering with a specific disease) samples. For example, while testing among the 10 cases of DMD, 8 are classified correctly by fuzzy logic and 2 are classified wrong. Therefore, Sensitivity == 8/10= 0.8.

Specificity =tneg/ neg

tneg is the number of true negatives (i.e. samples that were not suffering with specific disease and were correctly classified) an neg is the number of positive (i.e. samples that were actually not suffering with specific disease) samples and fpos is the number of false positives ("samples that are actually not suffering with a specific disease but were incorrectly classified). For example, while testing among the 51 cases that are not suffering with DMD, 47 are classified correctly by fuzzy logic and 4 are classified wrong. Therefore, Sensitivity = 47/51= 0.92.

The true positives, true negatives, false positives and false negatives are also useful in assessing the costs and benefits (or risks and gains) associated with a classification model.

Table 2.4: Comparative table of Measures of different disease

Measure	MD	PO	EM	MM	N	PL	MG
Specificity	0.92	0.9	0.98	0.96	0.98	0.98	0.92
Sensitivity	0.8	0.9	0.8	0.66	0.8	0.8	0.8

The results are shown in Table 2.4, in terms of sensitivity and specificity. The results indicate that the proposed method performs well in classifying NMD's. Plots of the seven results given in Table 2.4 are shown in ROC space in the Figure 2.4. For all the diseases, the results are above the diagonal, which represent good classification results.

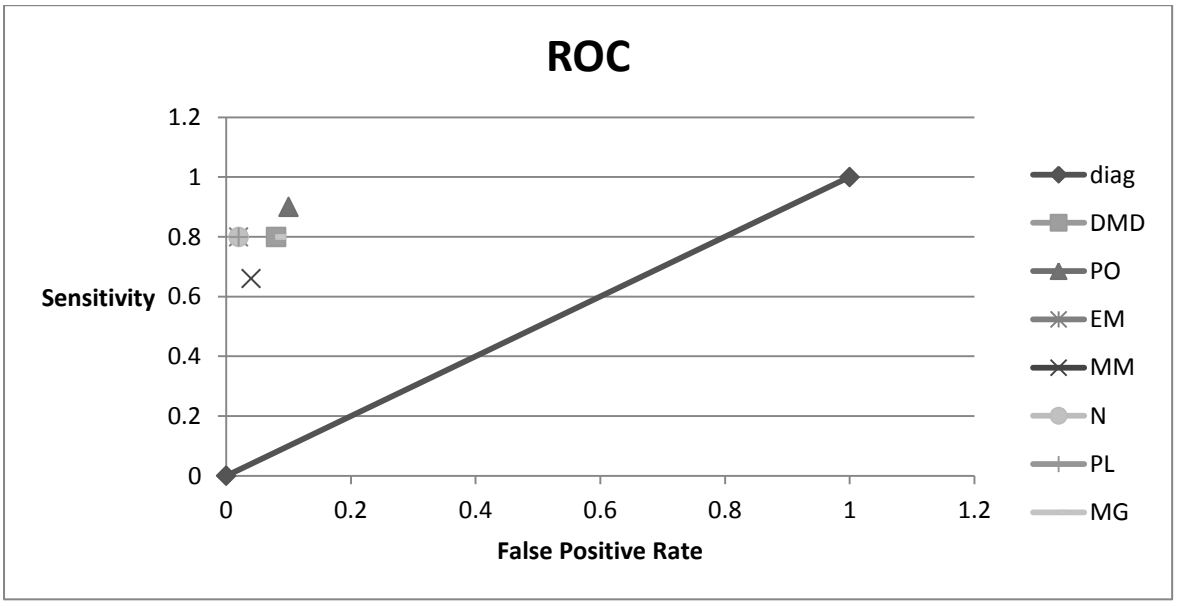


Figure 2.4: ROC Curve

2.3.1. Conclusion

This work integrates in the context of medical system development. It has been devoted particularly to classify NMDs based on the analysis of the EMG signal such as: amplitude, phase and duration and clinical parameters such as: physical, cognitive, psychological and motor parameters using fuzzy logic.

After presenting the limits of the classical approach and intelligent technique such as ANN, CBR and RBR, in solving the problem of classification in the medical domain, we have seen the reasons for choosing a new fuzzy method to achieve the goal of designing a system capable of making reliable diagnoses. Finally, the classification results were presented.

The results were satisfactory and were shown in the form of sensitivity and specificity. However, the design of the fuzzy model, including the fuzzy rule base and the membership functions, was rather hard to achieve although it may seem simple. This difficulty was due to the intuitive nature of the human way of thinking which cannot be easily transformed to a numerical model.

Chapter-3

Classification of EMG Based Diseases using Fuzzy Logic at Second Level

This chapter deals with the diagnosis of EMG based diseases using fuzzy logic at second level. Classification of EMG based diseases at first level using fuzzy logic is described in chapter 1. For the classification of EMG based diseases at second level using fuzzy logic, fuzzy based system is developed using eight muscular dystrophy diseases: duchenne muscular dystrophy (DMD), Becker muscular dystrophy (BMD), Congenital muscular dystrophy (CMD),Emery–Dreifussmuscular dystrophy (EDMD), Facioscapulohumeral muscular dystrophy (FSH), Limb-girdle muscular dystrophy (LGMD), myotonic muscular dystrophy (MMD) and Oculopharyngeal muscular dystrophy (OPMD) and using clinical parameters such as: muscular (muscle pain etc), cognitive (learning disability, hearing disability etc), motor parameters (difficulty in walking etc), psychological parameters (fatigue, anxiety etc.), internal ligual parameters(lung problem, chest pain etc) and EMG parameters such as: amplitude, duration, phase etc.

3.1. Muscular Dystrophy: sign and symptoms

Table 3.1 describes NMD diseases with their two important parameters: physio-psycho (PP) parameters and EMG signal characteristics (EMG). Physio-psycho parameter's further divided into four parts: muscular parameter which is further divided into two parts: Muscular(MUS) and motor(MOT) parameters such as: muscle pain (MP), muscle inflammation (MI)and muscle stiffness(MS)fibrillations(FI),fasciculation (Fa), muscle pain (MP), muscle inflammation (MI)and muscle stiffness(MS) difficulty in lifting above the head or shoulder (LH) and difficulty in rising above the chair (RC) (see columns 2–10 in Table 3.1); The cognitive parameters are visual disability (VD),

touch disability(TC), speech disability (SD), hearing disability (HD) and learning disability (LD) (see columns 12–15 in Table 3.1);The muscular psychological parameters are: fatigue (FT), anxiety (AN), depression (DP), isolation (IS), (see columns 16–21 in Table 3.1); The internal ligual parameters are (see columns 22–27 in Table 3.1) lung problem(LP), Cardiac arrhythmia(CA), congestive heart failure(CHF), chest pain(CP), heart muscle disease(HMD) and Skelton disorder(SKD) . The EMG parameters are also divided into two parts: spontaneous abnormality such as: positive sharp wave (PSW) and mytonic discharge (MDI) (see columns 28-31 in Table 3.1) and MUAP (motor unit action potential) parameters such as: amplitude (AM), duration (DU), phase (PH) and nerve conduction velocity (NVC) (see columns 32-35 in Table3.1). In Table 3.1 first column contain the disease and columns 2–35 6contains the symptoms of the diseases. The columns 2–27 contain ‘‘Y” if the respective symptom is present in the disease shown in the respective row. For example, Duchenne Muscular Dystrophy (DMD) has muscular symptoms such as: muscle pain, muscle in Flammarion and fibrillation. Therefore, the columns 2, 4 and 5contain ‘‘Y” as in Table 3.1. The other column of the Table 3.1 such as 22, 23 and 24 of a particular row contains ‘‘Y” or ‘‘N” depending upon the characteristics of MUAP of the disease.

3.2 Fuzzy Logic

The fuzzy model was elaborated based on experience and knowledge of neuromuscular diseases experts and literatures. These experts and literatures considered following inputs as important variables: physiological symptoms (Phy), Muscular (mus), motor symptoms (Mot), Cognitive symptoms (Cog), muscular psychological symptoms (mus psy), internal ligual parameters (int_lig) as well as on EMG test variables such as: Spontaneous activity (SPO) and MUAP parameters (MUAP).

Fuzzy rule base system consists of four major components: (1) fuzzification module which translates crisp inputs into fuzzy values through linguistic variables, (2) fuzzy rule base; (3) fuzzy inference method; (4) defuzzification.

Table3.1: **Signs and symptoms of muscular dystrophy at second level**

Diseases	Physio-psychological parameters																												EMG parameters							
	Muscular Parameter										Cognitive parameters					Muscular psychological						Internal ligual parameters						Spontaneous abnormality				MUAP parameters			
	Muscular				Motor																															
	MP	MI	MS	MT	MB	LH	RC	MM	MH	EM	VD	TD	LD	HD	SD	FT	AN	DP	IS	FN	DZ	LP	CA	CHF	CP	HMD	SKD	FI	FA	PSW	MD	AM	DU	PH	NCV
DMD	Y	Y	Y	Y	Y	N	Y	N	N	N	N	N	Y	N	Y	Y	Y	Y	Y	N	N	Y	Y	Y	N	N	Y	Y	Y	Y	N	Y	Y	Y	Y
BMD	Y	Y	Y	Y	Y	N	Y	N	N	N	N	N	Y	N	N	Y	N	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y
CMD	Y	N	N	N	Y	N	N	N	N	N	Y	N	Y	N	Y	Y	N	N	N	N	N	Y	N	N	N	N	Y	Y	N	Y	N	Y	Y	Y	N
EDMD	Y	N	N	N	N	Y	N	N	Y	N	N	N	Y	N	N	N	N	N	Y	N	N	N	Y	N	N	Y	Y	Y	N	N	N	Y	Y	Y	Y
FSH	Y	N	N	N	N	Y	N	Y	Y	Y	Y	N	Y	Y	Y	Y	N	N	N	N	N	Y	Y	N	N	N	N	Y	N	N	N	Y	Y	Y	N
LGMD	Y	N	N	Y	N	Y	Y	N	N	N	Y	N	N	N	N	N	N	Y	N	N	N	Y	Y	Y	N	N	Y	Y	N	N	N	Y	Y	Y	Y
MMD	Y	N	N	Y	N	N	Y	N	N	N	Y	N	Y	N	Y	N	N	N	N	Y	Y	N	Y	N	N	Y	Y	Y	N	N	N	Y	Y	Y	N
OPMD	Y	N	N	Y	N	N	N	Y	N	Y	Y	N	N	N	Y	Y	N	N	N	N	N	N	N	N	Y	N	N	Y	N	N	N	N	N	Y	Y

3.2.1 Fuzzification

In fuzzification step, numerical inputs and output variables are converted into linguistic terms or adjectives (such as low, high, etc.), and the corresponding degrees of the one or more

Several membership functions are determined. The fuzzification is done in following steps:

3.2.1.1Compute the domain interval of each input

The domain interval of variable means that most probability the variables lie in their domain intervals. It is computed as follow:

a. Represent the seven parameters mus, Mot, Cog, mus Psy, int_lig, SPO and MUAP given in table 3.1, into binary strings. Where number of bits are

equivalent to number of sub parameters taken under particular parameters. For example, muscular parameter is represented by 4 bits.

b. Take the minimum and maximum decimal value represented by binary string. For example, using five bits the minimum and maximum decimal numbers represented by string are 0 and 20. Therefore the domain interval for phy is [0, 20].

Similarly, the domain interval for Mot, Cog, mus Psy and int_lig, SPO and MUAP are computed. The domain interval for Mot are [0, 45] Cog [0, 31] and mus Psy are [0, 60], for SPO is [0, 14] and for MUAP is [0, 15].

3.2.1.2Divide each domain interval into regions

The next step in divide each domain interval into regions. The Physiological, Motor, Cognitive and Psychological symptom (Phy) are divided into three regions: high (H), medium (M), low (L). The SPO and MUAP activities are divided into three regions: high (H), medium (M), low (L). The corresponding fuzzy membership functions for input variables are shown in Figure 3.1. First column, in Table 3.1 contains the input parameters, 2nd and 3rd column contains the fuzzy set and their ranges. The 4th column contains the fuzzy membership expression for the corresponding input parameter in 1st column.

The domain interval of output is computed as follow:

1. Determine the degree of given inputs mus, Mot, Cog, mus Psy, int lig, SPO and MUAP in different regions. For this first convert the signs and symptoms given in Table 1, to its binary equivalent where Y is equal to '1' and N is equal to '0'. For example, the binary string equivalent to mus in DMD is '1111' as shown in Table 3.2. Then convert the binary string to equivalent decimal number. The equivalent decimal to '1111' is 15as shown in the Table 3.2. This is called, score of mus for DMD. Similarly, the score of each input for each disease is calculated and shown in right side of equal to sign in Table 3.2.

2. Assign a given inputs mus, Mot, Cog, mus Psy, int lig, SPO and MUAP to maximum degree.
3. Then, different weights are given to different inputs depending upon the number of bits used to represent the particular input. For example, the weight assigned to mus (W_{mus}) is 4 as 4 bit string is used to represent it. Similarly, the weight assigned to mot (W_{mot}), cog (W_{cog}), mus psy (W_{muspsy}), int lig (W_{intlig}), spo (W_{spo}), and MUAP (W_{muap}), are 6,5,6,6,4 and4.

4. Next step is to calculate the score of diseases as follows:

   Score of DMD = W_{mus}* Level of mus in DMD + W_{mot} * Level of Mot in DMD + W_{cog} + Level of Cog in DMD + W_{muspsy}* Level of mus Psy in DMD + W_{intlig} + Level of int lig in DMD + W_{spo} * Level of SPO in DMD +W_{muap} + Level of MUAP in DMD.

=4*3+6*3+5*1+6*3+6*3+4*3+4*3

=95

Table 3.2: Computation of score of diseases at second level

Diseases	mus	mot	cog	mus psy	intlig	Spo	MUAP	Score
DMD	1111=15	101000=40	00101=5	111100=57	111001=57	1110=14	1111=15	95
BMD	1111=15	101000=40	00100=4	100001=33	111111=63	1100=12	1111=15	85
CMD	1000=8	100000=32	10101=21	100000=32	100001=33	1010=10	1110=14	77
EDMD	1000=8	010010=18	00100=4	000100=4	010011=19	1000=8	1111=15	49
FSH	1000=8	010111=23	10111=23	100000=32	110000=48	1000=8	1110=14	83
LGMD	1001=9	011000=24	10000=16	001000=8	111001=57	1000=8	1111=15	66
MMD	1001=9	001000=5	10101=21	000011=3	010011=19	1000=8	1110=14	53
OPMD	1001=9	000101=5	10001=17	100000=32	000100=4	1000=8	0011=3	51

3.2.2Rule base

The defined fuzzy rule base is formed by 34 rules shown in Table 3.3 and therefore is not complete because with seven input features the number of combinations that can be made is greater than thirty. That doesn't mean that the model is poorly representative though because many feature combinations don't necessarily represent a real case or class. These rules were generated by some computation as mentioned in 3.2.1.1 and 3.2.1.2 and verified with the help of a NMD expert.

Table 3.3: Fuzzy Rule Base at second level

RULE	Mus	Mot	Cog	MusPsy	Intlng	SPO	MUAP	Diseases
R1	H	H	L	H	H	H	H	DMD
R2	H	H	L	M	H	H	M	BMD
R3	L	H	H	M	M	H	L	CMD
R4	L	M	L	L	L	H	L	EDMD
R5	L	L	H	M	H	H	L	FSH
R6	L	M	M	L	H	H	L	LGMD
R7	L	L	H	L	L	H	L	MMD
R8	L	L	H	M	L	L	L	OPMD
R9	H	M	L	H	H	H	H	BMD
R10	H	H	H	H	H	H	H	DMD
R11	H	H	L	H	M	H	H	BMD
R12	H	H	M	M	H	H	M	BMD
R13	M	H	L	M	H	H	M	FSH
R14	H	H	L	M	H	H	L	FSH
R15	L	M	H	M	M	H	L	CMD
R16	L	H	H	L	M	H	L	CMD
R17	L	H	H	M	M	M	L	CMD
R18	L	M	L	M	L	H	L	MMD
R19	L	M	L	L	L	M	L	EDMD
R20	L	H	L	L	L	H	L	MMD
R21	L	M	H	M	H	H	L	CMD
R22	L	L	H	L	H	H	L	LGMD
R23	L	L	H	M	H	M	L	LGMD
R24	L	M	M	L	H	H	M	LGMD
R25	L	H	M	L	H	H	L	CMD
R26	L	M	M	M	H	H	L	LGMD
R27	L	M	H	L	L	H	L	MMD
R28	L	L	H	L	L	M	L	EDMD
R29	M	L	H	L	L	H	L	MMD
R30	L	M	H	M	L	L	L	MMD
R31	L	L	M	M	L	L	L	EDMD
R32	L	L	H	M	L	M	L	MMD
R33	H	H	M	M	H	H	H	DMD
R34	H	H	M	H	H	H	H	DMD

2.2.3Fuzzy Inference and Defuzzification

Designed system uses inference mechanism Mamdoni approach. The programming environment MATLAB 6.1 along with the FUZZY LOGIC TOOLBOX was used for the implementation of the fuzzy model and the classification algorithm. For defuzzification process, designed system uses "Centroid" method**.** On the basis of above-mentioned fuzzy steps, a detailed schematic of the MIMO (multiple inputs and multiple outputs) fuzzy system applied in this study is depicted in Fig.3.1.

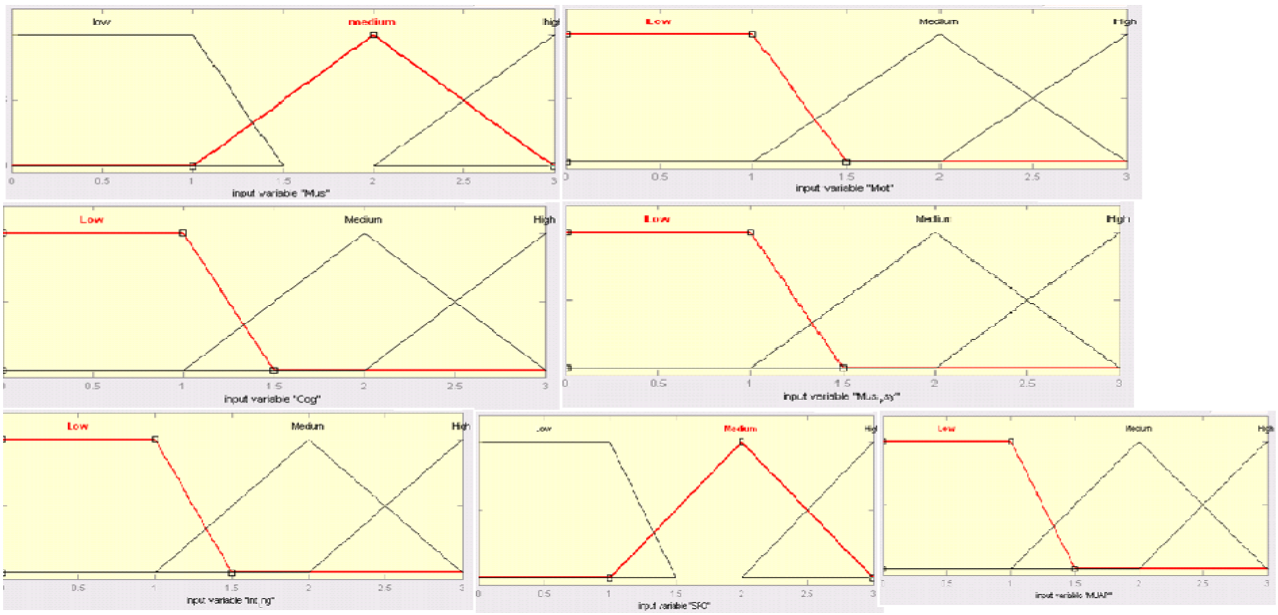


Figure 3.2: Membership function of input variables at Second level

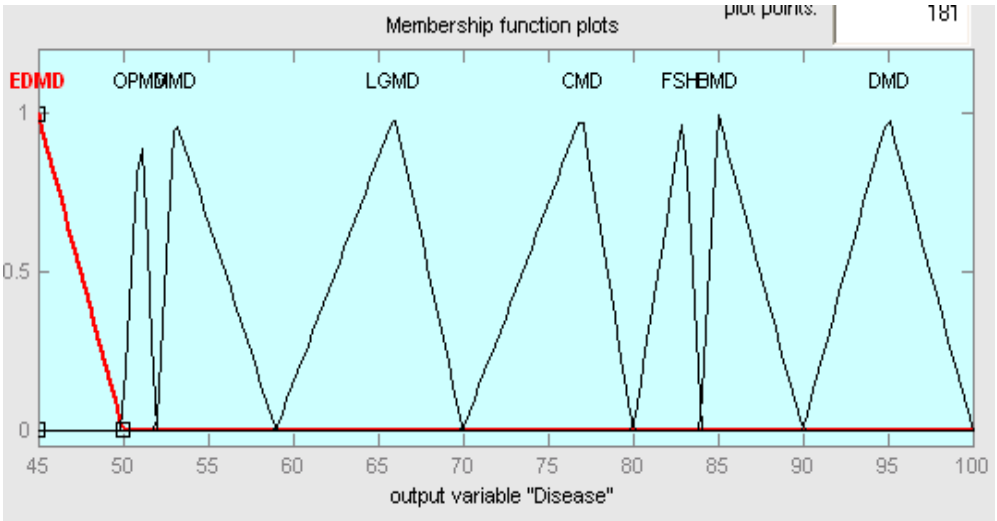


Figure 3.2: Membership function of output variables at Second level

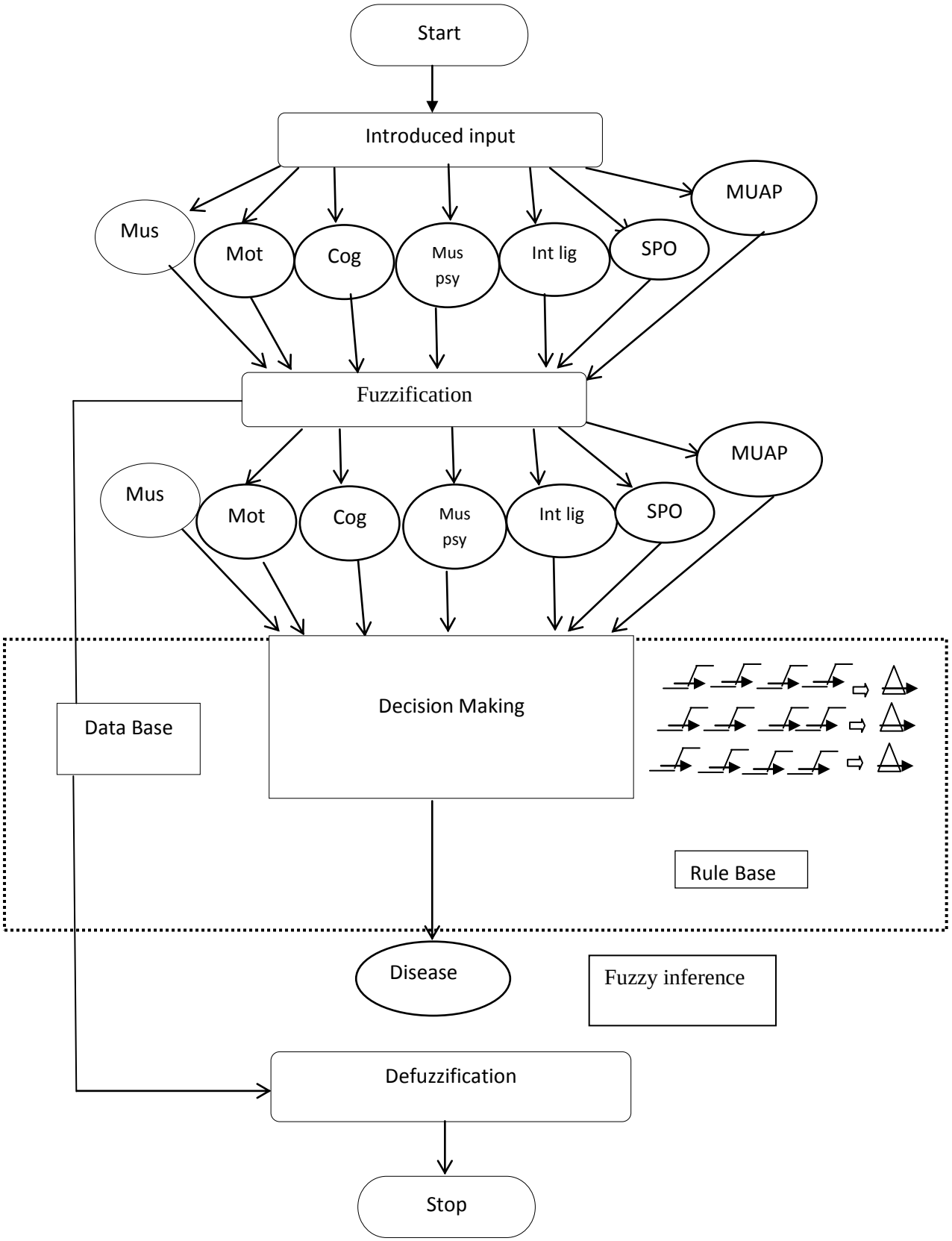


Figure 3.4: A detailed schematic of the MIMO fuzzy system applied in this study at second level.

3.3Result

The test data consist of 34cases. It was created from expert opinion and literature survey. It consists of 4 DMD cases, 4 BMD cases, 6CMD cases, 4 EDMD cases, 3 FSH cases, 5 LGMD cases and 7 MMD cases and 1 OPMD case. The accuracy of a classifier can be computed using sensitivity and specificity. For the given 34 classes, we consider in terms of positive tuples (diagnosis =any specific disease like DMD) versus negative tuples (e.g. diagnosis = not that specific disease like not DMD). True positives refer to the positive tuples that were correctly labeled by the classifier, while true negatives are the negative tuples that were correctly labeled by the classifier. False positives are the negative tuples that were incorrectly labeled by the classifier, while false negatives are the positive tuples that were incorrectly labeled by the classifier. These measures are defined as

Sensitivity = tpos /pos

tpos is the number of true positives (i.e. samples that were correctly classified suffering with a specific disease) and pos is the number of positive (i.e. sample that are actually suffering with a specific disease) samples. For example, while testing among the 7 cases of MMD, 5 are classified correctly by fuzzy logic and 2 are classified wrong. Therefore, Sensitivity == 5/7

Specificity =tneg/ neg

tneg is the number of true negatives (i.e. samples that were not suffering with specific disease and were correctly classified) an neg is the number of positive (i.e. samples that were actually not suffering with specific disease) samples and fpos is the number of false positives ("samples that are actually not suffering with a exact disease but were incorrectly classified). For example, while testing among the 34 cases that are not suffering with DMD, 30are classified correctly by fuzzy logic and 4 are classified wrong. Therefore, Sensitivity = 30/34.

The true positives, true negatives, false positives and false negatives are also useful in assessing the costs and benefits (or risks and gains) associated with a classification model.

Table3.4: specificity and sensitivity of diseases

Measure	DMD	BMD	CMD	EDMD	FSH	LGMD	MMD	OPMD
Specificity	0	0	0.94	0	0	0	0.88	0
Sensitivity	1	1	0.06	1	1	1	0.71	1

Table 3.4 shows the result in the form of specificity and sensitivity of diseases at second level and figure 3.5 shows the ROC curve of result at second level.

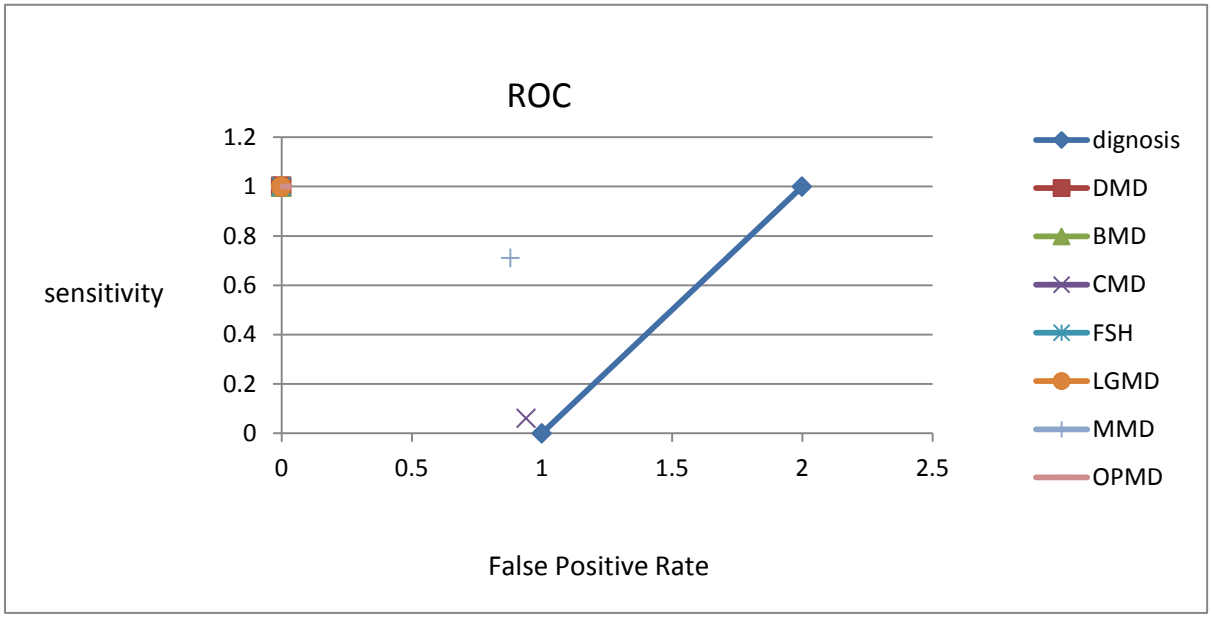


Figure 3.5: ROC Curve of result

3.3.2. Conclusion

It has been devoted particularly to classify muscular dystrophy diseases based at second level on the analysis of the EMG signal such as: amplitude, phase and duration

and clinical parameters such as: muscular, cognitive, Muscular psychological, Internal ligual, Spontaneous abnormality parameters using fuzzy logic.

After presenting the limits of the classical approach and intelligent technique such as ANN, CBR and RBR,I n solving the problem of classification in the medical domain, we have seen the reasons for choosing a new fuzzy method to achieve the goal of designing a system capable of making reliable diagnoses. Finally, the classification results were presented.

The results were satisfactory and were shown in the form of sensitivity and specificity. However, the design of the fuzzy model, including the fuzzy rule base and the membership functions, was rather hard to achieve although it may seem simple. This difficulty was due to then intuitive nature of the human way of thinking which cannot be easily transformed to a numerical mod.

Chapter-4

Neuro-Fuzzy System for Classification of EMG Based Diseases at Second Level

This chapter describes the neuro-fuzzy system for the diagnosis of EMG based diseases at second level. For the classification, Neurofuzzy system uses clinical parameters such as: cognitive parameter like learning disability, speech disability etc, Motor parameters like difficulty in walking etc and EMG parameters like amplitude, phase, duration etc.

4.1 Implementation

For classification of EMG based diseases using Neuro-fuzzy system, firstly, fuzzy system is developed. Classification of EMG based diseases using fuzzy logic at first level and second level are described in chapter 2 and chapter 3 respectively.

Training data (input and output variables) used in matlab**,** at second level are described below:

After implementation of fuzzy rules in matlab, firstly normalized the input variables and output variables that can train the data in neural network with the help of matlab normalized the data using following steps:

- Assign a given inputs muscular (Mus), motor (Mot), cognitive (Cog), muscular psychological (mus Psy), internal ligual (int lig), Spontaneous activity (SPO) and MUAP parameters (MUAP) to maximum degree. For example, in case of DMD, Mus will be in H set as shown in 2nd cell of row headed by R1 shown in table 3.3 in chapter 3 and similarly other parameters are computed. Different levels are given to different set. The level of H is 3, M is 2 and L is 1 and new table will be defined shown in table 4.1.

Training data is normalized using following equation:

$$N_e = X_i - X_{min} / X_{max} - X_{min}$$

Normalized training data is shown in table 4.2

Table 4.1: Rules in form of integers

Mus	Mot	Cog	MusPsy	Intlng	SPO	MUAP	Diseases
3	3	1	3	3	3	3	DMD
3	3	1	2	3	3	2	BMD
1	3	3	2	2	3	1	CMD
1	2	1	1	1	3	1	EDMD
1	1	3	2	3	3	1	FSH
1	2	2	1	3	3	1	LGMD
1	1	3	1	1	3	1	MMD
1	1	3	2	1	1	1	OPMD
3	2	1	3	3	3	3	BMD
3	3	3	3	3	3	3	DMD
3	3	1	3	2	3	3	BMD
3	3	2	2	3	3	2	BMD
2	3	1	2	3	3	2	FSH
3	3	1	2	3	3	1	FSH
1	2	3	2	2	3	1	CMD
1	3	3	1	2	3	1	CMD
1	3	3	2	2	2	1	CMD
1	2	1	2	1	3	1	MMD
1	2	1	1	1	2	1	EDMD
1	3	1	1	1	3	1	MMD
1	2	3	2	3	3	1	CMD
1	1	3	1	3	3	1	LGMD
1	1	3	2	3	2	1	LGMD
1	2	2	1	3	3	2	LGMD
1	3	2	1	3	3	1	CMD
1	2	2	2	3	3	1	LGMD
1	2	3	1	1	3	1	MMD
1	1	3	1	1	2	1	EDMD
2	1	3	1	1	3	1	MMD
1	2	3	2	1	1	1	MMD
1	1	2	2	1	1	1	EDMD
1	1	3	2	1	2	1	MMD
3	3	2	2	3	3	3	DMD
3	3	2	3	3	3	3	DMD

Table4.2 Normalized training data used in Neural Network

Mus	Mot	Cog	MusPsy	Intlng	SPO	MUAP	Exact Output	Network output
1	1	0	1	1	1	1	0	1.027e-008
1	1	0	0.5	1	1	0.5	0.14	0.14
0	1	1	0.5	0.5	1	0	0.42	0.42
0	0.5	0	0	0	1	0	0.85	0.85
0	0	1	0.5	1	1	0	0.28	0.28
0	0.5	0.5	0	1	1	0	0.71	0.71
0	0	1	0	0	1	0	0.57	0.57
0	0	1	0.5	0	0	0	1	0.99
1	0.5	0	1	1	1	1	0.14	0.14
1	1	1	1	1	1	1	0	4.033e-008
1	1	0	1	0.5	1	1	0.14	0.14
1	1	0.5	0.5	1	1	0.5	0.14	0.14
0.5	1	0	0.5	1	1	0.5	0.28	0.28
1	1	0	0.5	1	1	0	0.28	0.28
0	0.5	1	0.5	0.5	1	0	0.42	0.42
0	1	1	0	0.5	1	0	0.42	0.42
0	1	1	0.5	0.5	0.5	0	0.42	0.42
0	0.5	0	0.5	0	1	0	0.57	0.57
0	0.5	0	0	0	0.5	0	0.85	0.85
0	1	0	0	0	1	0	0.57	0.57
0	0.5	1	0.5	1	1	0	0.42	0.42
0	0	1	0	1	1	0	0.71	0.71
0	0	1	0.5	1	0.5	0	0.71	0.71
0	0.5	0.5	0	1	1	0.5	0.71	0.71
0	1	0.5	0	1	1	0	0.42	0.42
0	0.5	0.5	0.5	1	1	0	0.71	0.71
0	0.5	1	0	0	1	0	0.57	0.57
0	0	1	0	0	0.5	0	0.85	0.85
0.5	0	1	0	0	1	0	0.57	0.57
0	0.5	1	0.5	0	0	0	0.57	0.57
0	0	0.5	0.5	0	0	0	0.85	0.85
0	0	1	0.5	0	0.5	0	0.57	0.57
1	1	0.5	0.5	1	1	1	0	5.037e-008
1	1	0.5	1	1	1	1	0	7.046e-008

Performance is evaluated using feed forward back propagation, 7 neurons are used in input layer and 1 neuron is used in output layer. Training parameters are epochs is 100, goal is 0, max_fail is 5, men_reduc is 1, min_grad is 1e-010,mu is 0.001, mu_dec is 0.1, mu_inc is 10, mu_max is 10000000000, show is 25 and time is inf.Figure 4.1 shows the performance of training data.

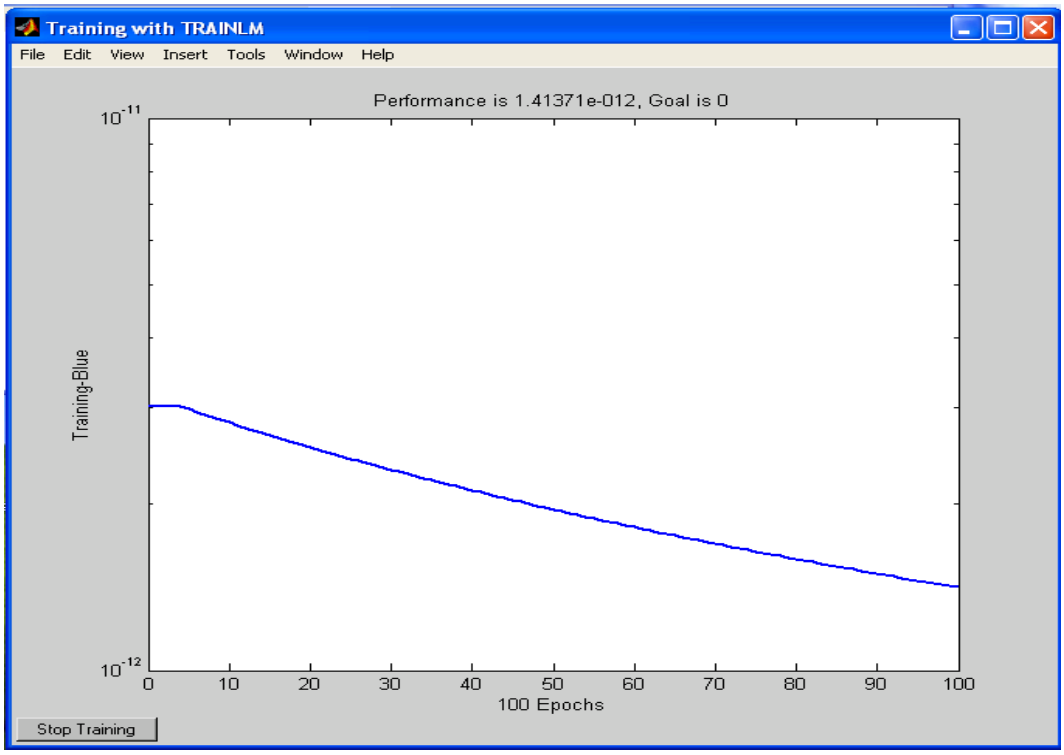


Figure 4.1: performance of training data

4.3 Result

The test data consist of 34cases. It was created from expert opinion and literature survey. It consists of 4 DMD cases, 4 BMD cases, 6CMD cases, 4 EDMD cases, 3 FSH cases, 5 LGMD cases and 7 MMD cases and 1 OPMD case. The accuracy of a classifier can be computed using sensitivity and specificity. For the given 34 classes, we consider in terms of positive tuples (diagnosis means any specific disease like DMD) versus negative tuples (e.g. diagnosis means not that specific disease like not DMD). True positives refer to the positive tuples that were correctly labeled by the classifier, while true negatives are the negative tuples that were correctly labeled by the classifier. False positives are the negative tuples that were incorrectly labeled by

the classifier, while false negatives are the positive tuples that were incorrectly labeled by the classifier. These measures are defined as

Sensitivity = tpos /pos

tpos is the number of true positives (i.e. samples that were correctly classified suffering with a specific disease) and pos is the number of positive (i.e. sample that are actually suffering with a exact specific disease) samples. For example, while testing among the 7 cases of MMD, 6 are classified correctly by neuro-fuzzy system and 1is classified wrong. Therefore, Sensitivity == 6/7.

Specificity =tneg/ neg

tneg is the number of true negatives (i.e. samples that were not suffering with exact disease and were correctly classified) an neg is the number of positive (i.e. samples that were actually not suffering with specific disease) samples and fpos is the number of false positives ("samples that are actually not suffering with a specific disease but were incorrectly classified). For example, while testing among the 34 cases that are not suffering with DMD, 30are classified correctly by Neuro-fuzzy system and 4 are classified wrong. Therefore, Sensitivity = 30/34.

Table4.4: specificity and sensitivity of diseases using neuro-fuzzy system

Measure	**DMD**	**BMD**	**CMD**	**EDMD**	**FSH**	**LGMD**	**MMD**	**OPMD**
Specificity	0	0	0.94	0	0	0	0.79	0
Sensitivity	1	1	0.84	1	1	1	0.85	1

Table 4.4 shows the specificity and sensitivity of each disease used at second level for the diagnosis of EMG based diseases using neuro-fuzzy system and figure 4.2 shows the ROC curve.

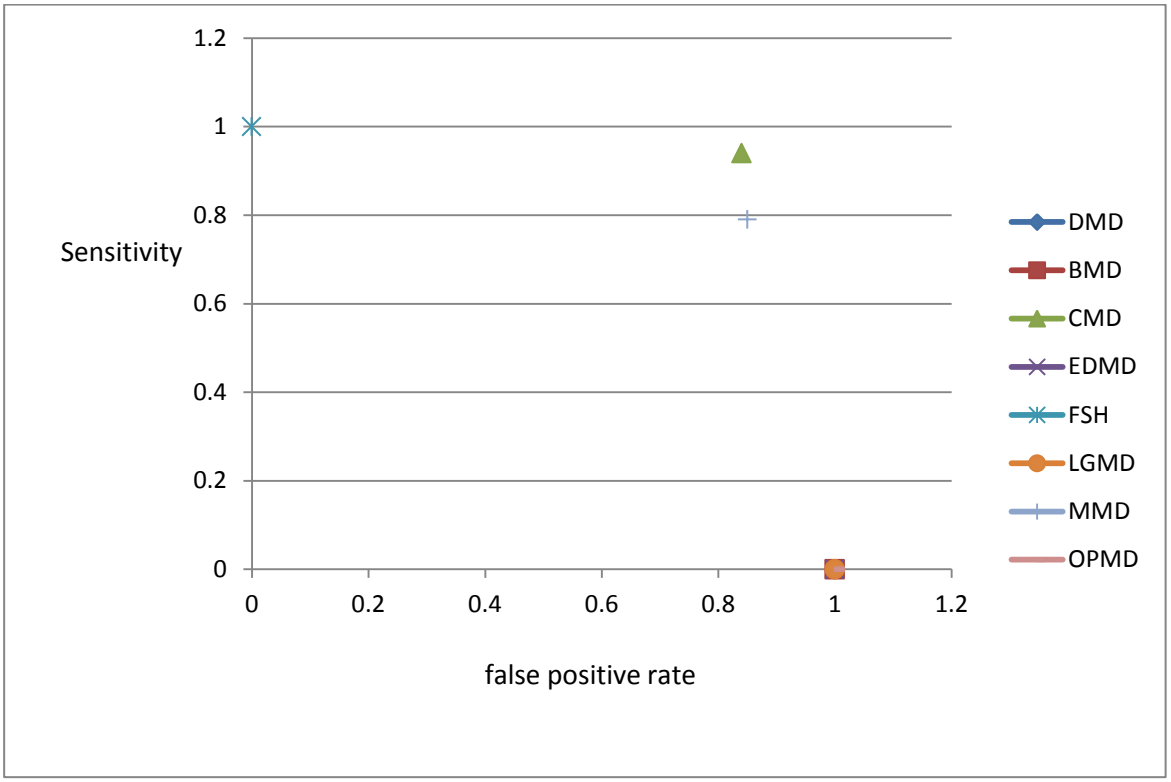


Figure 4.2: ROC curve

4.2 Interface for Neuro-Fuzzy System for Classification of EMG Based Diseases at Second Level

Interface for neuro-fuzzy system is designed in VB.net (Visual Basic) 2010. Screen shorts of the interface for the neuro-fuzzy system are shown in Figure 4.3, 4.4, 4.5 and 4.6.

Figure 4.3 shown the starting or first form of the interface and figure 4.4 shows the three buttons, first button for diagnosis at first level, second button for diagnosis at second level and third button is used to come out from the interface.

Figure 4.3: screen short of interface to start diagnosis.

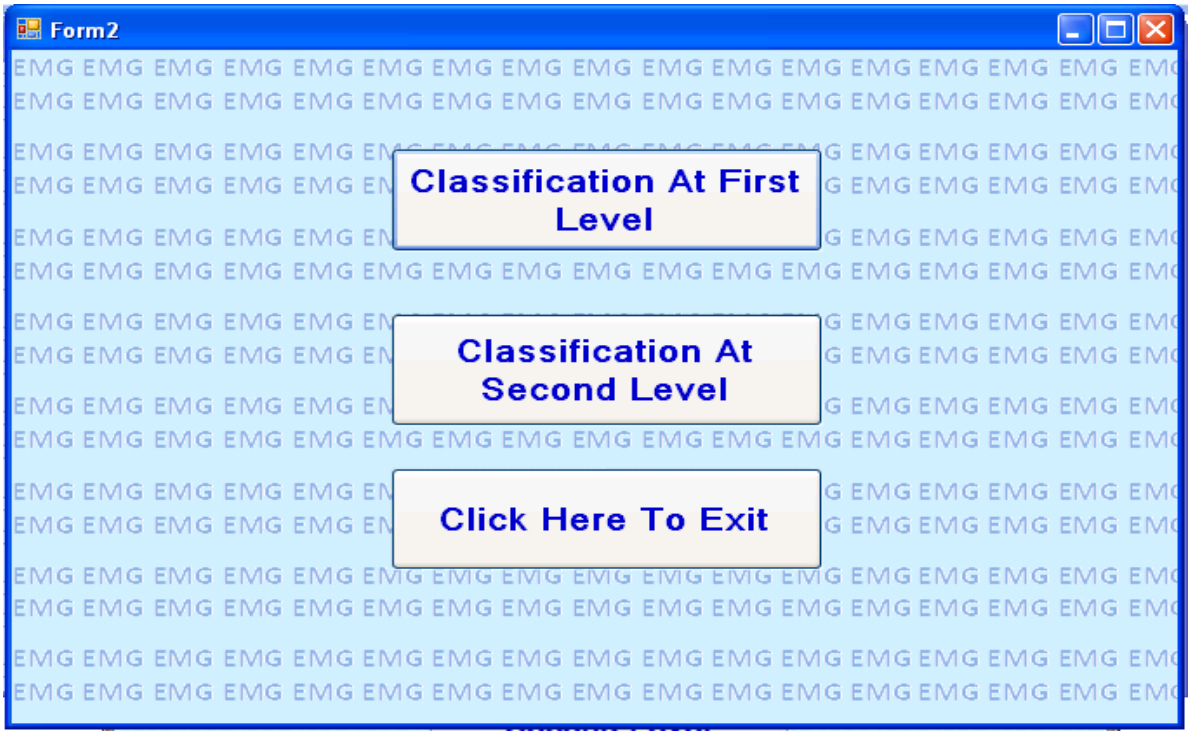


Figure 4.4 screen short of interface to select level for diagnosis

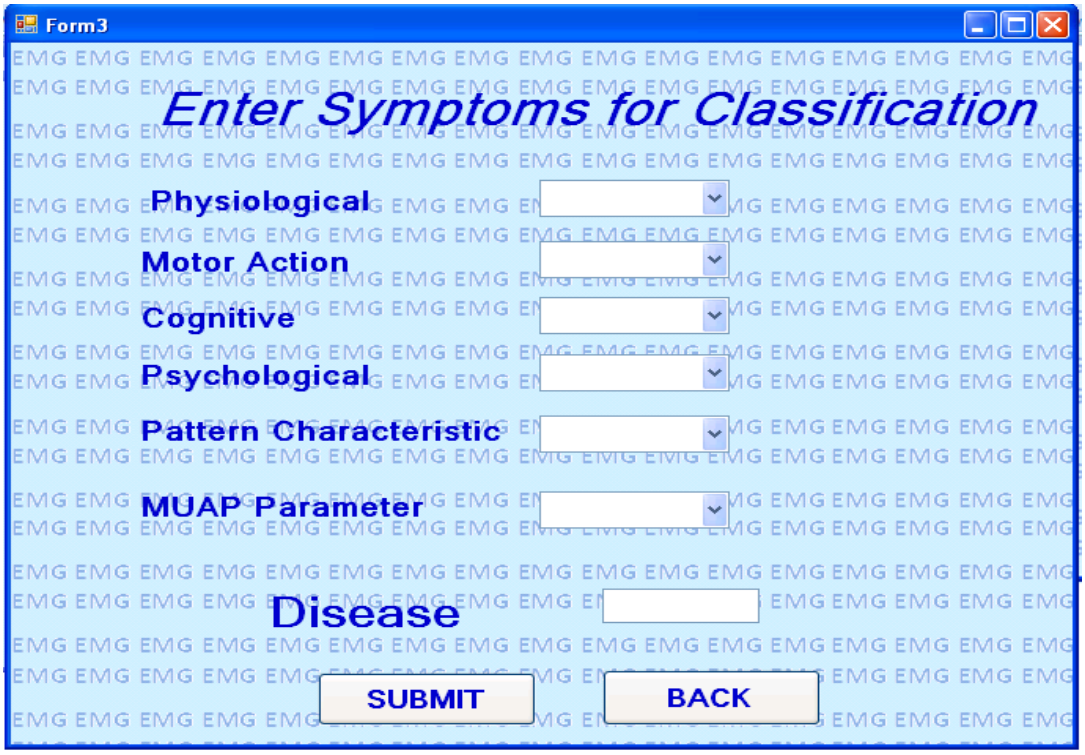


Figure 4.5: screen short of interface diagnosis at first level

As seen in figure 4.5, user can select symptoms in the form of high, medium, low and click on the submit. Disease will be displayed in text box (for example as shown in figure 4.6).

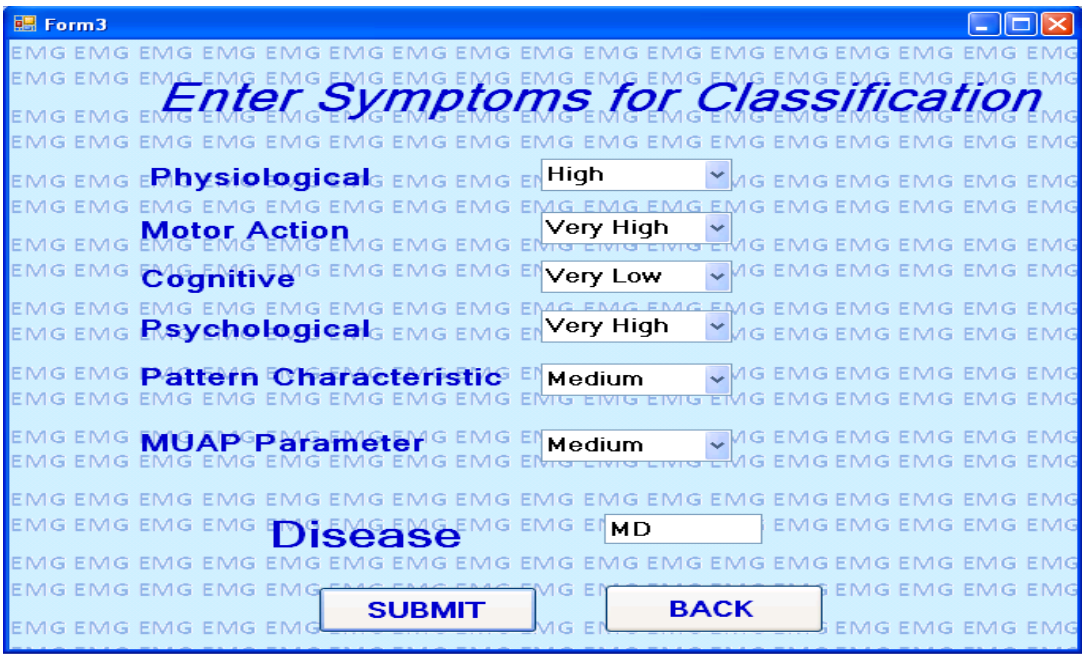


Figure 4.6: Result produced by interface using rules at first level

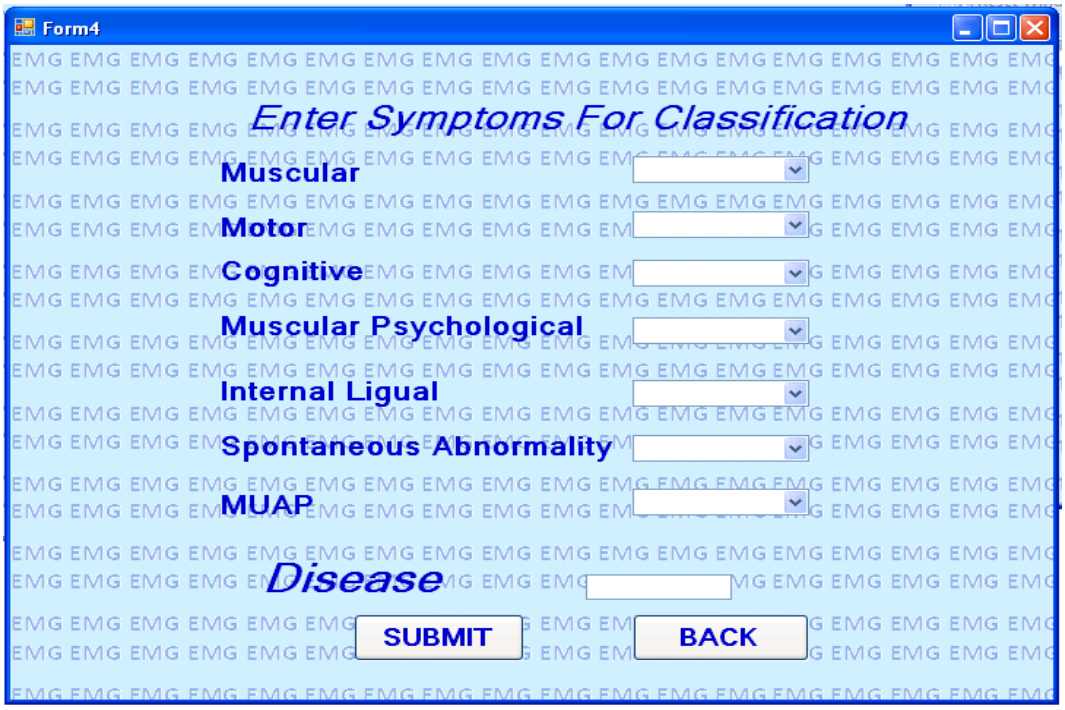


Figure 4.7: screen short of interface diagnosis at second level

As seen in figure 4.7, user can select symptoms in the form of high, medium, low and click on the submit. Disease will be displayed in text box (for example as shown in figure 4.8).

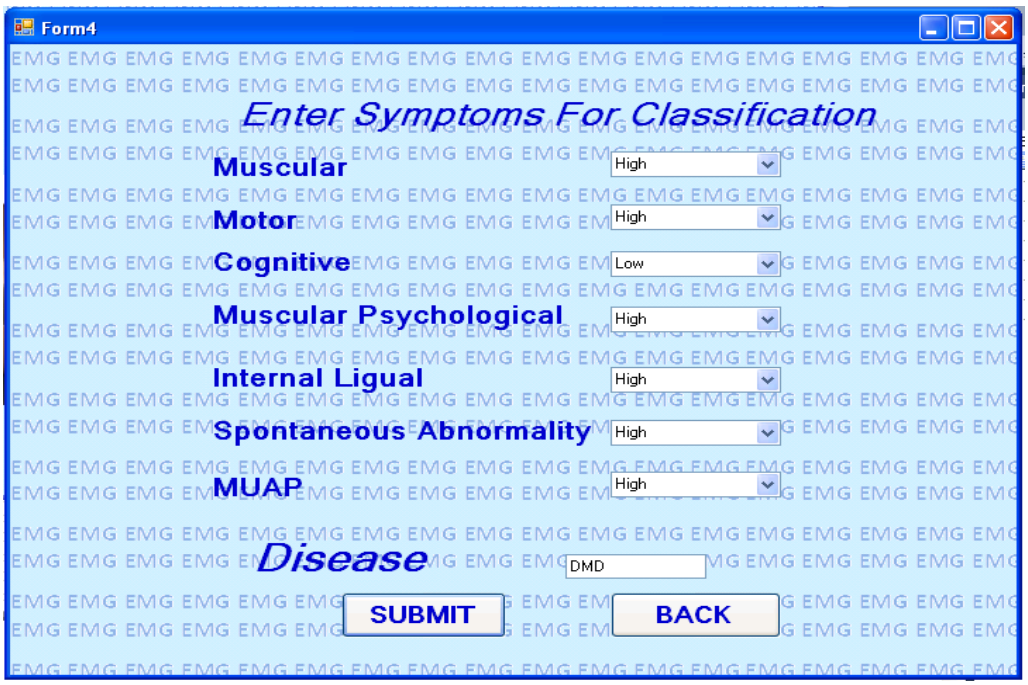


Figure 4.8: Result produced by interface using rules at second level

Chapter-5

Results and Performance evaluation

This chapter describes the results obtained by fuzzy at first level, fuzzy at second level and neuro-fuzzy at second level in the form of specificity and sensitivity.

5.1 Result using fuzzy logic for the Diagnosis of EMG based diseases at First Level:

Table 5.1 shows the result in the form of specificity and sensitivity of diseases at second level using fuzzy and figure 5.1 shows the ROC curve of result at second level.

Table 5.1: Comparative table of Measures of different disease

Measure	DMD	PO	EM	MM	N	PL	MG
Specificity	0.92	0.9	0.98	0.96	0.98	0.98	0.92
Sensitivity	0.8	0.9	0.8	0.66	0.8	0.8	0.8

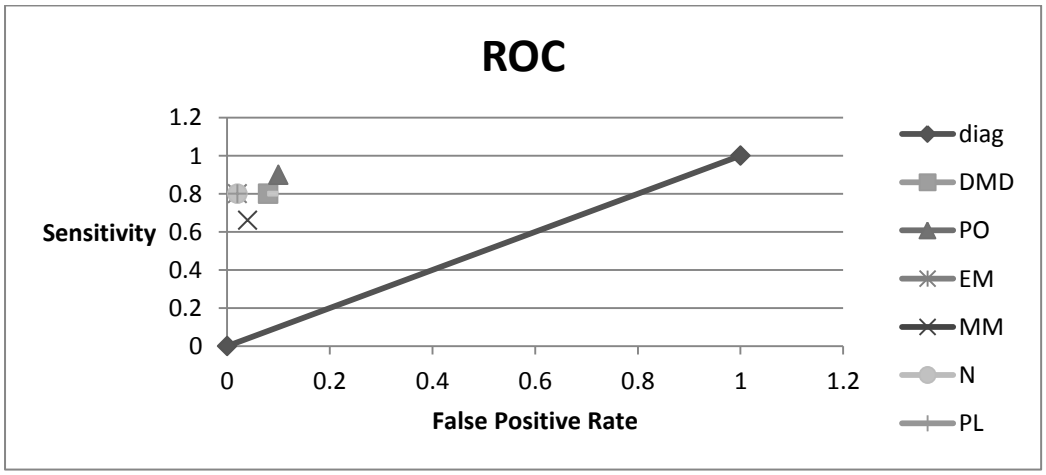


Figure 5.1: ROC Curve

5.2 Result using fuzzy logic for the Diagnosis of EMG based diseases at Second Level:

Table 5.2 shows the result in the form of specificity and sensitivity of diseases at second level using fuzzy and figure 5.2 shows the ROC curve of result at second level.

Table5.2: specificity and sensitivity of diseases

Measure	DMD	BMD	CMD	EDMD	FSH	LGMD	MMD	OPMD
Specificity	0	0	0.94	0	0	0	0.88	0
Sensitivity	1	1	0.06	1	1	1	0.71	1

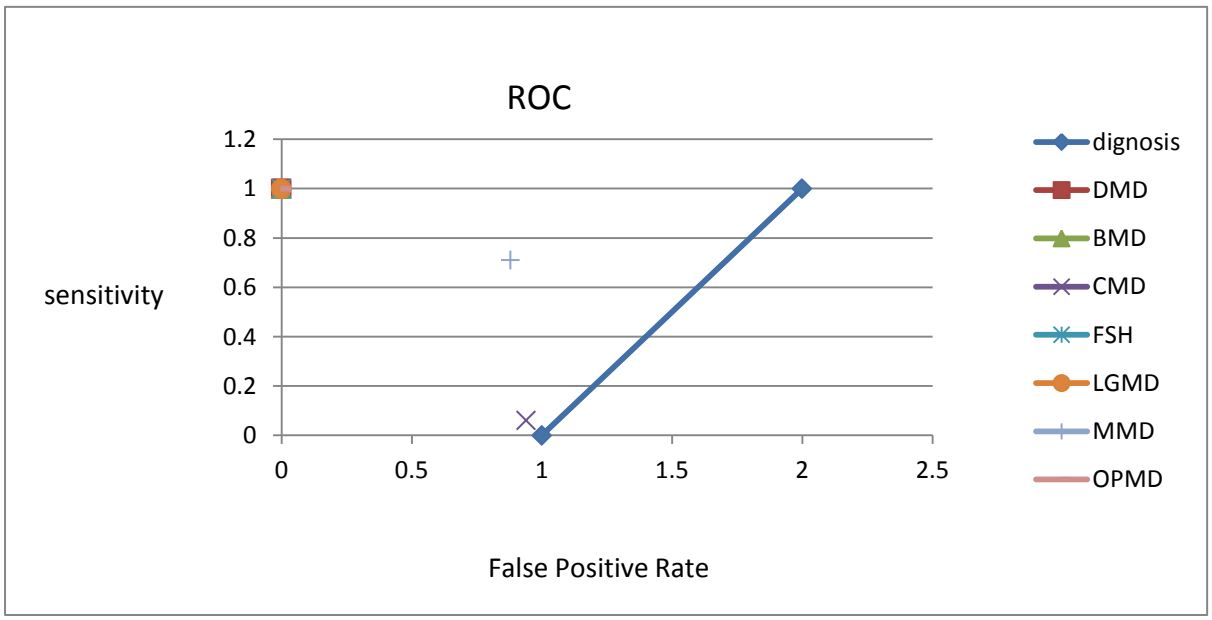


Figure 5.2: ROC Curve of result at second level

5.3 Result using Neuro-Fuzzy System for the Diagnosis of EMG based diseases at Second Level:

Table5.3: specificity and sensitivity of diseases using neuro-fuzzy system

Measure	DMD	BMD	CMD	EDMD	FSH	LGMD	MMD	OPMD
Specificity	0	0	0.94	0	0	0	0.79	0
Sensitivity	1	1	0.84	1	1	1	0.85	1

Table 5.3 shows the specificity and sensitivity of each disease used at second level for the diagnosis of EMG based diseases using neuro-fuzzy system and figure 5.3 shows the ROC curve.

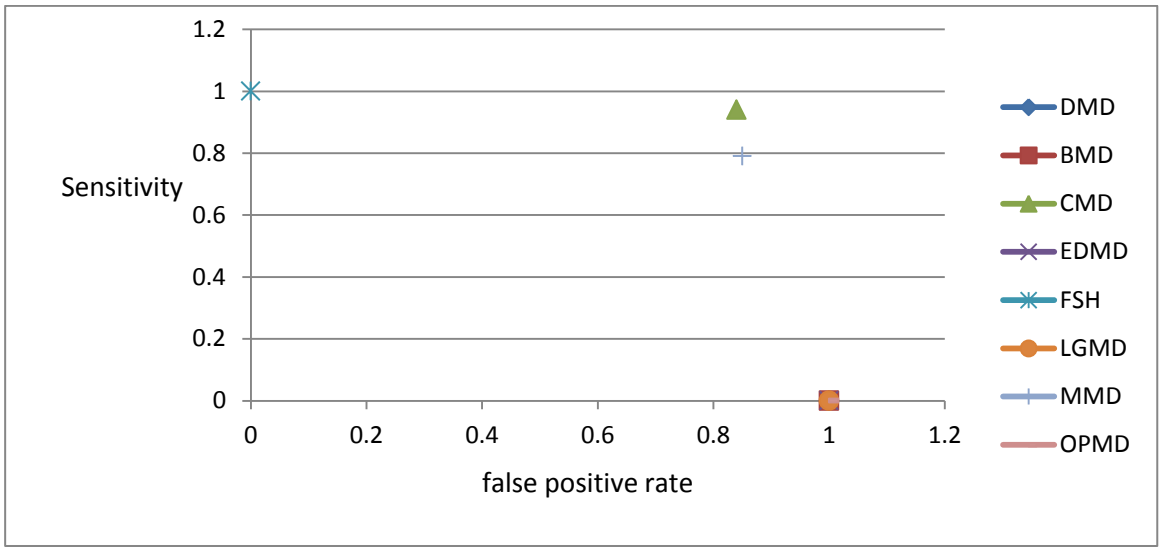


Figure 5.3: ROC curve of Results produced by Neuro-fuzzy

5.4 Performances Evaluation:

Fuzzy logic is used for the diagnosis of EMG based diseases at first level and at second level is shown in chapter 1 and 2 respectively, again fuzzy logic is used for the diagnosis of EMG based diseases at second level and in chapter 3, neuro-fuzzy is used for the diagnosis of EMG based diseases at second level.

Accuracy of fuzzy logic for the diagnosis of EMG based diseases at second level is 80% and accuracy of neuro-fuzzy for the diagnosis of EMG based diseases at second level is 98%.

Table 5.4 shows the Comparative table of Measures of fuzzy logic at first level of each disease and figure 5.4 shows the ROC curve of Comparative table of Measures of fuzzy logic at first level.

Table 5.4: Comparative table of Measures of fuzzy logic at first level

Technique/Level	Disease	Sensitivity	Specificity
Fuzzy at first level	MD	0.8	0.92
Fuzzy at first level	PO	0.9	0.9
Fuzzy at first level	EM	0.8	0.98
Fuzzy at first level	MM	0.66	0.96
Fuzzy at first level	N	0.8	0.98
Fuzzy at first level	PL	0.8	0.98
Fuzzy at first level	MG	0.8	0.92

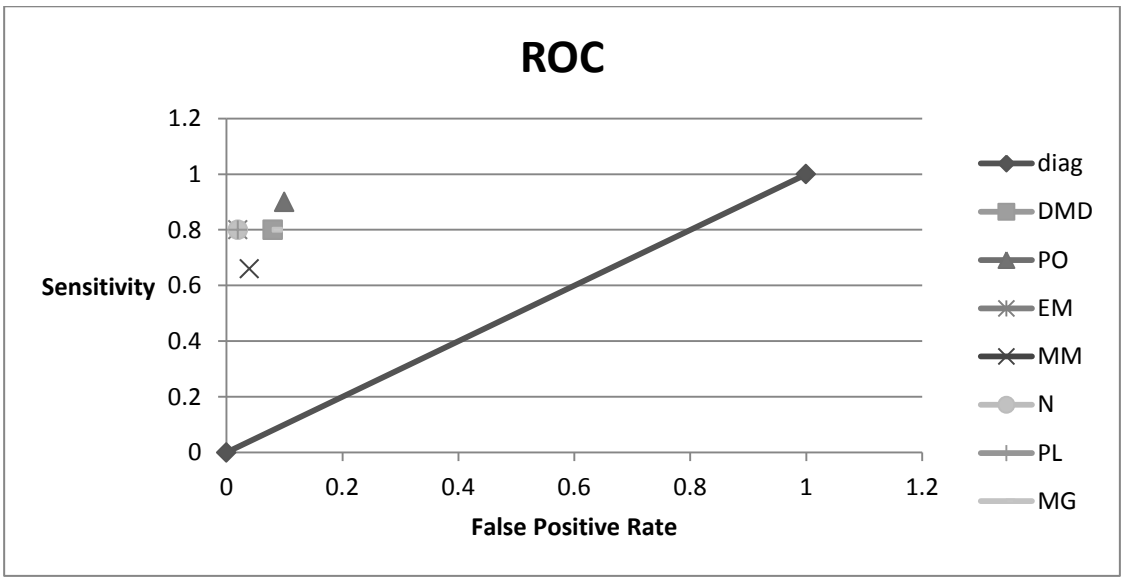
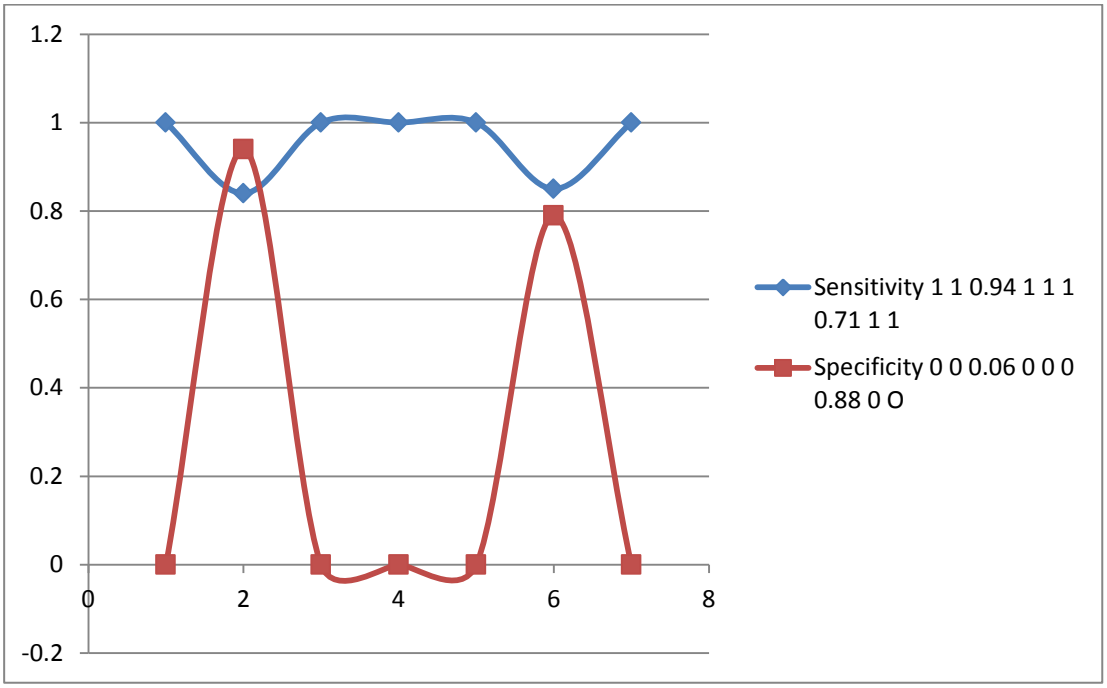


Figure 5.4: roc curve of Comparative table of Measures of fuzzy logic at first level

Table 5.5 shows the Comparative table of Measures of fuzzy logic and neuro-fuzzy system at second level on the basics of sensitivity and specificity. Figure 5.5 shows the Graph of Comparative Measures of fuzzy logic and neuro-fuzzy.

Table 5.5: Comparative table of Measures of fuzzy logic and neuro-fuzzy.

Technique/Level	Disease	Sensitivity	Specificity
Fuzzy at second level	DMD	1	0
Fuzzy at second level	BMD	1	0
Fuzzy at second level	CMD	0.94	0.06
Fuzzy at second level	EDMD	1	0
Fuzzy at second level	FSH	1	0
Fuzzy at second level	LGMD	1	0
Fuzzy at second level	MMD	0.71	0.88
Fuzzy at second level	OPMD	1	0
Neuro-fuzzy at second level	DMD	1	O
Neuro-fuzzy at second level	BMD	1	0
Neuro-fuzzy at second level	CMD	0.84	0.94
Neuro-fuzzy at second level	EDMD	1	0
Neuro-fuzzy at second level	FSH	1	0
Neuro-fuzzy at second level	LGMD	1	0
Neuro-fuzzy at second level	MMD	0.85	0.79
Neuro-fuzzy at second level	OPMD	1	0



Graph 5.1: Graph of Comparative Measures of fuzzy logic and neuro-fuzzy

On the basic of performance evaluation we can say that proposed method that is neuro-fuzzy system is best for the diagnosis of EMG based diseases at second level.

Chapter-6

Conclusion

Neuromuscular diseases are progressive in nature therefore their early diagnosis is very difficult. Some of the NMD are also not curable in the final stage. Therefore, we need a diagnostic method that accurately diagnoses the NMD in their early stage. It has been developed particularly to classify NMDs based on the analysis of the EMG signal such as: amplitude, phase and duration and clinical parameters such as: physical, cognitive, psychological and motor parameters using neuro-fuzzy system.

After presenting the limits of the classical approach and intelligent technique such as ANN, CBR and RBR, in solving the problem of classification in the medical domain, we have seen the reasons for choosing a new neuro-fuzzy system to achieve the goal of designing a system capable of making reliable diagnoses. The integration of fuzzy and neural network reduces the rules, decreases computational time, consumes the less memory and improves learning [19].

Chapter 2 describes the classification using fuzzy logic at first level, chapter 3 describes the classification using fuzzy logic at second level and chapter 4 describes the neuro-fuzzy system for the classification of EMG based diseases at second level. Finally, the classification results were presented.

The result has shown in the form of sensitivity and specificity. On the basic of performance evaluation we can say that proposed method that is neuro-fuzzy system is best for the diagnosis of EMG based diseases at second level.

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