Analysis of EMG Signals using Wavelet Analysis and Some Features

A Dissertation submitted in partial fulfilment of the
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Signal Processing & Digital Design

Submitted by

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CERTIFICATE

This is to certify that the dissertation titled "**Analysis of EMG Signals using Wavelet Analysis and Some Features**" submitted by **Ms. PREETI MEENA, Roll. No. 2K14/SPD/13**, in partial fulfilment of the requirements for the award of the degree of Master of Technology in "**Signal Processing and Digital Design (SPDD)",** Department of Electronics & Communication Engineering, Delhi Technological University, is a bonafide record of student's own work carried out by her under my supervision and guidance. To the best of my belief and knowledge, the matter embodied in this dissertation, has not been submitted for the award of any other degree or certificate, in this university or any other university or institute.

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DECLARATION

I hereby declare that all the information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. This report is my own work. I have fully cited all material by others, which I have used in my work. It is being submitted for the degree of Master of Technology in Signal Processing & Digital Design at Delhi Technological University.

Preeti Meena

M. Tech. (SPDD)

2K14/SPD/13

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Place: Delhi Technological University, Delhi

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ABSTRACT

ElectroMyoGram (EMG) is a method used to measure the problems in muscles and nerve cells of the body. Comparison of overall EMG waveform pattern and shape enables doctors to diagnose possible diseases. Currently there is computer based analysis which employs certain signal processing to diagnose a patient based on EMG recording. Signal processing usually takes the form of a transformation of a signal into another signal that is in some sense more desirable than the original.

The purpose of this research is to help in identifying the Normal, Myopathy and Neuropathy signal using the method of Discrete Wavelet Transform (DWT) and various classifiers which includes k-Nearest neighbour (kNN) approach, Artificial Neural Network (ANN) Classifier and Support Vector Machine (SVM) Classifier. DWT coefficients are used to extract the relevant information from the EMG input data which are Energy, Mean and Standard Deviation values. Then the extracted features data is analyzed and classified using the classifiers such as k-Nearest neighbour (kNN) approach, Artificial Neural Network (ANN) Classifier and Support Vector Machine (SVM) Classifier.

The proposed algorithm is implemented and also tested in MATLAB software. The EMG signal are being selected and tested from PhysioNet Database using MIT-BIH Database. The Classifier (SVM) used successfully classifies the Normal, Myopathy and Neuropathy signals with the rate of accuracy as 95.55%. The analysis system also can be achieved using rest of the classifiers such as kNN and ANN with accuracies of 73.33%,

88.88% respectively for each sample tested of Normal, Myopathy and Neuropathy classes proposed.

LIST OF PUBLICATIONS ARISING FROM THIS THESIS

1. Preeti Meena, Malti Bansal, "***Classification of Pseudo Random Numbers Using Support Vector Machine Classifier***", *International Journal of Advanced Research in Computer and Communication Engineering,* Vol. 5, Issue 5, pp. 718-722, May 2016.
2. Preeti Meena, Malti Bansal, "***Classification of EMG Signals using SVM-kNN***", *International Journal of Advanced Research in Electronics and Communication Engineering*, Vol. 5, Issue 6, pp. 1718-1724, June 2016.
3. Preeti Meena, Malti Bansal, "***Dezert-Smarandache Theory based Classification of EMG Signals***", *International Journal of Advanced Research in Computer and Communication Engineering,* Vol. 5, Issue 6, pp. 258-263, June 2016.

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LIST OF ABBREVIATIONS

EMG	–	ElectroMyoGram
AANEM	–	American Association of Neuromuscular & Electrodiagnostic Medicine
SEMG	–	Surface EMG
ICD	–	Implanted Cardiac Defibrillators
NCS	–	Nerve Conductivity Studies
DWT	–	Discrete Wavelet Transform
ARV	–	Average Rectified Value
VLR	–	Variable Learning Rate
AR	–	AutoRegressive
LDA	–	Linear Discriminant Analysis
MAV	–	Mean Absolute Value
PSO	–	Particle Swarm Optimization
RMS	–	Root Mean Square
MWM	–	Mother Wavelet Matrix
NEM	–	Needle Conductor Matrix
EDM	–	Euclidean Distance Measure

WDM	–	Weighted Distance Measure
MMLM	–	Modified Maximum Likelihood Method
SEM	–	Surface Conductor Matrix
kNN	–	k Nearest Neighbour
ANN	–	Artificial Neural Network
SVM	–	Support Vector Machine
KKT	–	Karush–Kuhn–Tucker

Chapter 1
INTRODUCTION TO ELECTROMYOGRAM

1.1) Overview

In the first chapter, brief information about the introduction, history, medical uses and techniques related to ElectroMyoGram (EMG) analysis is presented. This part discusses the ElectroMyoGram (EMG) analysis problems concerning health issue which encourage the present research. Then, the problem definitions from the previous studies, the signal decomposition, characteristics and thesis outline are presented.

1.2) Introduction

ElectroMyoGraphy (EMG) is a technique of recording the electrical movement of the muscular activities [1]. These are documented using an instrument called electromyograph. This instrument detects the electric potential that is, generated by muscle cells. For this detection, these cells must be electrically active. This biomedical signal is analysed to observe the medical abnormalities related to muscles and nerves in human body.

1.3) History

The first experiment on the treatment of EMG was started with the works of Francesco Redi in 1666. Walsh had also been ready to demonstrate the eel fish's muscle tissue which may generate a spark of electricity by 1773. Eight decades later, in 1849, Emil du Bois-Reymond discovered that it was possible to record the electrical activity for a muscle contraction. The primary actual recording of this activity was generated by Marey in 1890. In 1922, Gasser and Erlanger utilized an electronic instrument to indicate the electrical signals generated from muscles. Rough data can be obtained from the observation because of the random nature of the myoelectric signals. The potential of detecting such signals was improved steadily during the years of 1930s to 1950s. And, hence research started so that it is possible to use the improved electrodes for the study of muscles. The AANEM (American Association of Neuromuscular & Electrodiagnostic Medicine) was made in 1953 so that advancement in the science and clinical use of the techniques may be possible. Use of surface electromyogram (sEMG) started, for the treatment of additional specific disorders, within the 1960s by Hardyck and his team. Within the early 1980s, Cram and Steger introduced a clinical technique for scanning the different types of muscles, exploiting an electromyogram sensing device [2].

It became possible to produce small and light-weight instruments by the middle of the 80s for the integration techniques in electrodes. Now, at present, a variety of such amplifiers are commercially available. Cables that measured signals within the desired potential unit also became available by the early 1980s. Recent analysis has resulted in a very high understanding of the properties of electromyogram recording. The diagnostic procedure is progressively used for recording the superficial muscles in clinics, wherever contractile organ electrodes are used for identifying deep muscles or localized muscle activity.

There are several applications for the utilization of EMG. EMG is employed clinically for the identification of muscle problems and nerve fibers issues. It's used diagnostically by laboratories and by clinicians trained within the use of training program or technology assessment. EMG is additionally utilized in many varieties of analysis laboratories, together with those concerned in biomechanics, control, fibre bundle physiology, movement disorders, bodily property management, and therapy.

1.4) Medical Uses

Testing of EMG consists of medical sphere features. EMG signals can also be used as the signals for the movements of prosthetic hands, arms, and prosthetic lower limbs. EMG is considered as a medical instrument to detect the disease in the contractile organs, also as a learning physiology exploratory wave and for the control of various disorders. EMG signals are usually exploited to monitor neurotoxins in the muscles.

EMG could also be used for muscle problem observation like physiological condition with neuro-muscular blocking so that it is possible to avoid operative residual curarization. Curarization is powerful drug found in the muscles.

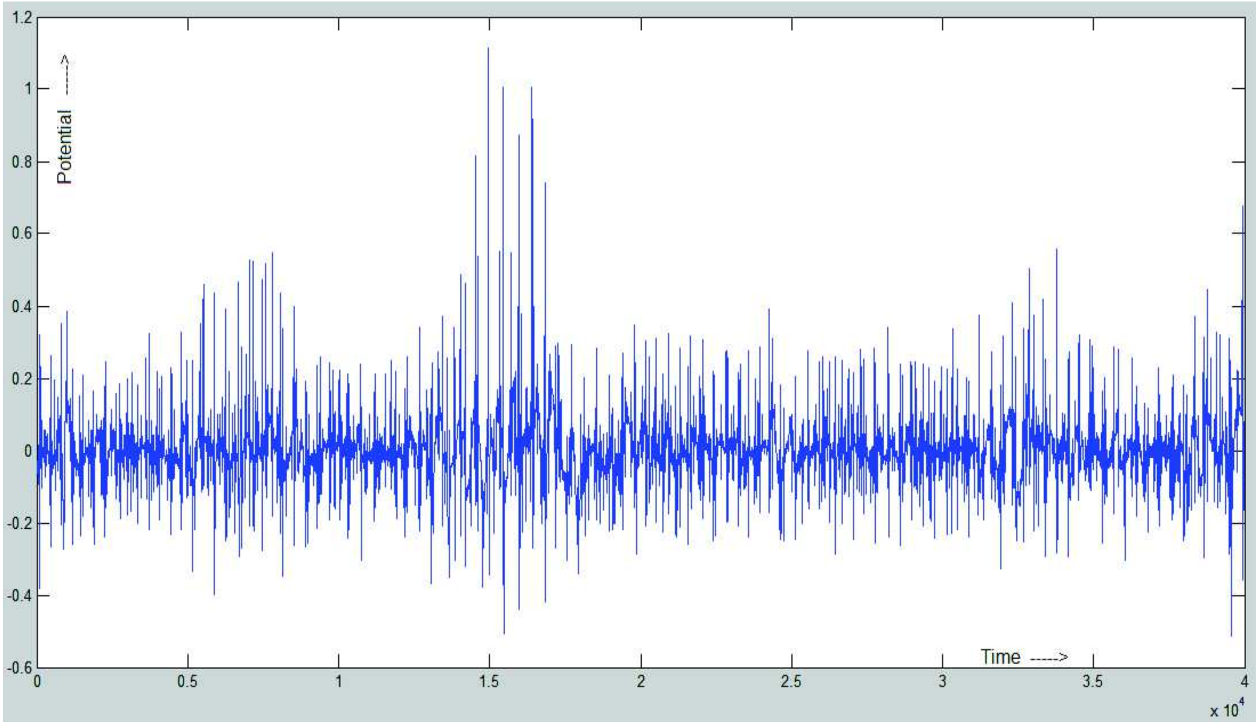

Fig.1.1: EMG signal of a healthy person

ElectroMyoGram is generally performed using various electrodiagnostic medical checks except within the real primary myopathic state. This helps in finding out the electrical activities of the nerves. This can be referred to as nerve conductivity studies (NCS).

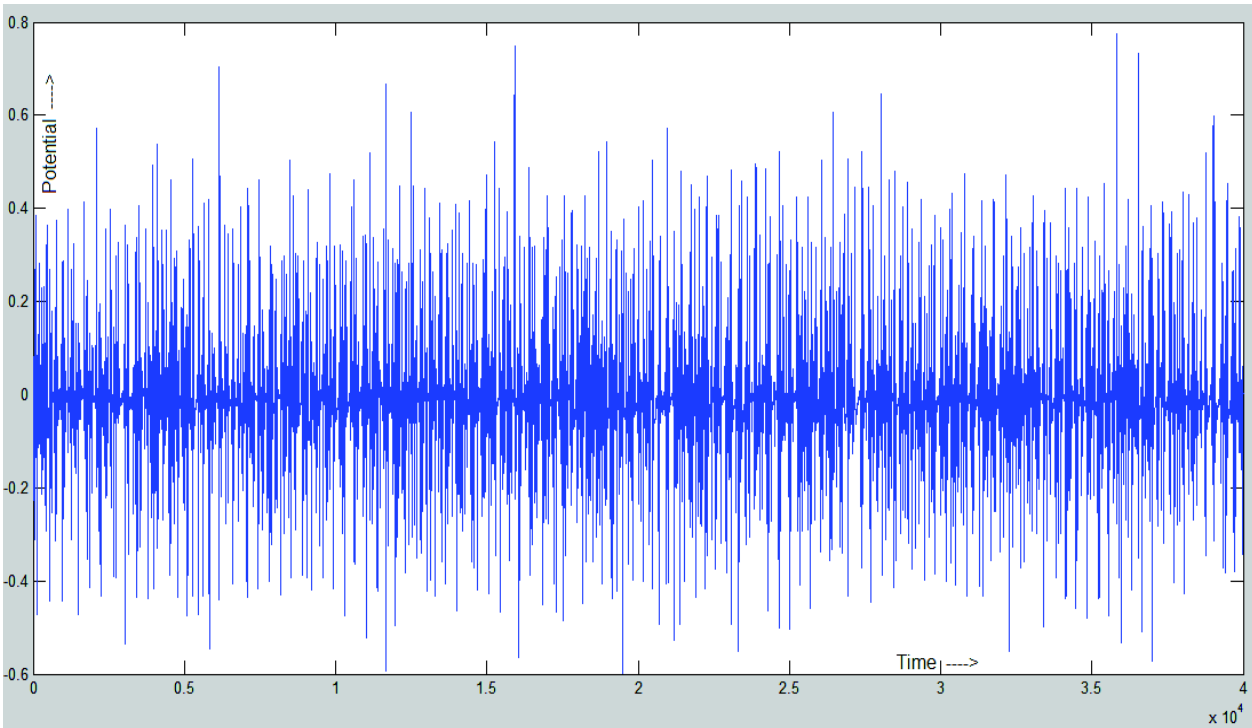

Fig.1.2: EMG signal of a myopathic patient

Usually, Electromyogram represents the pain within the limbs, weakness in the nerves, etc. EMG also concerns with medical disorders of the muscles. EMG helps in identifying the myopathic and neuropathic disorder or injuries. Among these, Myopathy is the muscle disease in which the muscle fibers do not function properly and results in muscular disease and Neuropathy is the nerve disease which can be defined as the weakness, numbness and pain due to the nerve damage and it generally occurs in the hands and feet. Waveforms for these two are shown in the Fig. 1.2 and 1.3 respectively. Less common medical conditions embody a myotrophic lateral pathology, myasthenia, and inherited disorder. Signals representing the three different types of EMG signals i.e., normal, myopathy and neuropathy are represented in the Fig.1.1, 1.2 and 1.3 respectively.

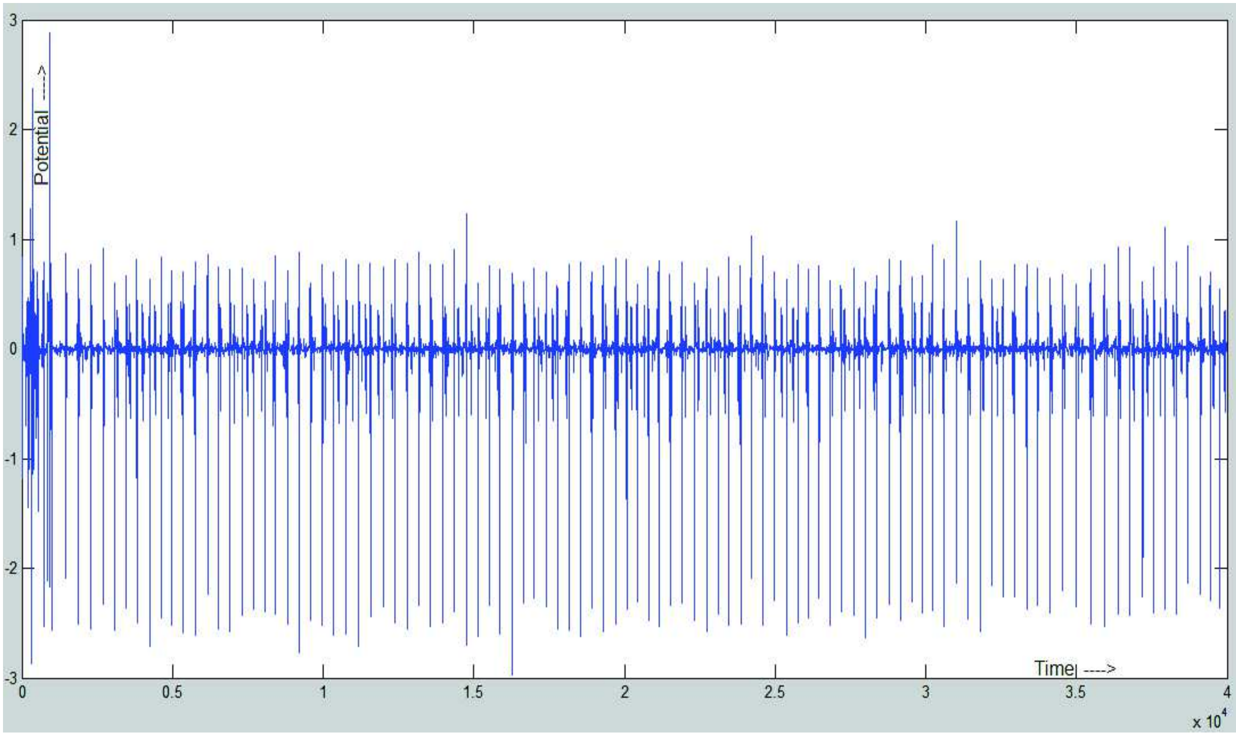

Fig.1.3: EMG signal of a neuropathic patient

1.5) Techniques Used for EMG

1.5.1) Skin preparation and Risks

The primary step before insertion of the needle conductor is skin preparation. This usually involves merely clean-up of the skin with an alcohol pad.

The actual placement of the needle conductor will be troublesome and depends on variety of things, like specific muscle choice and also the size of that muscle. Correct needle electromyogram placement is incredibly necessary for correct illustration of the muscle of interest, though electromyogram is simpler on superficial muscles because it is unable to bypass the action potentials of superficial muscles and observe deeper muscles. Also, the additional body fat in a person makes the EMG signal weak. And utilization of the electromyogram detector is best located at the belly of the muscle i.e., the longitudinal plane. The longitudinal plane may be thought of as a mediator among the motor purpose (middle) of the muscles and the tendonus insertion purpose.

Cardiac pacemakers and implanted cardiac defibrillators (ICDs) are used increasingly in the clinical practice, and no evidence exists indicating that performing routine electrodiagnostic studies on patients with these devices poses a safety hazard. However, there are theoretical concerns that electrical impulses of nerve conduction studies (NCS) could be erroneously sensed by devices and can result in unintended inhibition or triggering of output or reprogramming of the device. In general, the closer the stimulation site is to the pacemaker and pacing leads, the greater the chance for inducing a voltage of sufficient amplitude to inhibit the pacemaker. Despite such concerns, no immediate or delayed adverse effects have been reported with routine NCS [3].

No well-known contraindications exist from doing needle EMG or NCS on pregnant patients. Additionally, no complications from these procedures are addressed within the literature. Electric potential testing, likewise, has not been addressed to cause any issues if it's performed throughout maternity.

Patients with oedema or patients in danger for oedema are habitually cautioned to avoid transdermic procedures within the affected extremity, specifically veni-puncture, for preventing the development or worsening of oedema or inflammation. Despite the potential risk, the proof for such complications following veni-puncture is restricted. No such reports exist of inflammation, infection, or another complications associated with electromyogram performed within the setting of oedema or previous lymphatic tissue dissection. However, given the unknown risk of inflammation in patients with oedema, affordable caution ought to be exercised in doing needle examinations in lymphedematous regions to avoid complications. In patients with gross swelling and taut skin, skin puncture by needle electrodes might lead to chronic weeping of bodily fluid. The potential microorganism media of such bodily fluid and therefore the violation of skin integrity might increase the chances of inflammation. Before continuing, the doctor ought to weigh the potential risks of doing the study with the requirement to get the knowledge gained [4].

1.5.2) Surface and contractile organ EMG recording electrodes

There are two types of electromyogram: surface electromyogram and contractile organ EMG. Surface electromyogram assesses muscle operation by recording muscle activity from the surface higher than the muscle on the skin. Surface electrodes are ready to offer solely a restricted assessment of the muscle activity. Surface electromyogram may be recorded by a combine of electrodes or by a lot of complicated array of multiple electrodes. For the electromyogram recordings, potential drop (voltage difference) is measured between two electrodes. Limitations of this approach are the actual fact that surface conductor recordings are restricted to superficial muscles, are influenced by the depth of the hypodermic tissue at the positioning of the recording which might be extremely variable relying of the load of a patient, and can't dependably discriminate between the discharges of adjacent muscles.

Intramuscular EMG are often performed employing a form of differing types of recording electrodes. The only approach may be a monopolar needle conductor. This may be a fine wire inserted into a muscle with a surface conductor as a reference; or two fine wires inserted into muscle documented to every alternative. Most ordinarily fine wire recordings are for analysis or physiology studies. Diagnostic monopolar EMG electrodes are generally stiff enough to penetrate skin and insulated, with solely the tip exposed employing a surface conductor for reference. Needles for injecting therapeutic neurolysin or phenol are generally monopolar electrodes that use a surface reference, during this case, however, the metal shaft of a needle, insulated in order that solely the tip is exposed, is employed each to record signals and to inject. Slightly a lot of complicated in design is the coaxial needle conductor. These needles have a fine wire, embedded within a layer of insulation that fills the barrel of a needle, that has an exposed shaft, and also the shaft is the reference conductor. The exposed tip of the fine wire is the active conductor. As a results of this configuration, signals tend to be smaller if recorded from a coaxial conductor than once recorded from a monopolar conductor and that they are additional immune to electrical artifacts from tissue and measurements tend to be somewhat a lot of reliable. However, as a result of the shaft is exposed throughout its length, superficial muscle activity will contaminate the recording of deeper muscles. Single fiber EMG needle electrodes are designed to possess terribly small recording areas, and permit for the discharges of individual muscle fibers to be discriminated.

To perform contractile organ EMG, usually either a monopolar or concentrical needle conductor is inserted through the skin into the muscle tissue. The needle is then stirred to multiple spots among a relaxed muscle to compute each insertional activity and resting activity within the muscle. Traditional muscles exhibit a quick burst of muscle cell activation if excited by needle movement, however this seldom lasts quite 100ms. The two most typical pathologic kinds of resting activity in muscle are vellication and fibrillation potentials. A vellication potential is an involuntary activation of a motor unit among the muscle, typically visible with the oculus as a muscle twitch or by surface electrodes. Fibrillations, however, are solely detected by needle EMG, and represent the isolated activation of individual muscle fibres, typically because the results of nerve or muscle unwellness. Often, fibrillations are triggered by needle movement (insertional activity) and persist for many seconds or additional once the movement ceases.

After assessing resting and insertional activity, the electromyographer assess the activity of muscle throughout voluntary contraction. The shape, size, and frequency of the ensuing electrical signals are judged. Then the conductor is set back some millimetres at previous position and again, the activity is analyzed. This is often continual, generally till information on10–20 motor units are collected so as to draw conclusions regarding motor unit operation. Every conductor track provides solely a really native image of the activity of the complete muscle. Due to the complicated inner structure of the skeletal muscles, the conductor must be placed at numerous locations to get a correct study.

1.6) Maximal voluntary contraction

The main function of the EMG is to indicate that how well a muscle is doing in the human body. The test usually performed for the muscles is a very common approach and known as maximal voluntary contraction of the muscles [5].

Generally, automatically measured muscle force is awfully correlated with the processes of EMG signal activation. The electrical signals which need to be accessed using the surface electrodes are recorded from the muscle fibres in near approximation to the surface.

Muscles activation depends on various analytical ways which further varies depending upon their exploitation. Among these various ways, maximal voluntary contraction is a method which is used for analysing the target muscles. Consistent with the article, peak forces and average corrected EMG measures the methodology of knowledge reduction which ought to be utilized for accessing the main training exercises, [6] that are concluded by the “average corrected EMG information (ARV) is significantly less varying, If muscles activity of the main muscular structure is computed and compared to the large variable of EMG, hence, the researchers would mention that as ARV EMG information which ought to be documented with the large values of EMG extent.

EMG can also be utilized for representing the quantity of fatigue in the muscles during the period of exercise. The contraction and expansion within the electromyogram signals signifies the fatigue level in the muscles. Then it may be an increase within the amplitude, the quantity of the signal or period of the muscle and nerve impulse. It is also considered as an overall shift in the lower frequency values. Hence, here, only the changes in muscles (i.e. myopathy) and nerves (i.e. neuropathy) is considered for the project and analysis of that is done [7].

1.7) EMG Signal Decomposition

EMG signals are basically produced by the superposition of various motor unit action potentials coming from various different motor units. For a concentrated analysis, the measured electromyogram signals may be rotten into the corresponding motor unit action potentials. This potential from totally different motor units tend to own different shapes. Whereas motor unit action potentials that are recorded by an identical conductor from the identical motor unit are usually same. Especially motor unit action potentials size and form rely upon the position of the conductor that wherever the conductor is found in regards to the fibres. Electromyogram signals decomposition is non-trivial, though several strategies are projected.

1.8) EMG Signal Processing

In the EMG signal processing, rectification is done firstly. It converts the complete signal into one polarity frequency signal (generally positive). The main objective behind the rectification of a signal is to confirm that the raw signal doesn't average to zero. This is because of having positive and negative elements in the raw electromyogram signal. It simplifies the signals and computes the fast fourier transform (FFT). When the EMG wave is processed, full and half-length frequencies are sorted to confer for the rectification of the signal. The full length frequency creates a positive signal by shifting the dc level of the original wave making it all a positive wave. This is a very good method of rectification. As a result, it can conserve all the energy of the EMG for the analysis. Half-length rectification do the opposite of full-length rectification and generates negative wave. Due to this rectification, the information does not become zero and it may be utilized further for the analysis using algorithmic programs.

1.9) Electrical Characteristics

The electrical supply is that the muscle membrane potential of concerning –90 mV [8]. Measured electromyogram potentials vary between less than 50 μV and up to 20 to 30 mV, relying on the muscle underneath observation.

Typical repetition rate of muscle motor unit firing is regarding 7–20 Hz, relying on the scale of the muscle (eye muscles versus seat (gluteal) muscles), previous nerve fibre injury and alternative factors. Injury to motor units will be expected at ranges between 450 and 780 mV.

Muscle tissue at rest is often electrically inactive. When the electrical activity caused by the irritation of needle insertion subsides, the medical instrument ought to observe no abnormal spontaneous activity (i.e., a muscle at rest ought to be electrically silent, with the exception of the realm of the synapse, which is, beneath traditional circumstances, terribly impromptu active). Once the muscle is voluntarily shrunk, action potentials begin to seem. Because the strength of the muscular contraction is raised, a lot of muscle fibres make action potentials. Once the muscle is absolutely shrunk, there ought to seem a disorderly cluster of action potentials of variable rates and amplitudes (a complete enlisting and interference pattern).

EMG findings vary with the kind of disorder, the period of the disease, the age of the patient, the degree to that the patient may be cooperative, the kind of needle conductor accustomed study the patient, and sampling error in terms of range of areas studied in the muscle and therefore the number of muscles studied overall. analysing the electromyogram findings is typically best done by a personal aware by a centered history and physical examination of the patient, and in conjunction with the results of different relevant diagnostic studies performed together with most significantly, nerve physical phenomenon studies, but also, wherever acceptable, imaging studies like imaging and ultrasound, muscle and nerve diagnostic test, muscle enzymes, and serological studies.

1.10) Thesis Outline

The thesis has been organized in a manner in which it can provide smooth and continuous flow of information to the reader for the analysis of EMG signals. In this dissertation, there is division of chapters in five major ones. These five chapters are then subdivided into sections. These five chapters in this dissertation are as follows: Introduction to ElectroMyoGram, Literature Survey, Research Methodology, Results and Discussion and finally Conclusion and Future Scope of the project. The content of each chapter is briefly given as follows.

Chapter 1 is the first chapter in the thesis. This chapter is the introduction of the project and gives information about the background, history, medical uses of EMG, problems related and the proposed solutions for the EMG analysis system. Three types of EMG signals are also given in the chapter i.e., normal, myopathy and neuropathy signals.

Chapter 2 is the second chapter in the thesis and this chapter mainly focuses on the literature survey of the previous studies on the EMG analysis. This chapter deals with the past and current studies of the EMG analysis. This is the review of various applications and algorithms of features extraction with various classifiers.

Chapter 3 is the third chapter in the thesis. Here, the research methodology of the project is discussed in detail. This chapter tells about how the project is made and what are the methods and classifiers used in the project. This chapter tells about the flow of the project operation. This chapter discusses about the EMG analysis design and the implementation of DWT with the classifiers named as kNN, ANN, and SVM.

Chapter 4 is the fourth chapter of the thesis. In this chapter, discussion of the features extraction and classification results of EMG analysis is done. This part also tells about the MATLAB software development for the methods used. All discussions that concentrate on the result and performance of the EMG analysis using DWT with features (like energy, mean, standard deviation) and various classifiers used are presented.

Chapter 5 is the fifth chapter of the thesis. This chapter discusses about the conclusion and future work of the project. This chapter also describes the issues, limitations and therefore the recommendations for this project.

Chapter 2
LITERATURE SURVEY

2.1) Overview

The enhancement in the ElectroMyoGram (EMG) analysis is a part of biomedical signal processing. It has been done to obtain the muscle and neural diseases classification which has been studied by many of the researchers. Experimental and numerical works have been carried out in their studies. In the EMG analysis, the main objective is to propose such a method that improvement in the degree of accuracy in classifying the disease is possible.

In this chapter, literature survey begins with the reviewing of some of the previous studies of EMG signals. It is followed by reviewing the analysis of EMG signals through various methods in the past. Then the classification models that have been already used for EMG signals analysis are reviewed. This literature survey also highlights the limitations of the previous EMG analysis methods pertaining to current work.

2.2) Review of EMG Signals

EMG signal interpretation could be a growing and trendy analysis domain nowadays. A lot of analysis works are distributed by various scientists during this domain from the previous decade. A number of the medical specialty engineering labs in our country even have shown their interests during this analysis domains and started work. Still applied science has not been applied on this research field. The transient literature survey towards electromyogram signal associated with information domain work and signal interpretation techniques are characterised below.

Documentation of experiments were starting with discovering the generation electricity from specialised muscle of electric eel by FranescoRedi's initiative analysis proposal in 1666. In analysis field, a replacement chapter was included along with his noble work. Various scientists, analysis staff planned and incontestible numerous innovative and artistic articles and objects with an influence of Redi's work. In 1890, Marey introduced the term 'electromyography' and its activity behind actual reading. Within the short review of thought it proceed to conclude that although the particular plan originated from Redi's work while the term EMG was introduced by Marey. A replacement era became started with the visualisation of electrical signals from muscles by CRO in 1922 by Gasser and Erlanger. Although improvement of science and technology a lot of new various inventions relating to diagnostic procedure signal was done, however the necessary work began in 1960 with clinical usage of surface EMG. Hardyck and his analysis cluster were the primary practitioners to use of Surface EMG. J.G. Kreifeldt of Tufs University was described a technique to spot the ratio characteristics of surface detected diagnostic procedure for amplify, rectify activities [9]. A standard technique of first process surface detected electromographic (EMG) activity was to differentially amplify, rectify, and so sleek (using a low-pass filter) the corrected activity .The SNR depends, at least, upon the contraction level, style of smoothing filter, and also the quantity of smoothing for the actual filter. This outlined SNR is very important in signal communication issues of every a method and a theoretical nature. In 1975, D. Graupe et al. mentioned an approach to beat the popularity issues utilizing autoregressive-moving-average parameters and also the kalman filter parameters of the EMG statistic applying on restorative management purpose [10]. It had been shown that the ensuing known parameters yield sufficient data to discriminate between a little numbers of higher extremity functions. Afterward projected work, the characteristics of surface EMG signals from various stepping of human locomotive activities were described by Cecil Hershler and M.Milner [11]. accentuation consistency and repeatability of acquiring information, it had been given the characteristics of sur-face EMG signals from m. vastus lateralis and m. muscle leg bone throughout many steps of level walking below controlled repeat-able gait conditions at three various speeds for many subjects. The applied math analysis and also the pattern classification of electromyographic signals from the striated muscle and striated muscle of a paralytic person generated by separate lower arm movements. The contribution of this work was to enlighten the con-trolling purpose of prosthetic or unfortunate arm with marginal mental effort [12].The idea of restorative exploitation surface EMG began from the year 1975. The approach of an extended work of Graupe and Martin Cline, Peter C. Doerschuk et al. designed a system exploitation digital signal pro-cessing techniques for generating management signals for a multifunction lower arm restorative exploitation surface diagnostic procedure [13]. Though the most idea originated from Graupe and Cline's work however this small review concludes that a signal analysis technique is developed for discriminating a group of lower arm and wrist joint functions utilizing surface EMG signals. Information were obtained from four electrodes placed over the proximal forearm. The functions analyzed enclosed radiocarpal joint flexion/extension, radiocarpal joint abduction/adduction, and forearm pronation/supination. Experimental results on-normal sub-jects are given that demonstrate the benefits of exploiting the spacial and time correlation of the signals. This method ought to be helpful in generating management signals for prosthetic devices. Eric Hultman et al. designed a method for recording sEMG at the same time with electrical stimulation of human skeleton muscle [14]. R.M. Studer and his analysis cluster was described a formula for optimum adaptation of the signal of matched filter bank uses the detection of the motor unit nerve impulse waveforms by EMG. In clinical designation and medical care, its contribution was terribly high [15]. Swiss scientist An-dreas Gerber et al. created a replacement framework incorporated in worm victimisation for quantitative EMG analysis [16].In this review context it may be resulted that modification and alteration are there. In International Acoustics, Speech, and Signal process Conference, 1986, Chou Yitong given a technique for contractor electromyographic signals from the surface EMG signals utilizing EMG waveforms. During this technique he described the contractile organ signal from the surface signal that is a lot of vital for the long run researchers. [17]. OmryPaiss and G.F. Inbar investigated on the power of the autoregressive model of surface EMG to explain the method spectrum [18].

2.3) Review of Analysis of EMG Signals

In 1986, D.A. Winter and H.J. Yack designed the EMG patterns for sixteen muscles concerned in human walking and therefore the variability of patterns were also measured by them. They additionally enforced the patterns in many mechanical tasks of every muscle [19].This review section concludes that pattern recognition conception of many muscles in our body originated from this innovative plan. The technique of spacial filtering offered a replacement flexibility in computing of selective EMG activity configurations. Harald Reucher determined the performance of the configurations utilizing 2-dimensional spatial filters and compared the modeling results with experimental ones [20]. G. Hefftner et al. mentioned the exploitation of useful contractile organ stimulation to the muscles by movement and studied the system by identifying the electromyographic signals process [21]. In 1989, D.Graupe et al. delineated the usage of electromyographic sig-natures for dominating the electrical simulation in higher motor nerve fiber paraplegics to change them to run with the assistance of a walker. Here it had been additionally shown that the on top of lesion EMG management and also the below lesion EMG management serve complementary and also the crucial roles in FES, regard less of higher than lesion EMG management [22]. Gradually many ways of EMG management originated from the year 1989. A fast, easy EMG burst wave-form recognition formula had been developed by G. Dwyer with decoding the signal to yield the position, du-ration and strength of individual EMG bursts [23].The idea of varied formula originated to identify the EMG signal. With this formula, the EMG pattern was analysed to give upper motor neuron paraplegics with subject responsive management of FES for the objective of walker supported walking [24]. In Annual International Conference of the IEEE Engineering within the field of medication and Bi-ology Society, 1989, M.Z. Kermani planned a rule based strategy for the interpretation of motion patterns in an EMG (EMG)-controlled higher extremity prosthetic device [25]. Akira Hiraiwa et al. projected the analysis and classification of electromyographic signal pattern of prosthetic members by neural networks [26]. In IEEE conference, M. Bodruzzaman described a collection of contractile organ electromyographic signals that were collected from numerous patients' ramp muscle con-traction. The signals were tested for the chaotic behaviour utilizing spectral analysis and Poincare map techniques [27]. On same year, in another conference K. Ito mentioned an EMG controlled prosthetic forearm with three degrees of freedom exploiting tiny size supersonic motors [28]. This review discussion concludes that electromyogram Controlled pros-thesis approach began to explore. A sensitivity operation was outlined within the journal entitled "Boundary element analysis of the directional sensitivity of the concentric emg electrode". The discriminatory direction of sensitivity, blind spots, section changes, rate of attenuation, and vary of pick-up radius are often derived from that operation [29]. In 1994, Z.M Nikolic represented an electronic circuit for analog process of neural (electroneurogram or ENG) and muscular (electromyogram or EMG) signals in practical electrical stimulation (FES) systems [30].Temporal lightening of individual surface electro-myograph (EMG) waveforms and abstraction combination of multiple recording sites were individually been demon-strated by Edward A. Clancy to enhance the performance of electromyogram amplitude estimation [31]. The graphical machine utilizing prosthetic device was introduced wherever the concept of computing and mathematical logic used. A graphical machine exploiting prosthetic device was controlled by electromyogram (EMG) process, mentioned by E. Zahedi and H.Farahani. The integral of absolutely the worth (IAV) of the skeletal muscle and striated muscle of EMGs were used here and additionally a fuzzy k-means algorithm was utilized to classify the motion before causative a 3-degrees-of-freedom arm diagrammatically on a monitor [32]. A variety of electromyogram characteristics had been evaluated by M. Zardoshti-Kermanifor for the management of myoelectric higher extremity prostheses [33]. E.W. Abel et al. incorporated the neural network analysis and classification of the electromyogram signal interference pattern on comparison with healthy individuals with myopathic and neuropathic disordered patients [34]. Neural net-work analysis was additionally incorporated for comparative study of healthy individuals and dis ordered subjects. Three kinds of discrimination ways were used for comparison. Identification of motions of the neck and shoulders utilizing the electromyographic (EMG) signal exploiting three discrimination ways, the euclidean distance measure (EDM), the weighted distance measure (WDM) technique and therefore the modified maximum likelihood method (MMLM), were utilized to compare the traditional autoregressive (AR) and cepstral coefficients with closely positioned (C-type) and on an individual basis settled (S-type) conductor arrangements in 1996 [35]. Gwo-Ching chang and his team developed electromyogram (EMG) discrimination system to produce management commands for man-machine interface applications [36]. The disputed areas concerning the utilization of the electromyogram was mentioned by gary Karmen and Graham E. caldwell in 1996. From 1996 the foremost innovative and fascinating view of providing commands for man machine interface application intro-duced. an adaptive human-robot interface employing a applied math neural network that consists of a forearm controller and an arm controller and also the driving speed or grip force were controlled by electromyogram signal process was mentioned during a workshop on automaton and Human Communication. In 1998, the idea of a humanrobot interface was developed and incontestible by O. Fukura in IEEE international conference on artificial intelligence and automation [37]. An electromyogram signal recognition technique to spot the motion commands for dominating the prosthetic arm supported intelligence with multiple parameters were mentioned by Sang-Hui Park and Seok-Pil Lee. The prosthetic arm management mechanism and adaptation had been finished through appropriate real time learning ways utilizing the electromyographic signals by changing the motion of object [38, 39]. Electromyogram signals contains a superposition of delayed finite-duration waveforms that carry the knowledge regarding the firing of various muscle cell. The new approach of that electromyogram Interpretation technique was depicted by R. Gut in 2000.From this analysis the idea of the constant study of electromyogram Signal and analysis were obtained. Dario farina had been represented and compared among many algorithms used for estimating the values of amplitude, frequency, physical phenomenon rate of the surface electromyographic signal throughout voluntary contractions. Various dominant ways of movement of prosthetic arms were projected. The prosthetic hand was driven depending on electromyogram pattern discrimination utilizing neural network and therefore the feedback error learning theme was incorporated with it. Neuro-fuzzy technology was utilized to classify the diagnostic technique signal management exploiting moving ridge transformation to teach the controller and changed the training mechanism. D.Zennaro given a way to decompose multi-channel long-run contractile organ electromyogram (EMG) signals in 2003 [40]. H. Manabe projected a method for rising the identification accuracy of EMGbased speech recognition by applying existing speech recognition technologies in his journal titled “Multi-stream HMM for EMG-based speech recognition” [41]. Most of the models for surface diagnostic technique signal generation were dependent on the space changeability of the system within the direction of supply propagation. But L. Mesin and D. farina projected a model that wasn't space invariant and also the surface signal was detected with the direction of the muscle fibres, which can considerably deform with the propagation path. In IEEE international conference Zhao Jingdong given a five fingered under actuated prosthetic hand controlled by surface electromyographic (EMG) signals [42]. The management type of prosthetic hand was neural network learning techniques and therefore the parametic autoregressive model. It had been mentioned that the prosthetic hand management domain relies on an electromyogram motion pattern classifier which mixes Levenberg- Marquardt or variable learning rate (VLR) based neural network with constant autoregressive (AR) model and moving ridge network [43]. This motion pattern classifier will accurately establish flexion and extension of the thumb, the forefinger and also the middle finger, where the experimental results show that the classifier incorporates a potential application to the management of bionic man-machine systems as a result of its quick learning speed, high recognition capability. JunUk Chu and his analysis team developed an economical feature- projection technique that utilised a linear discriminant analysis for electromyogram pattern recognition. The main goal of this analysis study was to develop an economical feature projection technique for electromyogram pattern recognition. To the current situation, a linear supervised feature projection is projected that utilizes a linear discriminant analysis (LDA) [44]. Within the paper titled Signal process of the surface EMG to achieve insight into fiber bundle physiology, an outline of necessary advances within the development and applications of electromyogram signal process strategies, as well as spectral estimation, higher order statistics and spatiotemporal process were mentioned.

2.4) Review of Methods of Classification

Kelly et al. [45], represented some early work done to explore the practical applications of neural networks to the myoelectric signal analysis. Hopfield algorithmic rule was utilized to calculate the statistic parameters of the moving average signal model. The performance of two algorithms, specifically the Hopfield and consecutive statistical procedure algorithmic rule were compared and it had been resulted that Hopfield was 2 to 3 times quicker than the latter that was dependent on a typical EMG information. Some further results like the utilization of perceptron within the future myoelectric signal analysis were additionally mentioned.

Nishikawa and Kuribayashi et al. [46], Used neural network to discriminate hand motions for EMG-Controlled Prostheses. Here the neural network was exploited to learn the relation between EMG signals power spectrum and also the motion task desired by the disabled subjects.

Hudgins et al. [47], analyzed the electromyogram signals for dominant multifunction prosthetic device. Characteristics were extracted from many time segments of the myoelectric signal to preserve pattern structure. These characteristics were then classified utilizing a synthetic neural network. They discovered that the performance of their system increased as a result of the neural network's ability to adapt to little changes within the management patterns.

Francis H. Y. Chan et al. [48], proposed an approach for the classification of electromyogram (EMG) signals for multifunctional prosthetic devices. The main goal of the research was to improve the classification performance. For the same, fuzzy approach was utilized so as to get acceptable learning speed. Fuzzy rules were trained using the back propagation algorithmic program in the model. It was also compared with ANN methodology on four subjects, and it was observed that extremely similar classification results were obtained. It's superior to the latter in a minimum of three points with slightly higher recognition rate.

Kiguchi et al. [49], Developed a fuzzy controller to manage the elbow and spheroid joint angles of the skeletal system depends on the moving average worth of electromyogram signals from arm and shoulder muscles and therefore the generated wrist joint force. Nearly fifty fuzzy IF-THEN management rules were designed relied on the analyzed human subject‟s elbow and shoulder motion patterns within the pre-experiment.

Weir, R. Fff et al. [50], developed a new method multifunctional prosthetic hand mechanism which will be interfaced to the user employing a four myoelectric (EMG) controller depending on mathematical logic techniques. three to four electromyogram sites (the max. variety that might be isolated with-out having the cross-talk unacceptable) were utilized to management three or four degrees-of-freedom (DOF) within the prosthetic hand. Mathematical logic techniques were exploited to measure the electromyogram onset and classify user intent. Membership functions for every electromyogram channel were relied upon electromyogram signals analysed throughout a learning session. Normal clinical techniques were utilized to find the four sites. Rules recognizing the various electromyogram levels related to a specific operation are automatically generated depending upon the recorded electromyogram learning information. Results of experiments scrutinizing this controller with different management algorithms utilized in medical specialty control were conferred. The enforced controller was capable of providing seamless successive control i.e. successive management without having the intermediate shifting steps with an update rate of fifty millisecond.

Abidemi Bolu Ajiboye et al. [51], presented a heuristic fuzzy logic approach to multiple electromyogram (EMG) pattern recognition for multifunctional prosthesis control. Basic signal statistics (mean and standard deviation) were used for membership function construction, and fuzzy c-means (FCMs) data clustering was used to automate the construction of a simple amplitude-driven inference rule base. Other algorithms in current literature assume a longer period of unperceivable delay, while the system presented had an update rate of 45.7 ms with little post processing time, making it suitable for real-time application. Five subjects were investigated (three with intact limbs, one with a unilateral transradial amputation, and one with a unilateral transradial limb-deficiency from birth). Four subjects were used for system offline analysis, and the remaining intact-limbed subject was used for system real-time analysis. They discriminated between four EMG patterns for subjects with intact limbs, and between three patterns for limb-deficient subjects. Overall classification rates ranged from 94% to 99%. The fuzzy algorithm also demonstrated success in real-time classification, both during steady state motions and motion state transitioning. This functionality allowed for seamless control of multiple degrees-of-freedom in a multifunctional prosthesis.

Kazuo Kiguchi et al. [52], developed robotic exoskeletons to help motion of physically weak persons like senior, disabled, and harmed persons. The robotic skeletal system is controlled using the electromyogram (EMG) signals, since the electromyogram signals of human muscles are necessary signals to acknowledge however the user intends to be in motion. Even if the electromyogram signals contain important info, however, it's not terribly straightforward to predict the user's upper-limb motion (elbow and shoulder motion) supported the electromyogram signals in period of time due to the problem in utilizing the electromyogram signals as the controller input signals. They projected a robotic frame for human upper-limb motion assist, a stratified neuro-fuzzy controller for the robotic frame, and its adaptation technique.

Ahmet Alkan et al. [53], given a classification technique that classifies signals needed for a prosperous arm prosthetic device management by utilizing surface EMG signals. This work used recorded EMG signals generated by skeletal muscle and striated muscle muscles for four varying movements. Every signal has one single pattern and it's essential to separate and classify these patterns properly. Discriminant analysis and support vector machine (SVM) classifier are utilized to classify four arm movement signals. Before classification, correct feature vectors are derived from the signal. The feature vectors are generated by exploiting mean absolute value (MAV). The feature vectors were provided as inputs to the identification/classification system. Discriminant analysis utilizing various approaches, classification accuracy rates achieved from excellent (98%) to poor (96%) by employing a 10-fold cross validation. an SVM classifier offers a really appropriate average accuracy rate (99%) for four movements with the classification error rate 125th. Correct classification rates of the applied techniques are terribly high which may be utilized to classify EMG signals for prosperous arm prosthetic device management studies.

Abdulhamit Subasi et al. [54], given a unique PSO-SVM model that hybridized the particle swarm optimisation (PSO) and SVM to enhance the electromyogram signal classification accuracy. This optimisation mechanism concerned kernel parameter setting within the SVM learning procedure that considerably influences the classification accuracy. The experiments were conducted on the idea of electromyogram signal to classify into normal, neurogenic or myopathic. Within the projected methodology the electromyogram signals were transformed into the frequency sub-bands utilizing discrete wavelet transform (DWT) and a group of applied mathematics characteristics was extracted from these sub-bands to represent the distribution of wavelet coefficients. The obtained results concluded that the prevalence of the SVM methodology compared to standard machine learning ways, and recommended that any vital enhancements in terms of classification accuracy is achieved by the planned PSO-SVM organization. The PSO-SVM yielded an overall accuracy of 97.41% on 1200 electromyogram signals chosen from 27 subject records against 96.75%, 95.17% and 94.08% for the SVM.

Siti A. Ahmad et al. [55], stated a state primarily based mathematical logic classifier. They used the data from states of contraction to see the result output state for the system. The states are begin, middle and results of contraction. This classifier uses two sEMG signals because the management channel wherever the amputees ought to do wrist joint flexion, wrist joint extension and co-contraction, and every of these movements might be performed at their convenience. The classification results indicate that mathematical logic system might discriminate the output supported the states of contraction. From the investigation, it determined that, this kind of classifier might provide an additional study of classification result particularly within the middle of a contraction, compared to the beginning and finish of a contraction.

Yousef Al-Assaf et al. [56], during this paper, a technique that doesn't use any a priori information of hypotheses parameters to observe the transient modification in MES signals was given. That supported consecutively estimating the dynamic accumulation of generalized probability ratios. so as to permit detection of any frequency or energy changes, DCS is applied when signal decomposition on scales of a multi-scale illustration utilizing the Coiflet orthogonal transform with varying scales. Polynomial classifiers are utilized to classify four elbow and wrist joint movements exploiting the one MES channel. The input characteristics for the classifiers were obtained utilizing Multi resolution wavelet transform analysis. Even with one recording channel, promising continuous classification accuracy with adequate system reaction time is achieved. The utilization of a lot of recording channels, testing the projected methodology in addition to subjects and learning feature extraction techniques that need shorter analysis time are venues for future analysis.

Hardeep S. Ryait et al. [57], delineated mensuration of SEMG depends on variety of factors/parameters like amplitude, time and frequency domain properties. Within the investigation, analysis was carried (1) study the grip force vs. SEMG parameters at treatment points on the arm, utilizing single channel approach. In any respect the chosen treatment points a linear increment of sEMG was discovered. (2) Discriminate four elbow movements from various locations on the arm exploiting two channel approach with single parameter. The parameter for the analysis chosen was the root mean square (RMS) worth of sEMG. Further; principal element analysis was utilized to verify the elbow movement discrimination. Extension and rotary motion were the two operations that were discovered to be simple to comprehend by prosthetic devices. The choice of those locations was done on the idea of treatment points and anatomy of the elbow.

Luay Fraiwan et al. [58], conferred an initial point for giving learning to the patient to use prosthetic devices utilizing artificial point of prosthetic device. The projected system consists principally of an electromyography (EMG) system connected to the patient's arm (skeletal and striated muscles) and interfaced with a computer exploiting an information acquisition system. The computer uses Matlab to boost the electromyogram signals and observe the presence of events in them. These events are utilized to manage a virtual hand with different movements; grasping and wrist joint rotation. The system was tested on an issue which can perform the grasping and wrist joint rotation for 95 trials. The net success rate was found to be 84.6.

HaeOck Lee et al. [59], described a system which is externally powered and known as upper extremity prosthesis. The required elements to make a stronger prosthetic arm were divided into four subsystems: input, effecter, feedback. That was reviewed in terms of the subsystems. Every scheme performs its own task, however they're associated with one another and also they operate to form a prosthetic upper extremity that provides the movement to the unfortunate person.

Deepak Joshi et al. [60], mentioned the trends undergoing altogether with many steps concerned in EMG (Electromyogram) depends on prosthetic hand development. So as to reduce some limitations of the current prosthetic hands of primarily associated correct practicality and controllability, the prosthetic hand has been formed following a bio mechatronic approach relied on biologically impressed design solutions. The bulk of electrically powered prosthetic hands were depend on a straightforward method that limits motion to at least one degree of freedom. Formations of multi-articulated prosthetic hands have had restricted success because of their complexness and variety of mechanical elements. Classical EMG (myoelectric) controllers had become unsuccessful within the past, since they were depending on solely crucial existence or non-existence of an EMG signal. Recent work has approached this multifunctional management drawback employing a high amount of electrodes, although still considering solely a restricted a part of the EMG spectrum.

S. Herle et al. [61], formed an algorithm depends on an autoregressive (AR) model illustration and a neural network, for EMG signal classification. The results have shown that combining a low-order AR model with a feed forward neural network, a rate of classification of ninety eight are usually achieved, whereas keeping the method cost low. The solution planned is capable of dominant three joints (i.e. six movements) of the upper limb restorative. The inputs of the high-level controller are obtained from the classifier, whereas its outputs are applied as input signals for the low-level controller.

Ulvi Baspinar et al. [62], during this study, a home-made four channel sEMG electronic equipment circuit were designed for calculating electromyogram signals. The recorded sEMG signals were filtered with a band pass filter and later on wavelet dependent filtering was applied to get rid of unwanted noises. As a second step, the recorded and de-noised signals‟ characteristics were extracted. For classification of motions eight time domain and two frequency domain characteristics were used. There's no reduction applied to the characteristics for artificial neural network (ANN) classification whereas the characteristics were reduced in two dimension exploiting by Diffusion Map for fuzzy classification. Lastly, seven various motions were classified by ANN and Gustafson Kessel algorithmic program. Also, their classification performances were compared.

J. Rafiee et al. [63], conferred another new technique for feature extraction of forearm electromyographic (EMG) signals employing a planned mother wavelet matrix (MWM). A MWM as well as forty five potential mother wavelets is recommended to assist the classification of surface and contractile organ electromyogram signals recorded from multiple locations on the higher forearm for ten hand motions. Also, a surface conductor matrix (SEM) and a needle conductor matrix (NEM) are urged to pick out the right sensors for every combination of motions. For that purpose, electromyogram signals were recorded from sixteen locations on the forearms of six subjects in ten hand motion categories. The important goal in classification is to outline a correct feature vector which is ready to generate acceptable variations among the categories. The MWM enclosed the mother wavelets that build the best distinction between the two specific categories.

Abidemi Bolu Ajiboye et al. [64], projected an algorithmic rule based mostly upon neuro-fuzzy technology. We have a tendency to believe that due to the inherent “fuzziness” of human action, a manageable algorithmic rule depending on mathematical logic could have benefits for multifunctional prosthetic device control. They look for an appropriate compromise between the amounts of conductor sites used and processing quality, and thereby need no more than three to four managing sites to regulate three to four DOF. This approach delivers a lot of info to the system and, by utilizing mathematical logic, reduces the complexness of the process.

Lars H. Lindstrom [65], diagnostic technique is that the art of describing myoelectric signals. These signals are the electrical manifestation of the excitation method preceding the mechanical contraction within the muscles. The myoelectric signal, discovered with surface electrodes or concentrical needle electrodes, consists of questionable action potentials originating from the individual muscle fibers. The fibers of the muscle are functionally organized in subgroups, questionable motor units. The activity of every unit was controlled by a neuron situated within the neural structure with its nerve fiber extending to the muscle.

Foster B. Stulen et al. [66], throughout a sustained muscular contraction, the spectrum of the myoelectric signal is thought to endure compression as an operation of the time. Previous investigators have shown that the frequency compression is expounded to the decreasing conductivity rate of the muscle fibers. It projected that the frequency compression may be half-tracked by getting a continual estimate of a characteristic frequency of the spectrum, like the mean and median, or the quantitative relation of low-frequency elements to high-frequency elements of the spectrum. A theoretical analysis was performed to analyze the restrictions in estimating the three parameters, additionally as their sensitivity to the conductivity rate. A method is delineated, that determines an unbiased consistent estimate of the median frequency.

David T. Gibbons et al. [67], the utilization of electromyogram signals from residual muscles to manage above-elbow prosthetic device has been tried, however presents several issues, not the smallest amount being that the prosthetic device is beneath the open-loop management. A additional satisfactory management technique is extended physiological interoception wherever the inherent interoception feedback give at intervals an intact joint is employed to produce closed-loop management. Our technique is to manage the positioning of this on top of elbow prosthetic device utilizing the motion of the intact shoulder. Grasp, that doesn't involve positioning in area is on an individual basis controlled exploiting electromyogram signals from striated muscle and skeletal muscle muscles. A selection from a variety of linkages will modify the user to perform various tasks in several conditions.

Edward A. Clancy et al. [68], temporal lightening of individual surface diagnostic procedure waveforms and abstraction combination of multiple recording sites have on an individual basis been described to enhance the performance of electromyogram amplitude estimation. This investigation combined these two techniques by 1st lightening, then combining the information from multiple electromyogram recording sites to create an electromyogram amplitude estimate. A phenomenological mathematical model of multiple sites of the surface electromyogram wave form, with analytic resolution for an optimum amplitude estimate, is bestowed. Experimental surface electromyogram waveforms were then sampled from multiple sites throughout non-fatiguing, constant-force, isometric contractions of the skeletal muscle or striated muscle muscles.

C. P. Fermo et al. [69], this work presents the event of a detector for identifying human muscular contraction, that captures myoelectric signals (EMG), so as to regulate a myoelectric prosthetic device of superior limb. It's projected a technique for managing the synthetic hand, depending on the myoelectric signal. This way, the patient incorporates an additional efficient and easier management of the movement of the prosthesis, so resulting in a quicker adaptation. Through a projected management strategy, a technique to investigate the pattern of the myoelectric signal are often outlined. Thus, many forms of prosthesis of the synthetic hand are often obtained by an easy binary signal or through the analysis of the myoelectric signal pattern.

Ishibuchi, H. et al. [70], this paper proposed the rule weight of every fuzzy rule that may be applied in fuzzy rule-based classification systems. First, they projected heuristic ways for rule weight specification. Next, the planned ways were compared with existing ones through matlab simulations on artificial numerical examples and real-world pattern classification issues. Simulation results show that the projected strategies exceed the prevailing ones within the case of multiclass pattern classification issues with several categories.

Ishibuchi, H. et al. [71], this paper examines the impact of rule weights in fuzzy rule-based classification systems. Every fuzzy IF-THEN rule our system has antecedent linguistic values and one subsequent category. They used a fuzzy reasoning technique supported one winner rule the classification part. The winner rule for a replacement pattern is that the fuzzy IF-THEN rule that has the most compatibility grade with the new pattern. Once they use fuzzy IF-THEN rules with certainty grades, the winner is decided because the rule with the utmost product of the compatibility grade and also the certainty grade, the impact of rule weights was illustrated by drawing classification boundaries exploiting fuzzy IF-THEN rules with/without certainty grades. It's conjointly shown that certainty grades play a very important role once a fuzzy rule-based classifier could be a mixture of general rules and specific rules. Through matlab simulations, they show that approachable fuzzy rule-based systems with high classification performance are often designed while not modifying the membership functions of antecedent linguistic values once they used fuzzy IF-THEN rules with certainty grades.

2.5) SUMMARY

Table 2.1: Comparison of some Previous Methods

Paper	Work
Ahmet Alkan et al. [53]	Discriminant analysis and support vector machine (SVM) classifier, four different arm movement signals
Abdulhamit Subasi et al. [54]	Particle swarm optimization (PSO) and SVM, normal, neurogenic or myopathic
Hardeep S. Ryait et al. [57]	PCA, factors/parameters like amplitude, time and frequency domain properties,
Ulvi Baspinar et al. [62]	ANN and Gustafson Kessel algorithm, seven different motions were classified
Ishibuchi, H. et al. [70]	Heuristic methods for rule weight specification,
Ishibuchi, H. et al. [71]	Winner rule for a new pattern is the fuzzy IF-THEN rule

Chapter 3
RESEARCH METHODOLOGY

3.1) Overview

This chapter discusses about the research methodology used for the analysis of the electromyogram (EMG) signals by utilizing MATLAB. Here, the approaches used for the analysis are stated. The analysis system of ElectroMyoGram signals is performed in three steps: (a) Pre-processing of the signals utilising discrete wavelet transform, (b) feature extraction by computation of Energy, Mean and standard deviation and (c) classification procedures exploiting kNN, ANN and SVM classifiers for analysis features are going to be explained. Also, a short simulation procedure is conferred during this chapter.

3.2) Electromyogram Analysis System - Overview

The well-being of any population gives a contribution to the progressive property of development in the region of the real-time world. Practically, all the studies assists for the up-keeping of human well-being and also for the medication observation. The analysis of bio-medical application tools such as electromyogram can simplify to strengthen the human support and might contribute individuals to check quickly and efficiently for the health condition. This also facilitates to lift the influence and powerful bio-medical applications.

The analysis of ElectroMyoGram (EMG) signals is widely utilized for identifying several viscous diseases. These are the most illustrative reason for the mortality among the developed countries. Electromyogram analysis system provides a robust tool to simulate the human muscle signals. The performance of such detection systems heavily depends upon the accuracy and reliability within the identification of the signals, which is very important in computing the muscles illness. The myopathy and neuropathy detection of electromyogram wave is a crucial topic. This section explores the strategies utilized to collect information for analysis, the isolation of the required information, and also the experiments accustomed analyse the bio-signal information. Fig.3.1 represents the technique utilized in the EMG Analysis.

Fig.3.1: EMG Signals Classification

3.3) System Requirement

This major project is improved by using the software tool named as MATLAB (MathWorks Inc.). It is a mathematical computing and programming language software tool utilized here for modeling the muscles signal in complicated algorithmic programs. MATLAB is a high-level language and interactive environment that enables to perform complex intensive tasks faster than traditional programming languages. This software is easy from all other commonly used developed languages such as C and C++. MATLAB codes are also being used because it could recite the data set of EMG signals easily. The EMG signal is imported from the files i.e. .dat and converted into the excel files i.e. .xls.

3.4) Pre-Processing using Discrete Wavelet Transform

Features extraction is extracting and converting the input data information into a set of features which called feature vector, by reducing the data representation pattern. The features set will extract the relevant information from the input data in order to perform the classification task. The transform of a signal is just another form of representing the signal. It doesn't modify the data content inbuilt within the signal.

Wavelet theory is that the arithmetic related to building a model for a signal, system, or process. A wavelet could be a wave that has its energy focused in time. it's an periodical rippled characteristic however additionally has the flexibility to permit synchronous time and frequency analysis and it's an appropriate tool for transient, non-stationary or time-varying phenomena. WT contains a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges.

As quoted in Mahmoodabadi et al. [72], the signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid. Also, native options will be described higher with wavelets that have native extent.

The wavelet transform uses multi-resolution technique by that several frequencies are analysed with different resolutions. It's skilful of describing the signals in several resolutions by compressing and dilating the basis functions. The basis function in wavelet analysis is defined by two parameters which are scale and translation. A basis function that is mother wavelet is used in wavelet analysis. For a wavelet of order N, the basis function can be represented in Equation 3.1:

$$\psi(n) = \sum_{j=0}^{N-1} (-1)^j c_j (2n + j - N + 1) \tag{3.1}$$

3.4.1) Discrete Wavelet Transform

The discrete wavelet transform (DWT), that may be a time-scale illustration of the digital signal is obtained using digital filtering techniques, is found to yield a quick computation of wavelet transform. It's simple to implement and adopts dyadic scales and translations in order to reduce the amount of computation time, which results in better efficiency of calculation.

The DWT which also referred to as decomposition by wavelet filter banks is computed by successive low pass filter (LPF) and high pass filtering (HPF) of the discrete time- domain signal as the process shown graphically in Figure 3.2.

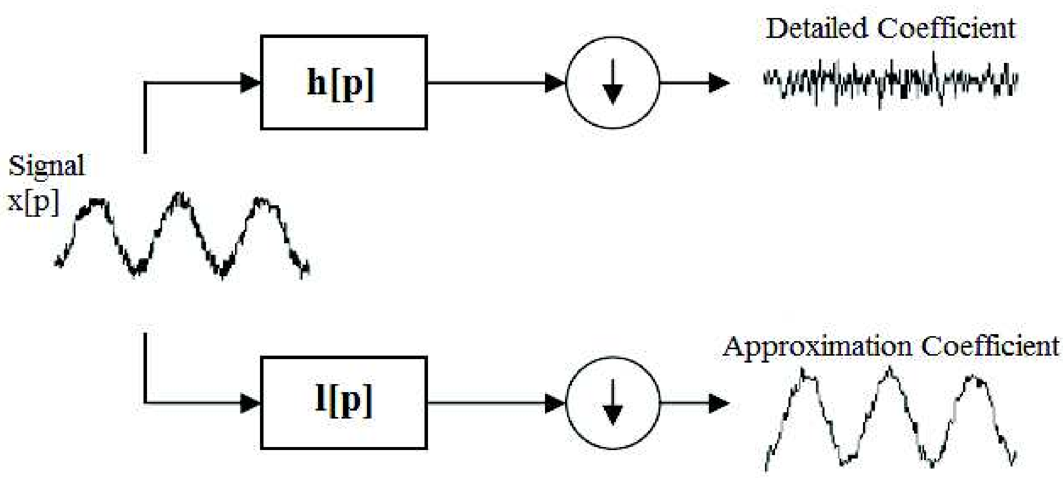

Fig.3.2: Filter Bank Signal Decomposition

The different cut-off frequencies are used for the analysis of the signal at different scales to measure the amount of detail information in the signal and the scale is determined by up-sampling and down-sampling process where D and A denoting for details and approximations, while c representing coefficients. The approximations of the signal are what define its identity while the details only imparts nuance.

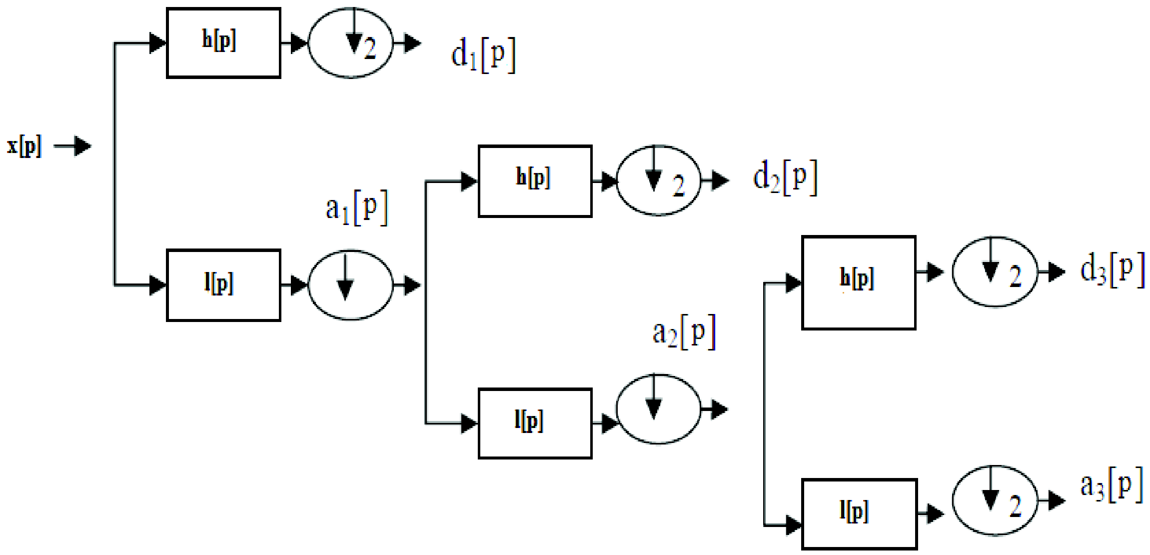

Fig.3.3: Three Level Wavelet Decomposition Trees

Figure 3.3 show the decomposition process is iterative. It connects the continuous-time multiresolution to discrete-time filters. The signal is denoted by the sequence input signals x[p], wherever n is a number responded to a series of high-pass filters to analyse the high frequencies, and with a series of low-pass filters to research the low frequencies. Every stage consists of two digital filters and two down-samplers by 2 to provide the digitized signal. The low pass filter is denoted by l[p] whereas the high pass filter is denoted by h[p]. At every level, the high pass filter produces detail information, d[p], whereas the low pass filter related to scaling operation produces coarse approximations, a[p]. The down-sampled outputs of 1st high pass filters and low-pass filters give the detail coefficients, d_1[p] and also the approximation coefficients, a_1[p]. The primary approximation is distributed once more and this method is sustained. The filtering and decimating method is sustained till the specified level is reached. The utmost range of levels depends on the length of the signal. Solely the last level of approximation is save among all levels of details that provides sufficient data. The DWT of the original signal is then obtained by concatenating all the coefficients, a[p] and d[p], starting from the last level of decomposition. The signal decomposition can mathematically be expressed in Equation 3.2 and Equation 3.3:

$$y_{hi}[k] = \sum x[n].g[2k-n] \tag{3.2}$$

$$y_{lo}[k] = \sum x[n].h[2k-n] \tag{3.3}$$

Utlizing this approach, at lower frequencies, the frequency resolution becomes arbitrarily good while at high frequencies, the time resolution becomes arbitrarily good. In DWT the signals can be represented by approximations and details. The detail at level j is defined as Equation 3.4:

$$D_j = \sum_{k \subset z} a_{j,k} \psi_{j,k}(t) \tag{3.4}$$

Where, Z is the set of positive integers.

Then, the approximation at level J is defined by the equation as:

$$A_t = \sum_{j>J} D_j \tag{3.5}$$

Finally, the signal f (t) can be represented as:

$$f(t) = A_j = \sum_{j \leq J} D_j \tag{3.6}$$

In DWT where a scaling function is used, which are related to low-pass and high-pass filters, respectively. The scaling function can be represented as Equation 3.7 and Equation 3.8:

$$\phi(n) = \sum_{j=0}^{N-1} c_j \phi(2n-j) \tag{3.7}$$

$$\phi_{j,k}(t) = \sqrt{2^j}.\phi(2^j t - k) \tag{3.8}$$

3.4.2) DWT Implementation

In the scope of this thesis, feature extraction was conducted by applying wavelet analysis techniques to patient data, thus providing EMG characteristic point detection capabilities. Since most recently published detectors are dependent on some standard libraries of the database and restricted detection of waves, this application is an attempt to expand the horizons of current research efforts.

The input selection of feature extraction methods applied in this thesis has to select well to make sure which components of a inputs best represent the given pattern of EMG signals. Since the details wavelet coefficients contain a significant amount of information about the signal, the detail wavelet coefficients of EMG signal of each subject were calculated. The DWT implementation procedure is discussed as follow in Figure 3.4.

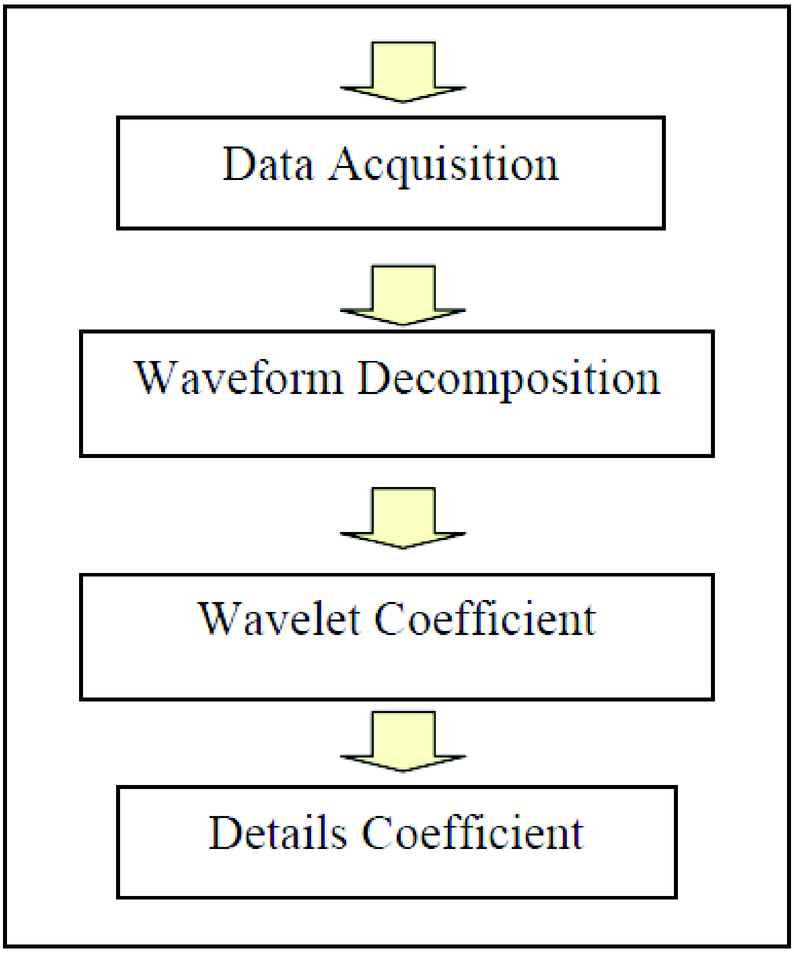

Fig.3.4: Feature Extraction Technique

3.5) Feature Extraction Procedure

Selection of acceptable wavelet and also the range of decomposition level is extremely necessary in DWT. the levels of the selected DWT are chosen by specifying those elements of the signal that correlate well with the frequencies needed for classification of the signal are maintained within the wavelet coefficients.

The general wavelet decomposition of DWT procedure involves three steps. The results of distributed signal can shows the necessary details and approximation coefficients that represent the initial signal. The fundamental version of the procedure follows the steps written below.

- Choose a type of DWT.

- Choose a wavelet family name.
- Choose a decomposition level 10 which can calculate the DWT decomposition of the signal level 10.

The DWT wavelet families are chosen during this characteristic extraction methodology and also the electromyogram signals were distributed into time-frequency representations exploiting single-level one-dimensional DWT decomposition. The wavelet names of Coiflet wavelet filters of order 5 have been choosing and the number of decomposition levels was chosen to be 10. Thus, the EMG signals were decomposed into the details coefficients D_{1}-D_{10} and one final approximation coefficient, A_{10}.

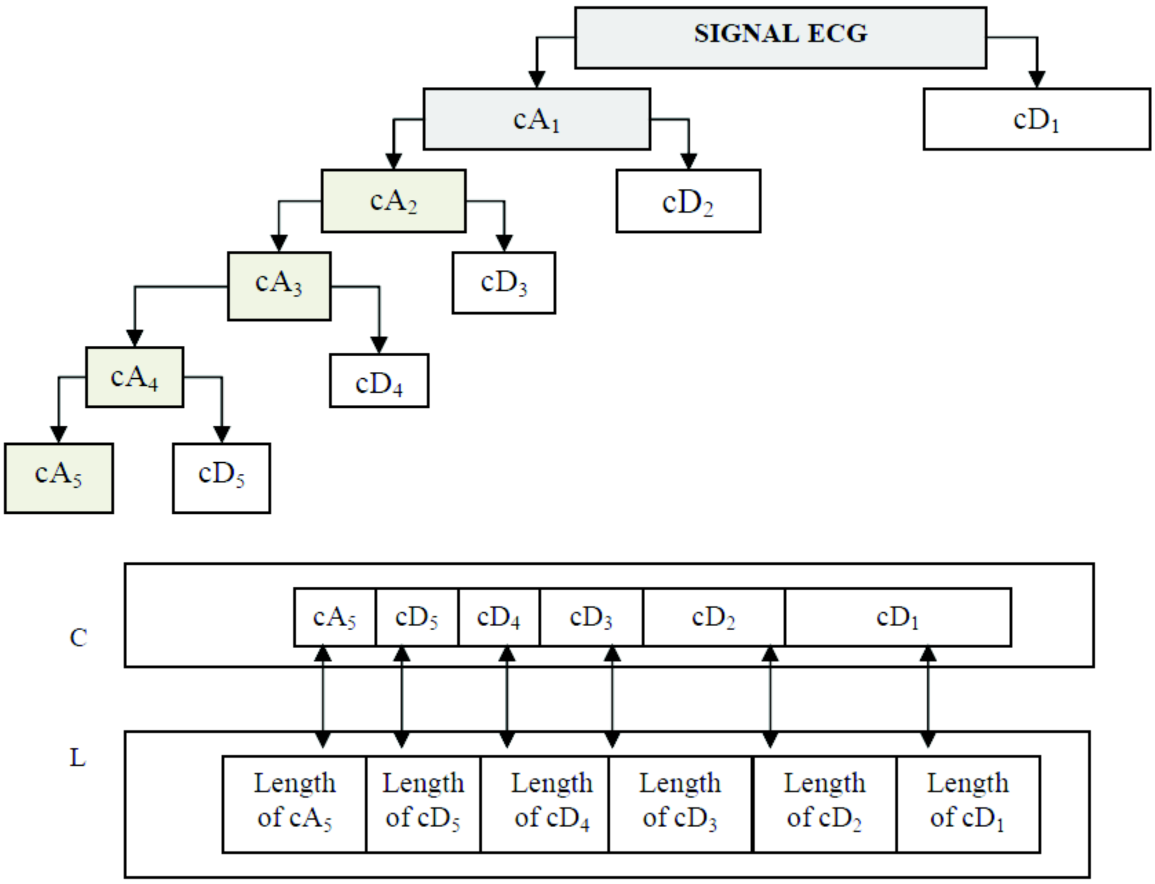

Fig.3.5: DWT decomposition: Steps of EMG Analysis

The result of applying the Coiflet wavelet of order 5 which is more suitable to detect changes of EMG signal is evaluated. The wavelet filter with scaling function more closely similar to the shape of the EMG signal achieved better detection. Coef wavelet family is similar in shape to EMG signal and their energy spectrums are concentrated around low frequencies the signal is approximated by omitting the signals high frequency components. The ECG signal and the details for five wavelet scales are schematically shown for better illustration in Figure 3.5.

3.5.1) Coefficients Extraction

The computed DWT coefficients give a compact explanation that shows the energy distribution of the signal in time and frequency. Therefore, the computed details and approximation DWT coefficients of the electromyogram signal were used because the characteristics vector representing the signals.

In this study, from the initial intervals of electromyogram signal, five customary measures parameters used are used. An EMG signal of 150 separate information was chosen as thought of nerve cells signals information. For every electromyogram signals, the detail DWT coefficients of fourth level (75 coefficients) were computed. So as to diminish the domain of feature vectors, statistics over the set of the DWT coefficients were used. The subsequent quantitative options were exploited to represent the time–frequency distribution of the electromyogram signals: The flows of the calculated DWT constant are shown in Figure 3.9 below.

- Energy of the DWT coefficients of every EMG signals sample.

$$Energy = \sum_{w}\sum_{j}\left|D_j^w\right|^2 \tag{3.9}$$

- Mean of the DWT coefficients of every EMG signals sample.

$$Mean = \frac{\sum_{w} z_w}{w} \tag{3.10}$$

- Standard deviation of the DWT coefficients of every EMG signals sample.

$$\text{Standard Deviation} = \sqrt{\frac{\sum_{w}(z_w - mean)^2}{w}} \tag{3.11}$$

3.6) Classifiers

3.6.1) k-Nearest Neighbour (kNN) Classifier

A KNN classifier is based on the idea that the role of a (natural) class is to predict the values of features for members of that class. Examples are grouped in classes because they have common values for the features. Such classes are often called natural kinds. In this section, the target feature corresponds to a discrete class, which is not necessarily binary.

K nearest neighbours may be a straightforward algorithmic program that stores all obtainable cases and classifies new cases depending on a similarity calculation (e.g., distance functions). KNN has been employed in pattern recognition and applied mathematics estimation as a non-parametric technique, already, within the starting of 1970's.

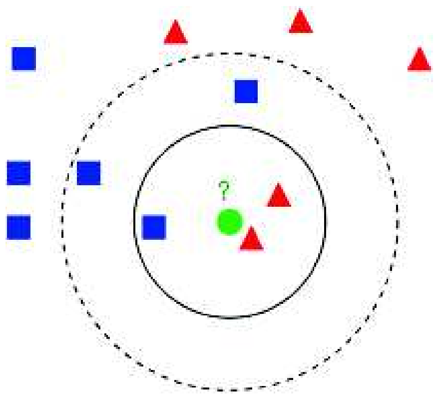

Fig.3.6: kNN Classification

A case is assessed by a majority vote of its neighbours, with the case being assigned to the category most typical amongst its K nearest neighbours measured by a distance measuring formulae. If K = 1, then the case is just assigned to the category of its nearest neighbour.

$$Euclidean\_Distance = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{3.12}$$

$$Manhattan\_Distance = \sum_{i=1}^{k}|x_i - y_i| \tag{3.13}$$

$$Minkowski\_Distance = \left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q} \tag{3.14}$$

Choosing the optimum value for K is best done by initial inspecting the information. In general, an oversized K value is a lot of precise because it reduces the net noise however there's no guarantee. Cross-validation is also a way to retrospectively verify a perfect value of K by utilizing a freelance dataset to validate the K value. Traditionally, the best K for many datasets has been between 3 and 10. That produces far better results than 1NN.

3.6.2) Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is an informatics paradigm that's give information by the approach of biological nervous systems, like the brain. The key part of this paradigm is that the novel structure of the data evaluation system. It's composed of an oversized range of very high interconnected evaluation vectors (neurones) operating in unison to resolve specific issues. ANNs, like subjects, learn by example. An ANN is designed for a particular application, like pattern recognition or information classification, through a learning method. Learning in biological systems involves changes to the nerve connections that exist between the neurones.

An artificial nerve cell could be a device with several inputs and one output. The nerve cell has the modes of operation; the learning mode and also the utilizing mode. Within the learning mode, the nerve cell is trained to model (or not), for specific input patterns. Within the utilizing mode, once a trained input pattern is detected at the input, its associated output becomes the required output. If the input pattern doesn't belong within the trained list of input patterns, the firing rule is employed to detect if it is need to show or not.

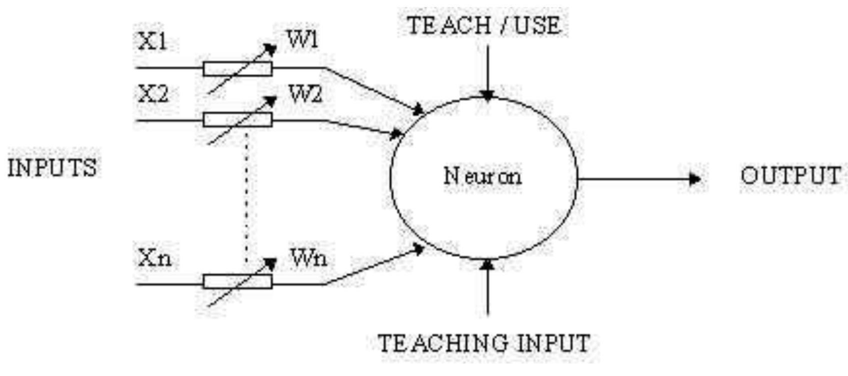

Fig.3.7: A simple neuron

Feed-forward ANNs (figure 3.8) enable signals to travel a way only; from input to output. There's no feedback (loops) i.e. the output of any layer doesn't have an effect on that very same layer. Feed-forward ANNs tend to be simple networks that associate inputs with outputs. They're extensively employed in pattern recognition. This kind of organisation is additionally observed as bottom-up or top-down.

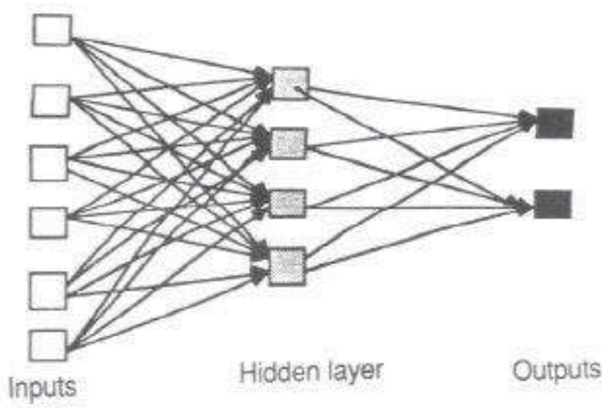

Fig.3.8: Simple feedforward network

3.6.3) Support Vector Machine (SVM)

In the classification of the EMG signals generated using different sources, SVM is a classifier which is used. It is a supervised learning model [73] as it is firstly trained using the associated learning algorithms with the labelled data. Then with the help of this trained model, tested data is analyzed. These are exploited in the regression analysis. SVMs can be helpful in various applications. These includes text categorization, hand-written characters recognition etc. Experimental results shows, SVM achieves higher accuracy than other traditional models. SVMs also find its application in the field of medical sciences with nearly 80% of accuracy in classifying the samples accurately.

For this, a set of training random numbers, each marked for one of the classes is used to train the SVM. Then the pseudo random numbers are tested on this trained SVM and the random numbers are classified into the classes to which they belong. SVM can easily with efficient results performs non-linear classification using kernel trick in which dimensionality is increased for the feature space.

Let y_i, j =1, 2, . . . ,K, be the features of EMG signals for the training Y. Numbers taken belong to one of the three sources (or classes). These features are supposed to be separable linearly. Now, the objective is to design a hyperplane such as

$$h(y) = \omega^T y + \omega_0 = 0 \tag{3.15}$$

Then the separation of a support vector from the hyperplane is given by

$$D = \frac{|h(y)|}{\|\omega\|} \tag{3.16}$$

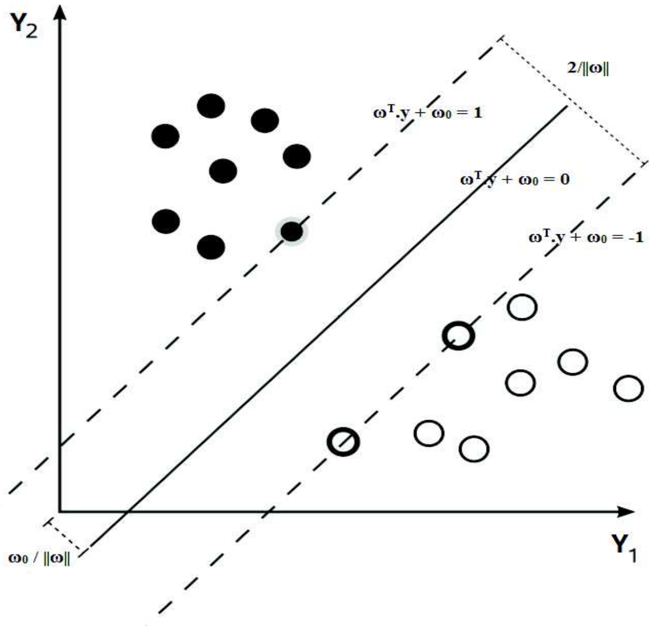

Fig.3.9: Linear Classifier

Now, ω, ω_0 are selected such that the value of h(y) should be at the support vector points. This is equivalent with

1. Having a margin of

$$\frac{1}{\|\omega\|}+\frac{1}{\|\omega\|}=\frac{2}{\|\omega\|}$$

2. Requiring that

$$\omega^T y+\omega_0 \geq 1, \forall y \in \omega_1 \tag{3.17}$$

$$\omega^T y+\omega_0 \geq -1, \forall y \in \omega_2 \tag{3.18}$$

Now, for each value of y_j, we represent the corresponding class by z_j. Hence, for this, calculate ω, ω_0 so that:

$$\text{minimize } F(\omega,\omega_0) \equiv \frac{1}{2}\|\omega\|^2 \tag{3.19}$$

subject to

$$z_j(\omega^T y+\omega_0) \geq 1 \quad , j = 1, 2, \ldots, \tag{3.20}$$

This is done as minimizing (3.19) will make the separation between support vector and hyperplane maximum. Some constraints need to be followed by the SVM. Here are the Karush–Kuhn–Tucker (KKT) conditions [74] that the minimizer has to satisfy are as follows:

$$\frac{\partial}{\partial \omega} L(\omega, \omega_0, \eta) = 0 \tag{3.21}$$

$$\frac{\partial}{\partial \omega_0} L(\omega, \omega_0, \eta) = 0 \tag{3.22}$$

$$\eta_j \geq 0 \quad , \text{j} = 1, 2, \ldots, \text{K} \tag{3.23}$$

$$\eta_j [z_j(\omega^T y + \omega_0) - 1] = 0 \quad , \text{j} = 1, 2, \ldots, \text{K} \tag{3.24}$$

More formally, SVM will design a hyperplane in a higher dimensional space using the kernel trick which can be exploited for the classification purpose. But here, three classes of the signals present are related to different sources and no need of kernel function is there during this classification. Here, multiclass SVM is sufficient for the given set of EMG signals.

3.6.4) Multiclass SVM

Multiclass SVM aims to label the test datasets of EMG signals by exploiting SVMs. In this, the main approach used is to convert the multiclass problem into binary problem which will be done multiple times.

There are some methods through which such conversion is possible. Such methods include: (i) one-versus-one (or Pairwise approach), (ii) one-against-all. In the Pairwise classification, every classifier is assigned with instance to one of the classes. Then, the votes are counted for the assigned class. Finally, the class with maximum number of votes is assigned the instance classification.

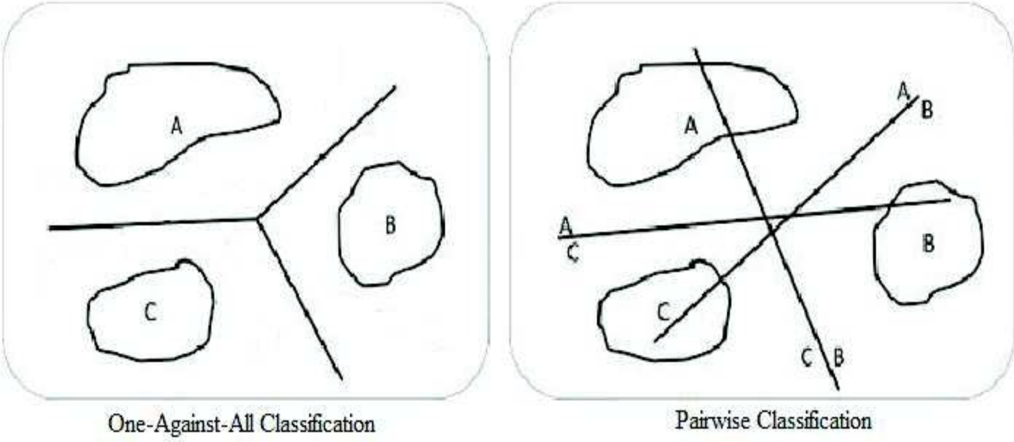

Fig.3.10: Multiclass SVM

For this research work, one-versus-all approach is used. In this approach, Tested dataset is classified using an output function whose highest value defines the class to which that data is to be allocated.

Applications:

SVMs can be used to solve various real world problems:

- SVMs are helpful in text and hypertext categorization as their application can significantly reduce the need for labelled training instances in both the standard inductive and transductive settings.
- Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes after just three to four rounds of relevance feedback.
- SVMs are also useful in medical science to classify proteins with up to 90% of the compounds classified correctly.
- Hand-written characters can be recognized using SVM.

Classification is an important branch in data mining, support vector machine (SVM) as a new method of machine learning which has great advantage. However, the approach seems to have its deficiencies when process large volume data. Here we introduce the rough set into support vector machine, and present a new classified method based on rough set and support vector machine (SVM). SVM algorithm is the first to reduction for sample data sets, to delete the redundant condition attribute and conflicting sample objects, to simplify the sample space in ensure the resolving power of sample sets case using the theory of rough set. Then the algorithm of Rough set-SVM can produce the SVM data classification system based on information structure of pre-processing and can speed up SVM training speed and reduce the complexity of the system structure. The specific process of this algorithm is:

- Input: (x1, t1), (x2, t2)………, (xn, tn).
- Define a kernel trick.
- Find kernel matrix k, $k_{ij} = k(xi, xj)$.
- Find target matix $T = t.t^T$.
- Find coefficient matrix A, $A_{ij} = k_{ij}.T_{ij}$, for all i, j.
- Find the system of linear equation in λij.

$$\text{i.e. } A.M = 1 \text{ where, } M = \begin{matrix} \lambda 1 \\ \vdots \\ \lambda n \end{matrix}.$$

- Solve the systrm of linear equations i.e. λ1, λ2,…, λn.
- Find $b = \frac{1}{N}[\sum tn - \sum \lambda m.\, tm * \sum k(Xn, Xm)]$.
- Find $w^T \varphi(x) = \sum \lambda n.\, tn.\, k(Xn, Xm)$.
- Find the hyperplane, $w^T \varphi(x) + b$.
- Testing: If sign $(w^T \varphi(x) + b)$ is +ve => +1.

Sign $(w^T \varphi(x) + b)$ is –ve => -1.

3.7) Summary

A brief outline of the work is shown in the block diagram in Figure. It is briefly described as follows:

Table 3.1: Description of dataset used

EMG Signals	Training	Testing	Total
Normal	35	15	50
Myopathy	35	15	50
Neuropathy	35	15	50

EMG Dataset: MIT-BIH database of Physionet bank ATM is used to load the EMG signals. Table 3.1 represents the description of the dataset used.

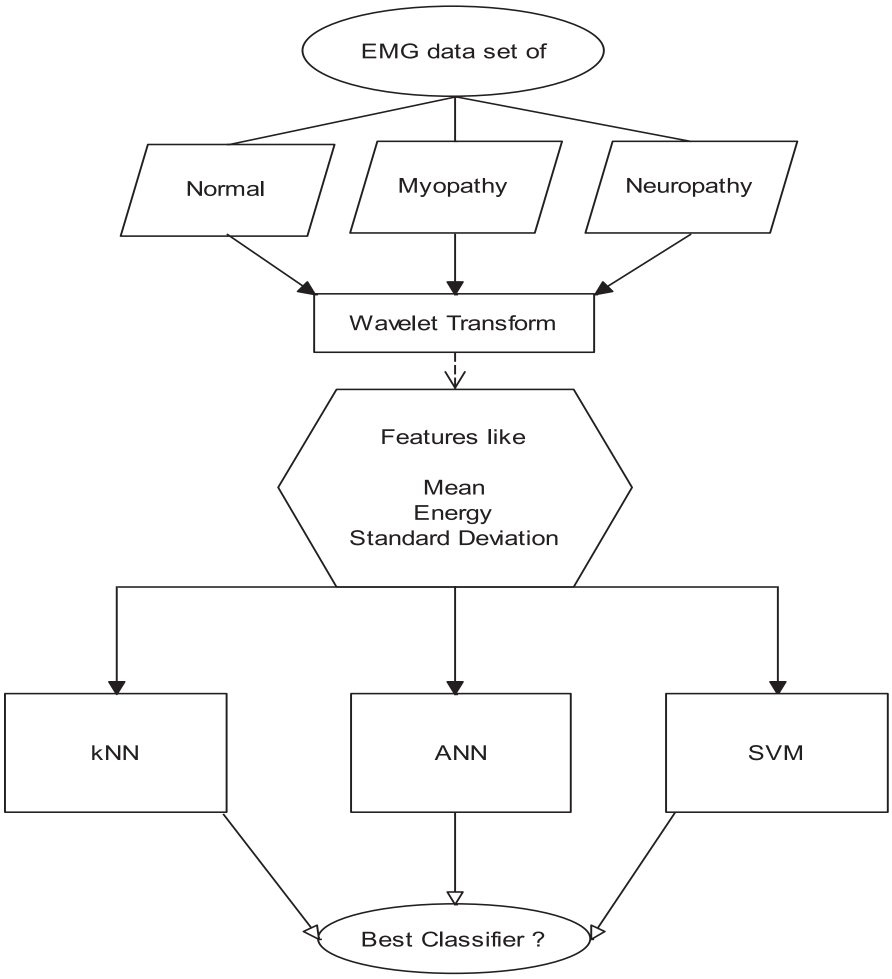

Fig.3.11: Block Diagram of EMG Signals Classification

Computing the wavelet transform and their features: Discrete wavelet transform (DWT) of the EMG signals are computed and the Features such as Energy, Mean and Standard Deviation of the D4 coefficient are calculated for each and every dataset of the different types of EMG signals taken. These calculated features serve as an input to train and test the classifiers.

Classification: During the classification, class of the samples of EMG signals are identified utilizing the computed features. This feature set consists of energy, mean and standard deviation that should efficiently characterize the variations in the input EMG signals for accurate detection and classification of the EMG signals. After that, these features are applied on to the various classifiers such as kNN, ANN and SVM classifiers so that training provided using these features may results in efficient results of classification when the testing data is given to the classifiers to classify the EMG signals into their corresponding classes.

Chapter 4
RESULTS & DISCUSSION

4.1 Overview

This chapter discusses about the results coming from the classification of ElectroMyoGram (EMG) signals. It also discusses about the analysis of EMG signals by using the MATLAB. The discussion on the results of EMG analysis includes pre-processing by discrete wavelet transform with feature extraction (like energy, mean and standard deviation). After that, the classification results from the various classifiers such as kNN, ANN and SVM will be explained. Comparison of the results from various classifiers is also presented in this chapter.

4.2 Analysis of EMG using DWT

Now, the EMG signal is analysed using discrete wavelet transform. For this, Coiflet wavelet family is selected and different types of EMG signals are applied.

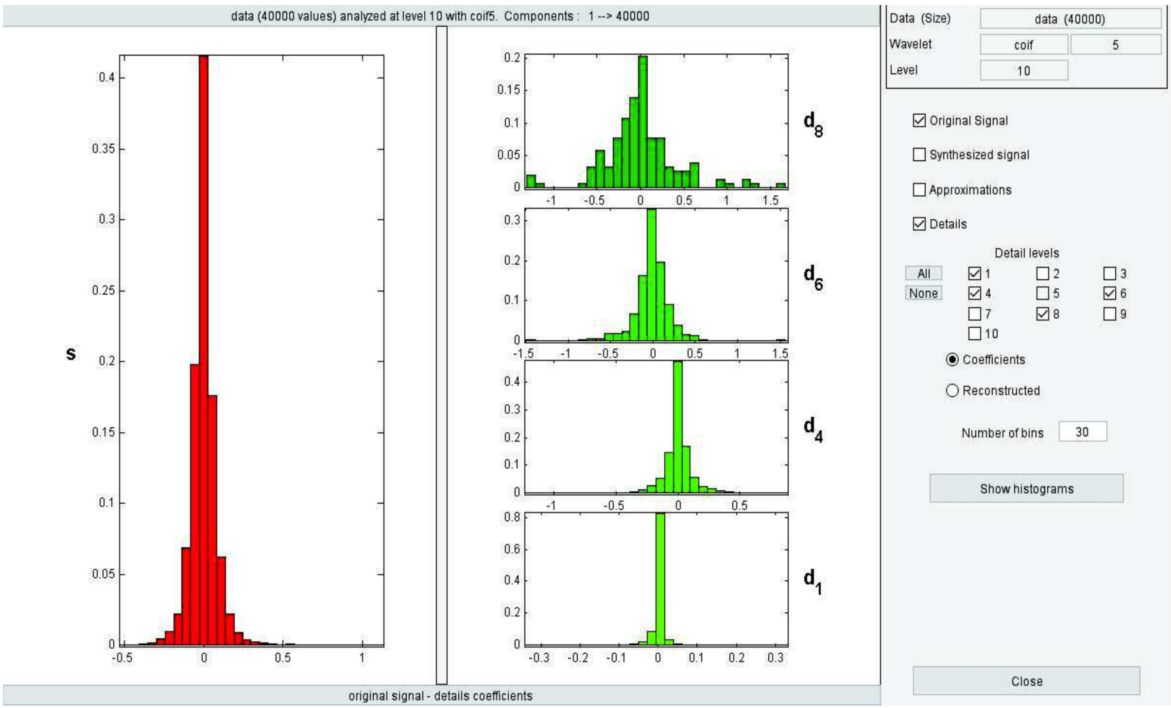

Fig.4.1: DWT of Healthy person EMG

Coiflet wavelet of order 5 is chosen for the same. Wavelet Transform breaks the signal into its approximation and detailed coefficients. D_1-D_2 are the high frequency coefficients and is considered as noise for the EMG signal. Same is the case with the approximation coefficient A_{10} which is considered as the low frequency component and hence neglected.

Now, it is seen in the form of the histogram of the signal's wavelet coefficients and it is observed that the D_4 coefficient resembles the most with the original signal. Hence this coefficient contains the maximum of the information of the original signal. Fig. 4.1-4.3 are shown the wavelet transforms of the original signals i.e. normal, myopathy and neuropathy respectively.

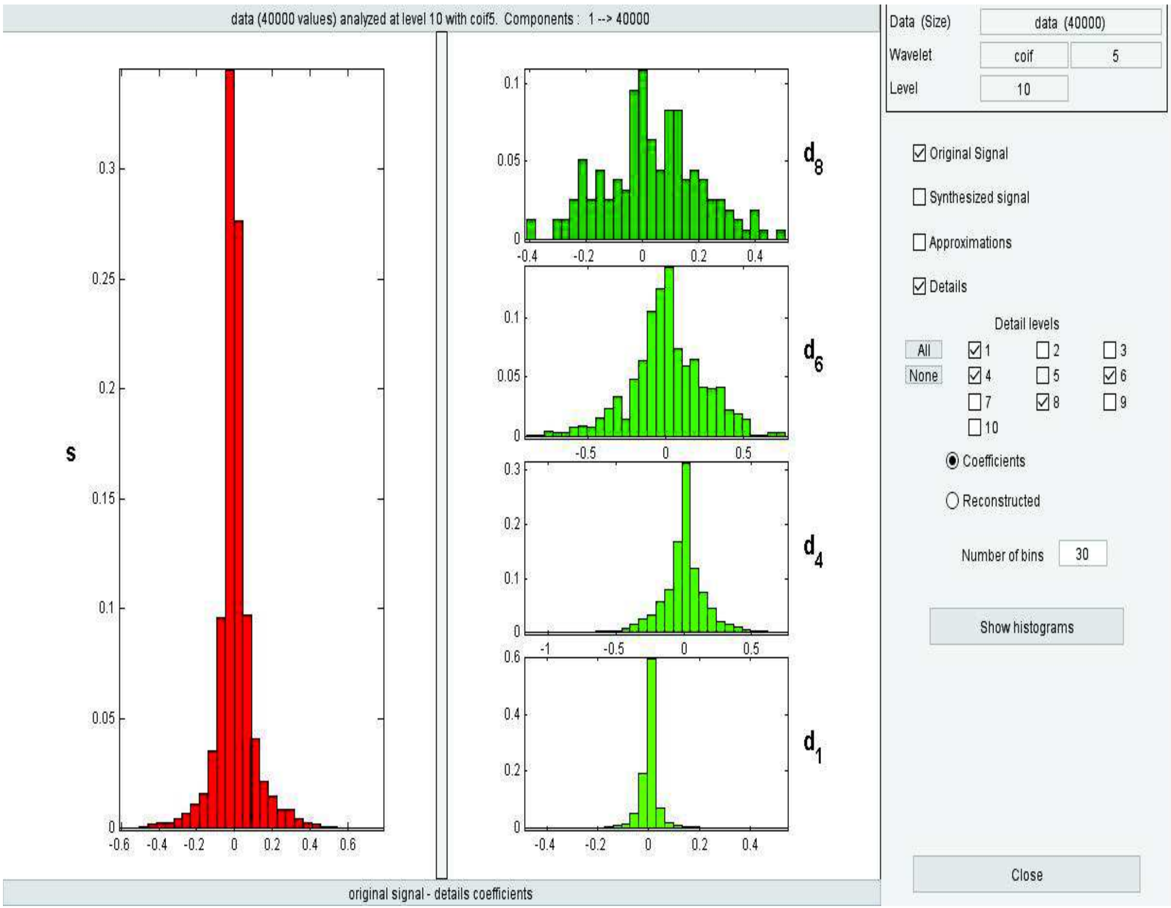

Fig.4.2: DWT of Myopathy EMG

The DWT coefficients are shown in the form of histogram as it is very clear from the histograms that the D_4 coefficient is in maximum resemblance with the original signal. Sample of each signals taken are wavelet transformed using the coiflet wavelet of order 5.

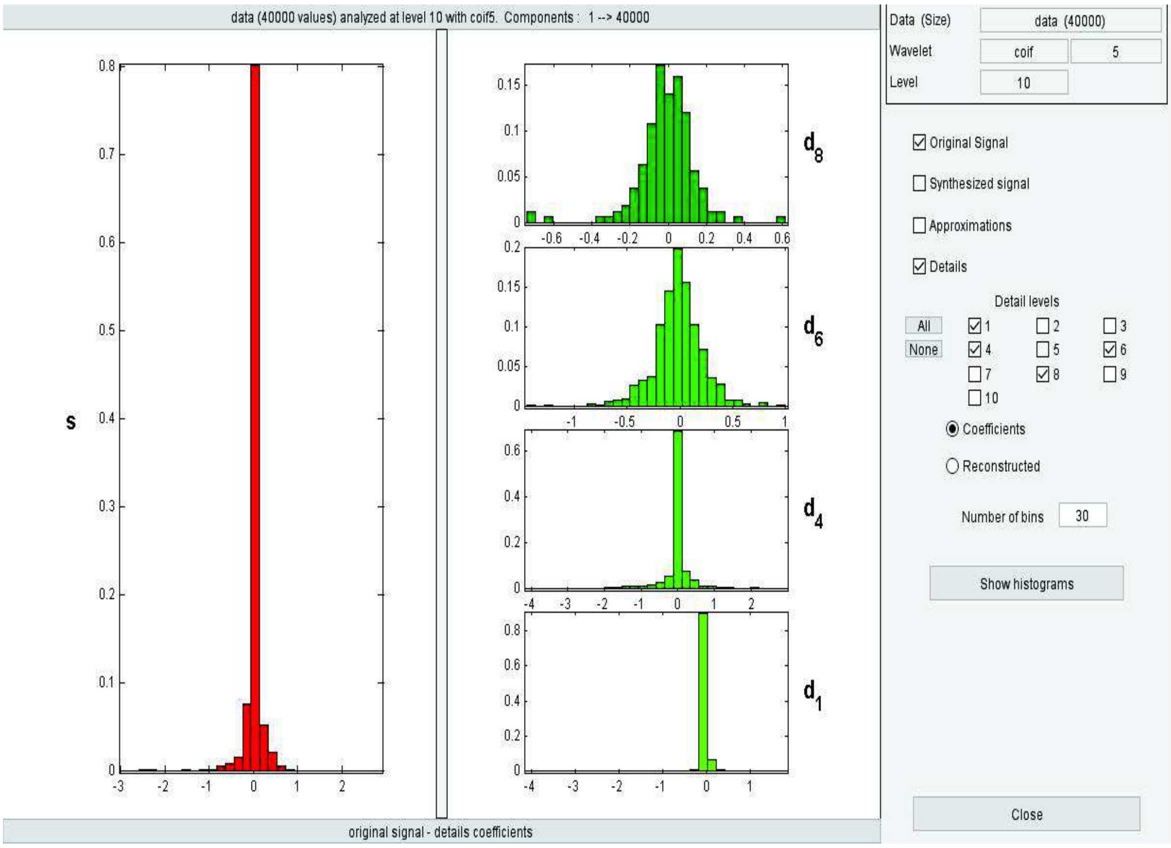

Fig.4.3: DWT of Neuropathy EMG

In each sample, detailed coefficient i.e. D_4 is selected for the further feature extraction procedure in which energy, mean and standard deviation are used as the features for the EMG signals.

4.3 Features Extraction of EMG

Next, the features are computed for the D_4 coefficients of the different types of EMG signals used in the project i.e. Normal signal, Myopathy signal and Neuropathy signal. These features are the energy of the signal, mean value of the signal and the standard deviation in the signal, shown in the equation 3.9-3.11.

In the Table 4.1, energy of the EMG signals are shown for the three types of signals used. These values are computed in the MATLAB using the detailed coefficient (D_4) of the coiflet wavelet family of order 5. Here, 35 samples of each type of signals are utilized only as these are used to train the classifiers.

Table 4.1: Energy values for the EMG Signals

S.No.	Normal	Myopathic	Neuropathic
1	76.54	53.78	103.34
2	49.43	29.93	68.45
3	61.22	29.56	111.98
4	59.16	47.32	79.45
5	62.67	46.73	79.97
6	80.98	88.97	76.45
7	44.87	29.85	58.48
8	58.46	39.32	78.76
9	46.52	35.34	58.34
10	33.89	22.56	49.95
11	54.32	37.99	72.56
12	55.78	38.42	81.12
13	53.34	32.34	80.67
14	56.67	50.89	63.87
15	36.43	31.54	42.89
16	50.92	43.42	61.67
17	39.54	28.65	49.95
18	35.56	27.98	46.65
19	93.55	46.52	175.42

20	**47.53**	**26.98**	**68.45**
21	**70.78**	**38.11**	**121.69**
22	**90.98**	**22.73**	**248.78**
23	**229.76**	**22.88**	**1178.47**
24	**64.34**	**27.97**	**115.98**
25	**48.89**	**26.56**	**83.67**
26	**47.34**	**26.89**	**84.56**
27	**79.67**	**38.99**	**144.87**
28	**57.67**	**40.11**	**78.94**
29	**49.67**	**33.07**	**71.56**
30	**56.45**	**47.87**	**62.89**
31	**74.86**	**42.97**	**116.67**
32	**112.57**	**45.46**	**188.78**
33	**46.78**	**21.12**	**95.75**
34	**53.89**	**31.79**	**82.19**
35	**67.95**	**40.56**	**102.93**

In the Table 4.2, mean value of the EMG signals are shown for the three types of signals used. These values are also computed in the MATLAB using the detailed coefficient (D_4) of the coiflet wavelet family of order 5 in the discrete wavelet transform. Here also, 35 samples of each type of signals are utilized only as these are used to train the classifiers.

Table 4.2: Mean values for the EMG Signals

S.No.	Normal	Myopathic	Neuropathic
1	8.64	7.32	9.92
2	6.93	5.44	8.06
3	7.76	5.42	10.42
4	7.56	6.85	8.62
5	7.87	6.82	8.73
6	8.98	9.42	8.53
7	6.47	5.45	7.34
8	7.54	6.25	8.52
9	6.68	5.92	7.34
10	5.72	4.73	6.71
11	7.18	6.15	8.14
12	7.38	6.18	8.74
13	7.03	5.66	8.76
14	7.38	7.12	7.64
15	5.85	5.60	6.16
16	6.97	6.57	7.48
17	6.01	5.34	6.67
18	5.78	5.28	6.35
19	9.56	6.82	13.05

20	**6.64**	**5.18**	**7.94**
21	**8.26**	**6.16**	**10.75**
22	**9.48**	**4.75**	**15.54**
23	**15.08**	**4.77**	**34.26**
24	**7.84**	**5.28**	**10.52**
25	**6.78**	**5.12**	**8.73**
26	**6.64**	**5.16**	**8.87**
27	**8.75**	**6.24**	**11.82**
28	**7.43**	**6.32**	**8.62**
29	**6.87**	**5.74**	**8.15**
30	**7.35**	**6.86**	**7.54**
31	**8.57**	**6.54**	**10.48**
32	**10.49**	**6.72**	**13.56**
33	**6.58**	**4.56**	**9.43**
34	**7.24**	**5.62**	**8.67**
35	**8.06**	**6.34**	**9.89**

Next, in the Table 4.3, standard deviation values are shown of the EMG signals for the three types of signals used. These values are also computed using the detailed coefficient (D_4) of the coiflet wavelet family of order 5 in the discrete wavelet transform in the MATLAB. Here also, 35 samples of each type of signals are utilized only as these are used to train the classifiers.

Table 4.3: Standard Deviation values for the EMG Signals

S.No.	Normal	Myopathic	Neuropathic
1	2.64	0.32	5.92
2	1.73	0.44	4.06
3	1.76	0.42	6.42
4	2.56	0.85	5.62
5	3.87	0.82	4.73
6	2.98	0.42	5.53
7	2.47	0.45	5.34
8	2.54	0.25	5.52
9	2.68	0.92	6.34
10	2.72	0.73	6.71
11	1.18	0.15	5.14
12	3.38	0.18	6.74
13	3.03	0.66	4.76
14	2.38	0.12	5.64
15	2.85	0.60	5.16
16	1.97	0.57	4.48
17	2.01	0.34	6.67
18	1.78	0.28	5.35
19	2.56	0.82	5.05

20	**2.64**	**0.18**	**4.94**
21	**2.26**	**0.16**	**5.75**
22	**1.48**	**0.75**	**6.54**
23	**2.08**	**0.77**	**4.26**
24	**2.84**	**0.28**	**5.52**
25	**2.78**	**0.12**	**6.73**
26	**1.64**	**0.16**	**4.87**
27	**1.75**	**0.24**	**4.82**
28	**2.43**	**0.32**	**5.62**
29	**3.87**	**0.74**	**5.15**
30	**2.35**	**0.86**	**4.54**
31	**1.57**	**0.54**	**6.48**
32	**2.49**	**0.72**	**5.56**
33	**3.58**	**0.56**	**5.43**
34	**2.24**	**0.62**	**5.67**
35	**2.06**	**0.34**	**6.89**

4.4 Classification of EMG Signals

From the tables 4.1-4.3, we have feature vectors of the EMG signals which are now utilized in various classifiers for the training of those classifiers and then signals will be tested. On the basis of these features, classifiers will classify the signals into their respective classes. For the classification purpose, three classifiers are exploited here i.e. kNN, ANN and SVM classifiers.

4.4.1 Classification using kNN Classifier

Firstly, k-Nearest Neighbours classifier is used for the classification of the different types of EMG signals i.e. Normal, Myopathy and Neuropathy.

Performance of a classification algorithm can be measured by a specific table layout which is called the Confusion Matrix. It is called so because it makes it easier to see whether the method is confusing the result of classification between the two classes. Each column in confusion matrix shows instances in the predicted class and each row shows instances in the actual class. Confusion matrix is shown in the Table 4.4.

Table 4.4: Confusion matrix

	PREDICTED CLASS		
ACTUAL CLASS		Abnormal	Normal
	Abnormal	TP	FN
	Normal	FP	TN

Where TP, TN, FP, and FN are given as:

- True Positive (TP): Abnormal signal correctly identified as abnormal.
- True Negative (TN): Normal signal correctly identified as normal.
- False Positive (FP): Normal signal incorrectly identified as abnormal.
- False Negative (FN): Abnormal signal incorrectly identified as normal.

It is shown by the confusion matrix in the Table 4.5 that how many of the tested samples are classified accurately.

Table 4.5: Confusion matrix from kNN

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	**11/15**	**01/15**	**03/15**	**73.33%**
Myopathy	**02/15**	**12/15**	**01/15**	**80.00%**
Neuropathy	**04/15**	**01/15**	**10/15**	**66.67%**

And from the results in Table 4.5, only an accuracy of 73.33% is observed, and hence further improvement is required. Therefore, for the betterment of results, another classifier is used and i.e. Artificial Neural Network (ANN) classifier. It is explained in the next sub-section.

4.4.2 Classification using ANN Classifier

Artificial Neural Network is the next classifier used in this research. For this classifier, the samples of the various signals which have already computed values of energy, mean and standard deviation are utilized to train the classifier. Then on this trained classifier, other samples are tested and it was observed that results of the classification obtained from the classifier are much better than the previous one used classifier.

Table 4.6: Confusion matrix from ANN

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	**14/15**	**00/15**	**01/15**	**93.33%**
Myopathy	**01/15**	**13/15**	**00/15**	**86.67%**
Neuropathy	**01/15**	**01/15**	**13/15**	**86.67%**

The confusion matrix for the classification results of the Artificial Neural Network (ANN) classifier is shown in the Table 4.6. The results obtained with this classifier have an accuracy of 88.88%. But this is further increased using another classifier named Support Vector Machine (SVM) classifier i.e. explained in the next sub-section.

4.4.3 Classification using SVM Classifier

Support Vector Machine is the next classifier exploited in this project. For this classifier also, samples of the various EMG signals, which have already been used to compute the parameters like energy, mean and standard deviation, are utilized to train the classifier. Then, on this trained classifier, samples of EMG signals are tested and it was observed that results of the classification obtained from the classifier have a great improvement compared to the previous models used as classifiers.

Table 4.7: Confusion matrix from SVM

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	15/15	00/15	00/15	100%
Myopathy	00/15	14/15	01/15	93.33%
Neuropathy	00/15	01/15	14/15	93.33%

The confusion matrix for the classification of the EMG signals using the Support Vector Machine (SVM) classifier is shown in the Table 4.7. The results obtained using this classifier gave an accuracy of 95.55%. These are highly efficient results and can be considered as a very good classifier for the classification of the different types of EMG signals used in this project.

4.5 Comparison of All the Classifiers Used

Table 4.8: Comparison of three classifiers

Classifier Name	Accuracy(%)
kNN	73.33
ANN	88.88
SVM	95.55

In the Table 4.8, comparison of all the classifiers used in this research work is shown. It can be concluded from the table that SVM classifier gives the maximum accuracy results in classifying the EMG signals. It is also shown by the graph shown in the Fig. 4.4.

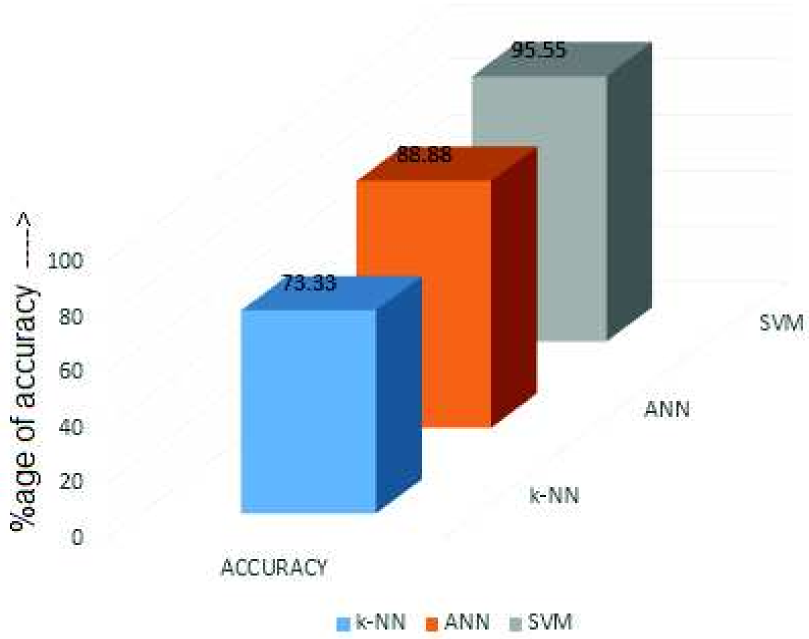

Fig.4.4: Comparison of the Results obtained from the classifiers

Chapter 5
CONCLUSION & FUTURE SCOPE

5.1) Overview

This chapter discusses the conclusion and future work of ElectroMyoGram (EMG) Analysis using Discrete Wavelet Transform with features like Energy, Mean, Standard Deviation and the classifiers including the limitation during the project.

5.2) Conclusion

The EMG signals are usually non-repeatable and contradictory in nature. Therefore, to classify such signal, a classifier able to tolerate indecisions in data is requisite. SVM classifier has the capability to classify EMG signals. In the presented work, feature extraction and classification of the EMG signal for three categories: normal, myopathy and neuropathy, and to provide quantitative information of weight held by the subject was done. The system was implemented in MATLAB. To evaluate the performance of the implemented system, it tested in 45 datasets with three different types of EMG signals. The results obtained show that the success rate of the SVM classifier is 95.55%.

It is also observed that the quality of EMG signals is affected by routine activity of the subject, which is reflected by the variations in energy, mean and standard deviation values of the EMG signal.

5.3) Limitations

Three classifiers used in this project gives very efficient results. But with such good results, they also have some limitations which are as follows:

- Three parameters i.e., energy, mean and standard deviation are used as the features of the EMG signals which sometimes are not enough in to differentiate the signals.
- In kNN classifier, value of the parameter k (number of nearest neighbours) need to be determined. Distance based learning is not clear that which type of distance (as shown in chapter 3, section 3.6.1) to use to produce the best results.

- In ANN classifier, model produce best results when the dataset is large. But with increase in number of datasets, number hidden layers increases in the network and hence, the complexity of the circuit also increases.
- In SVM classifier, results obtained are straight forward with give and take solutions. In this, no further learning of the classifier is present. Only the results obtained after testing are considered as the final results. Due to this problem, a large amount of memory is also required in this classifier.

5.4) Future Scope

In the presented work, only three parameters i.e., energy, mean and standard deviation are utilized to classify three different types of EMG signals. Some more parameters can also be considered to raise the accuracy of classification. Hybrid of the classifiers can also be used to increase the efficiency for the classification of the different types of EMG signals.

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APPENDIX I: Published Research Papers

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Classification of Pseudo Random Numbers Using Support Vector Machine Classifier

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Abstract: The paper studies about the randomness and its application in the field of cryptography. It is already known to have randomness having applications in the fields of gaming, gambling, statistics etc. But, in applications such as cryptography, randomness has a vital role. As with the use of these random numbers only, a highly secure message can be formed. So, Pseudo Random numbers classification is proposed in this paper so that sources of these random numbers can be classified for the enhancement in the security level. The result shows good accuracy of classification of these random numbers i.e. classified using multi-SVM.

Keywords: Cryptanalysis, Multi-SVM, PRNGs, TRNGs.

I. INTRODUCTION

In this world, randomness is the dearth of certainty in an event. It can be easily understood with the help of randomness that proper random numbers generation is a quite complicated process. Random numbers are helpful in various purposes which include creating files keys for encryption, creating a representation for selecting the random trials from large datasets. A random sequence for any event has no particular order and does not follow a logical pattern.

Randomness has found its applications in the fields of art, science, statistics, cryptanalysis, gaming etc. In the field of cryptanalysis, goal is to make a message as hard to crack as possible. It is done by disguising the parameters used to encode the message from the context in which it is conceded. For example, randomness, in randomized trials, are helpful in testing the hypotheses. Pseudo Random numbers are useful in video games such as video poker. In 1946, [1] introduced a method to generate Pseudo Random numbers. In this method, middle digit of the previous number takes the place of the next successive number. First of all they took a kernel value, and calculated the square in which they nominated the middle digits of that number and took it as the kernel value for next successive Pseudo Random number. This way, middle digits of previous numbers act as the kernel value for the successive number. In 1949, [2] proposed a method named Linear Congruential Generator (LCG). This algorithm comes out as the best algorithm for the generation of Pseudo Random numbers. It is very fast and easy to comprehend at the same time. Its execution is also very informal. In this, with the help of a simple linear equation, they attained a Pseudo Random sequence. The source of the equation was the modulo arithmetic. Modulo arithmetic is a very useful tool in which numbers wrap around after reaching a certain value. Quadratic congruential generator 1 and Quadratic congruential generator 2, uses a quadratic equation, are very greatly based on the idea of Linear congruential generator as these two do not use the linear equation. [3] also generates another Pseudo Random number generator, named Blum Blum Shub, that was proposed in 1986. These Pseudo Random numbers generated using various different methods can increase their number of applications if the source of that random number is identified. Support Vector Machine is a model which is derived from a theory known as statistical learning [4]. Compared to Neural Network (NN) approaches [5], SVMs exhibit higher generalization capability, robustness, lower efforts are required for classifier selection during the training period [6] and finest solution is obtained by this algorithm. [7] proposed a technique which performs classification of multi-classes problem (known as multiclass SVM) into the single one, rather into binary classification of multiple sets. Now, through this paper, an experiment has been done for separating the different kinds of Pseudo Random numbers generated from different sources. For this, three set of Pseudo Random numbers are selected with different sources, each representing a separate class. Then using the model named SVM, classification of these numbers are done and results are represented in the form of an image output showing three classes of Pseudo Random numbers which are well separated using the SVM.

The paper is organised as follows. Section II provides details about definitions and explanations of the methods used. Section III provides the process, explained using algorithm, of the proposed method. Section IV contains the classification results followed conclusion in Section V.

II. PROPOSED METHOD

A. True Random Numbers Generator (TRNG)
In the applications like cryptography, sources for generating the random numbers should be of high quality so that a high quality design may produce. There are so many good quality sources exists for the generation of true random numbers, at present, to design a cryptographic system. But, unfortunately, cryptographic analysis is done with only few of the existing true random number

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generators. This is because a design made using TRNGs produces the sequence of numbers of such kind that these numbers show a definite level of association due to its bandwidth and temperature drift limitations.
So, due to issues in manipulating the TRNGs, there is difficulty in designing such a system. TRNGs also create deterministic disturbances in the cryptographic system design. Solution to this problem is to design such a system which can use analogue randomness sources. Therefore, due to design flaws occurring using TRNGs and lack of random data in TRNGs, Pseudo random numbers generators came in use.

B. Pseudo Random Numbers Generators (PRNG)
Theories of researches on Pseudo Random numbers with the results being so positive that Pseudo Random numbers generated using modern algorithms look exactly as they are really random. According to the meaning of the word 'Pseudo', Pseudo Random numbers are not as such as we might presume. Essentially, PRNGs are the algorithms which utilize simple pre-calculated data and mathematical formulaes [11] to generate the random numbers. Linear congruential is a good design of PRNGs.
The linear Congruential Generator (LCG) is defined by using a recurrence relation:

$$Y_{k+1} = (\alpha . Y_k + \gamma).(|r|) \qquad (3)$$

where,
α, $0 < \alpha < r$ = multiplier
γ, $0 <= \gamma < r$ = incremental
r, $r > 0$ = modulus
Y_0, $0 <= Y_o < r$ = seed value
And, Y is the sequence of Pseudo Random values

$$Gcd(\gamma, r) = 1 \qquad (4)$$

$\beta = (\alpha - 1)$ is multiple of q for every q dividing r
β is multiple of 4 if r is multiple of 4

Another PRNG that exists is Quadratic Congruential Generator i.e., shown in the equation

$$Y_{k+1} = (\alpha Y_k^2)(|r|) \qquad (5)$$

Quadratic congruential generator 2 is defined as,

$$Y_{k+1} = (\alpha Y_k^2 + \beta Y_k + \gamma)(|r|) \qquad (6)$$

Blum Blum Shub is another PRNG which follows the equation for PRNG as:

$$Y_{k+1} = Y_k^2(|r|) \qquad (7)$$

Here, Y_r = seed value
Y_{k+1} = Pseudo Random number generated
r = uv, where u and v be the two prime numbers of large values. In this algorithm, output is derived from Y_K at each step. Then the output is the least significant bit of Y_{K+1}.

Blum Blum Shub follows the following steps:
1. Generate u and v as two big prime numbers.
2. $k := u \cdot v$
3. Choose t belongs to R [1, k − 1], the random seed. Choose a random number s, such that neither u nor v is a factor of t.
4. $Y_0 := t_2 \pmod k$
5. The sequence is defined as $Yj = Y_{2j-1} \pmod k$ and $Z_j :=$ parity(Y_j).
6. The output is $Z_1, Z_2, Z_3, \ldots$.

PRNGs are efficient [12] which means that they can generate the random numbers in a short extent. These are deterministic also as certain sequence can be reproduced at the future stage if the primary point of the structure is known. If determinism is handy, same sequence is to be repeated at further stage. Efficiency can also be considered as a distinguishing characteristic if there are large number of pseudo random numbers are present. PRNGs also have one more property which is hardly desirable and i.e. periodic nature [13]. This property states that the sequence obtained should be repeatable. At present, modern algorithms of PRNGs are periodic with such a period that it can be ignored for most practical cases as it is so long.

As it is beneficial to have a sequence which can be easily repeatable, hence, the above stated characteristics of PRNGs make them a very much suitable for the applications where randomness is the basic necessity. Among such applications, popular ones includes simulation and modeling applications but are not suitable for the applications such as gambling and data encryption, where the numbers are really unpredictable.

C. Comparison of PRNGs with TRNGs
In comparison with PRNGs [14], the characteristics of TRNGs are quite different. These characteristics are helpful in distinguishing both. Firstly, TRNGs are ineffective as compared to PRNGs because former takes considerably a very large time to generate the numbers. They are also known by the name of non-deterministic random number generators because it is not possible with the help of TRNGs that random numbers sequence can be reproduced.

Athough, by chance, same numbers sequence may, of course, occur several times. TRNGs is non-periodic. The basic differences [15] between PRNGs and TRNGs are very easy to understand because PRNGs produce random numbers by using pre-calculated data and mathematical formulaes. An outlook is shown in the Table I in which the characteristics of the two types of random number generators are compared.

Even the numbers generated from TRNG seems random, but they are really predetermined. TRNGs are considered more suitable, approximately, in such applications in which PRNGs are failed to find their applications. These includes security in data transfer, gambling, games etc. However, less efficient and non-deterministic nature of TRNGs doesn't allow such generated random numbers to produce satisfactory results for the applications like simulation and modeling. This is because TRNG is not able to generate the amount of data which is required for these applications.

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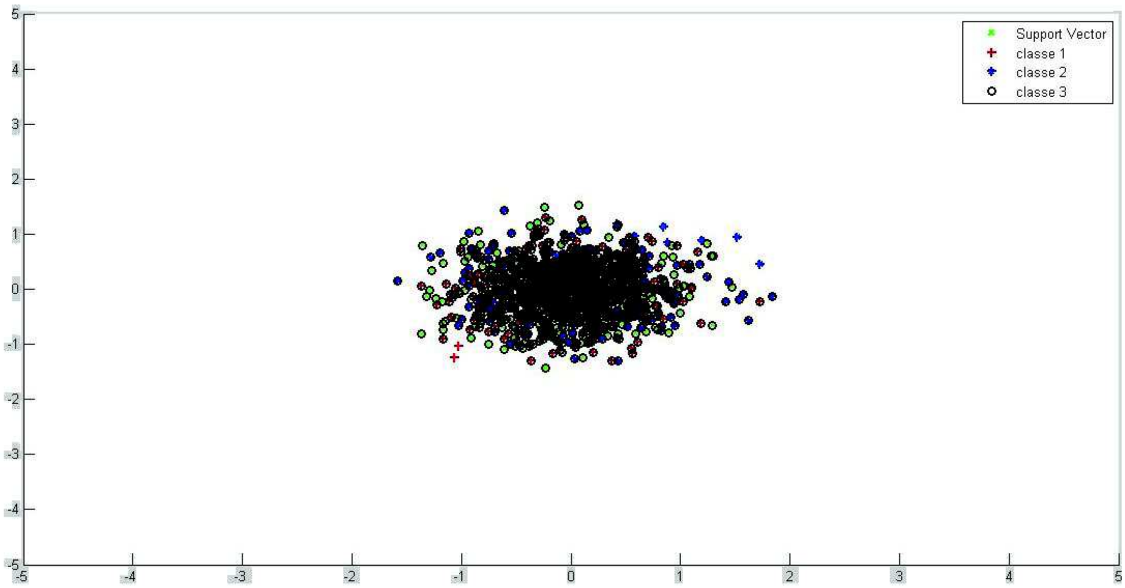

Fig. 1. Mixture of three classes Pseudo Random Numbers

TABLE I COMPARISON OF PRNGS AND TRNGS

Characteristics	True RNGs	Pseudo RNGs
Efficient	Less	more
Nature	Random	Deterministic
Repeatablity	Non-repeatable	Repeatable

Table II shows the various fields of applications and generators suitable in each field.

TABLE II SUITABLITY OF GENERATOR : APPLICATION-WISE

Application	Most Suitable Generator
Generation of keys for data encryption	True RNG
Random Sampling (e.g., medicine selection)	True RNG
Sports and Gambling	True RNG
Lotteries and Draws	True RNG
The Arts	Varies
Simulation and Modelling	Pseudo RNG

Hence, according to its application in the simulation and modelling, Pseudo Random numbers are used during this research. Three different types of Pseudo Random numbers generated are mixed and classified again separately using a classifier. The classifier is explained in the next sub-section.

D. Classifier

In the classification of the pseudo random numbers generated using different sources, SVM is a classifier which is used. It is a supervised learning model [16] as it is firstly trained using the associated learning algorithms with the labelled data. Then with the help of this trained model, tested data is analyzed. These are exploited in the regression analysis. SVMs can be helpful in various applications. These includes text categorization, hand-written characters recognition etc. Experimental results shows, SVM achieves higher accuracy than other traditional models. SVMs also find its application in the field of medical sciences with nearly 80% of accuracy in classifying the samples accurately. For this, a set of training random numbers, each marked for one of the classes is used to train the SVM. Then the pseudo random numbers are tested on this trained SVM and the random numbers are classified into the classes to which they belong. SVM can easily with efficient results performs non-linear classification using kernel trick in which dimensionality is increased for the feature space. Let y_i, j =1, 2, . . . ,K, be the pseudo random numbers for the training Y. Numbers taken belong to one of the three sources (or classes). These random numbers are supposed to be separable linearly. Now, the objective is to design a hyperplane such as

$$h(y) = \omega^T y + \omega_0 = 0 \tag{8}$$

Then the separation of a support vector from the hyperplane is given by

$$D = \frac{|h(y)|}{\|\omega\|} \tag{9}$$

Now, ω, ω_0 are selected such that the value of h(y) should be at the support vector points. This is equivalent with

1. Having a margin of

$$\frac{1}{\|\omega\|} + \frac{1}{\|\omega\|} = \frac{2}{\|\omega\|}$$

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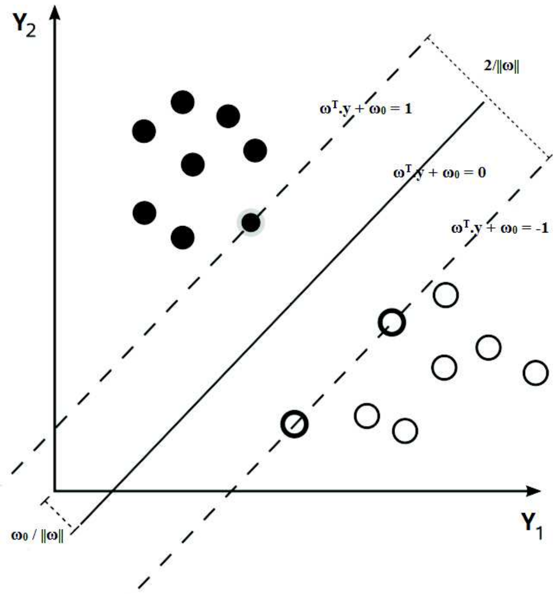

Fig. 2. Linear Classifiers

2. Requiring that

$$\omega^T y + \omega_0 \geq 1, \forall y \in \omega_1 \quad (10)$$

$$\omega^T y + \omega_0 \geq -1, \forall y \in \omega_2 \quad (11)$$

Now, for each value of y_j, we represent the corresponding class by z_j. Hence, for this, calculate ω, ω_0 so that:

$$\text{minimize} \quad F(\omega, \omega_0) \equiv \frac{1}{2}\|\omega\|^2 \quad (12)$$

subject to

$$z_j(\omega^T y + \omega_0) \geq 1 \quad , j = 1, 2, \ldots, \quad (13)$$

This is done as minimizing (12) will make the separation between support vector and hyperplane maximum. Some constraints need to be followed by the SVM. Here are the Karush–Kuhn–Tucker (KKT) conditions [17] that the minimizer has to satisfy are as follows:

$$\frac{\partial}{\partial \omega} L(\omega, \omega_0, \eta) = 0 \quad (14)$$

$$\frac{\partial}{\partial \omega_0} L(\omega, \omega_0, \eta) = 0 \quad (15)$$

$$\eta_j \geq 0 \quad , j = 1, 2, \ldots, K \quad (16)$$

$$\eta_j [z_j(\omega^T y + \omega_0) - 1] = 0 \quad , j = 1, 2, \ldots, K \quad (17)$$

More formally, SVM will design a hyperplane in a higher dimensional space using the kernel trick which can be exploited for the classification purpose. But here, three classes of random number are present generated from different sources and no need of kernel function is there during this classification. Here, multiclass SVM is sufficient for the given set of pseudo random numbers generated from three different sources.

E. Multiclass SVM

Multiclass SVM aims to label the test datasets of random numbers by exploiting SVMs. In this, the main approach used is to convert the multiclass problem into binary problem which will be done multiple times.

There are some methods through which such conversion is possible. Such methods include: (i) one-versus-one (or Pairwise approach), (ii) one-against-all. In the Pairwise classification, every classifier is assigned with instance to one of the classes. Then, the votes are counted for the assigned class. Finally, the class with maximum number of votes is assigned the instance classification.

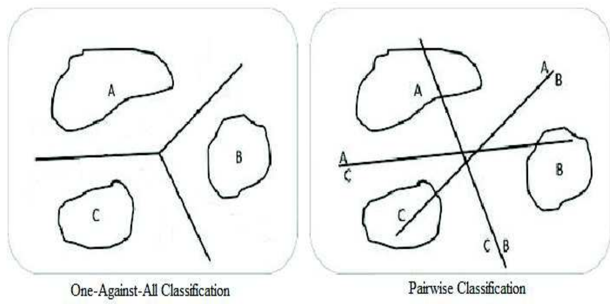

Fig. 3. Multiclass SVM

For this research work, one-versus-all approach is used. In this approach, Tested dataset is classified using an output function whose highest value defines the class to which that data is to be allocated.

III. EXPERIMENTAL VIEW

Here, multiple 1-dimensional data points to be categorised into three different classes. These different types of classes are the Pseudo Random numbers generated using three different types of PRNGs. Thus we have vectors. In addition to binary classification, we also scrutinize the use of multiclass classification for the problem at hand which we have used in this research. In one-against-all classification approach, there is a single binary SVM is exploited for each class so that members of that class can be separated from the members of other classes. We create sequences of Pseudo Random numbers and extract attributes pertaining to runs of various lengths which are then normalized and given as input to the SVM for training and cross validation. These three types of Pseudo Random numbers are first mixed and used as a single collection of all the numbers. A different set of sequences is generated by changing the bias of occurrence of particular outcomes and this set is tested on the trained classifier. And the algorithm for the same process is shown here as under:

Algorithm

Classification of Pseudo random numbers generated from three different types of sources using SVM Classifier.

Input: I: Input data, V: Support vectors

1. Assigning different class labels to each of the three set of pseudo random numbers, divide them into their

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classes for training.
2. Add these training datasets to the support vector set named as V.
3. Then make a loop for these divided set of random numbers.
4. If any random number does not belongs to any of the class labels, then add that random number to the set V.
5. Break, if inadequate random numbers are found.
6. end loop.
7. Trained exploiting the resulting classifier i.e. SVM model.
8. Test, with the unlabelled random numbers, so as to validate the results.

IV. RESULTS

Now, in the results of the research, matlab simulation is shown. Matlab simulation shows the results as the outcomes of classification of the Pseudo Random numbers using the SVM classifier. In the fig. 4 shown, three classes (Class 1, 2 and 3) of Pseudo Random numbers are classified using SVM classifier.

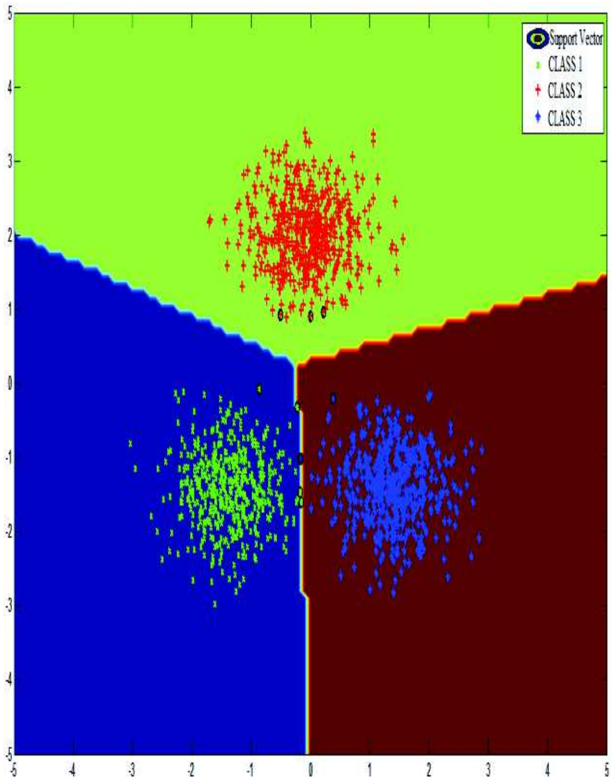

Fig. 4. Classification using SVM

As it was already shown in the fig. 1 that, firstly, three types of Pseudo Random nubmers generated using three different sources were mixed. Then these are very well classified by the SVM classifier using the algorithm that is already discussed in section III. Random numbers shown with green colour is class 1, red colour is class 2 and shown with blue colour is class 3. From the results, it can be seen that Pseudo Random numbers are very well separated using the SVM classifier. And it shows nearly 100% accuracy in classifying the Pseudo Random numbers.

V. CONCLUSION

This paper shows the successful classification of Pseudo Random numbers in their one-to-one classes using Support vector machine (SVM) classifier. We are able to get the optimum path to get the specific results which other classifiers were not able to deliver accurately and this accuracy can be further improved by using some more invariances as the features which can be used to classify these Pseudo Random numbers.

Our research can be helpful in the field of cryptanalysis. Cryptanalysis includes security in sending a message. Hence, this classification of Pseudo Random number's sources helps in enhancing that level of security in sending those messages. This enhancement in cryptanalysis surely booms the field of security.

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Classification of EMG Signals using SVM-kNN

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Abstract **–Electromyography (EMG) is a way to measure the electrical activity of the contraction of muscles and nerves.There are so many methods already developed, in the time and frequency domains, for EMG signals analysis. In this research, a method is proposed for the EMG signals analysis using their coiflet wavelet transform and with their features such as mean, energy and standard deviation. These features are then utilized on three different types of EMG signals like normal, myopathic and neuropathic signals to classify them. The method proposed can automatically classifies these signals into their respective classes. For this, various classifiers are used in this research but it is observed that SVM-kNN classifies the signals with highest accuracy in comparison to the other classifiers. SVM-kNN has come with 95% (approximately) accuracy which is also very compared to the other methods used earlier.**

Index terms **--- Electromyography, Wavelet transform, SVM, SVM-kNN.**

I. INTRODUCTION

Electromyography (EMG) is an analytic way to access the health of muscles and nerves. Motor neurons present in the body transmit electrical signals that cause muscles to contract. These changes in muscles contraction is recorded in the form of graph using EMG.

EMG signals classification is an important analysis and anorganisedstudy is required for their classification. For the same reason, number of computer-based quantitative

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EMG analysis algorithms have been developed.Among these algorithms, some of the already used feature extraction techniques includes Discrete wavelet transform (Daubechies-6) [1], AR modelling [2], autoregressive cepstral analysis [3], PSO [4], wavelet packet energy [5] etc. These methods were utilized by other researchers for the features extraction in the EMG signals that were used during their research. Then, these features are exploit in the classifiers to classify the signals used. Classifiers that are already exploitedincludes Fuzzy [5], Artificial neural networks (ANN) [6], Fuzzy-genetic [7], Neuro-fuzzy [8], Deep fuzzy neural network [1], SVM [9]etc. All these models give satisfactory and even good results. But, for better result performance in terms of accuracy,SVM-kNN is utilized here because SVM-kNN can also provide efficient results in the field of classification.

In this paper, a method is proposed for EMG signals classification. A brief overview of the proposed method is shown in the block diagram in Fig.1. As shown in the figure, three different types of EMG signals (Normal, Myopathy and Neuropathy) are taken. Detail coefficients of coiflet of order 5 of the EMG signals are computed. Then, for D4 coefficient, features like mean, energy and standard deviation are calculated. At last, using these calculated features, classifiers like SVM and SVM-kNN are exploited to classify the EMG signals and the best classifier from them is find out.

The organisation of different sections of the paper is as follows: Section 2 provides a brief overview of the proposed method in the form of a block diagram. Section 3 provides details about the dataset used, definitions and explanations of the methods used. Section 4 provides the process, explained using block diagram, of the proposed method. Section 5 contains the classification results followed by conclusion in Section 6.

II. BLOCK DIAGRAM

A brief outline of the work is shown in the block diagram in Figure. As shown in the figure, three different types of EMG signals (Normal, Myopathy and Neuropathy) are taken. Detail coefficients of coiflet of order 5 of the EMG signals are computed.

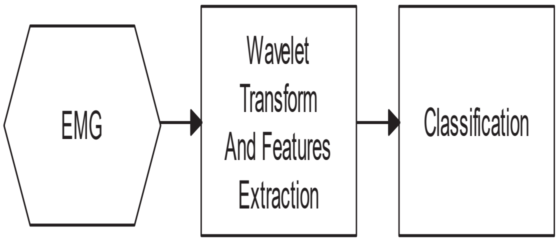

Fig.1.EMG Signals Classification

Then, for D4 coefficient, features like mean, energy and standard deviation are calculated. At last, using these calculated features, classifiers like SVM and SVM-kNN are exploited to classify the EMG signals and the best classifier from them is find out.

III. Proposed Method

A. Data Set Used

Data set of EMG signals is loaded from the MIT-BIH database.

From the data set, waveforms of three types of EMG signals are taken and shown in the Fig. 2. These waveforms represent the normal, myopathy and neuropathy signals.

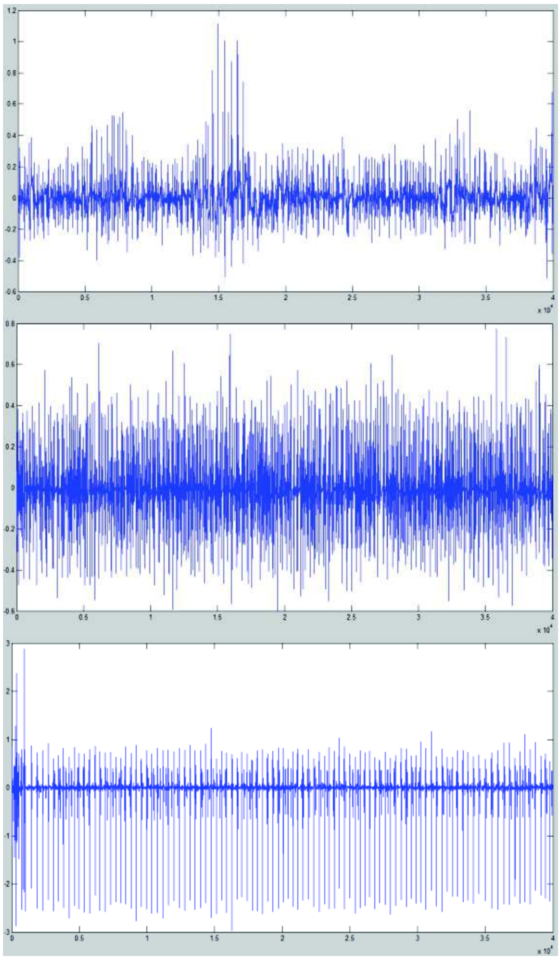

Fig.2. EMG Signals – Normal, Myopathy and Neuropathy

A description of the data set is shown in the Table I.

Table I
Description of dataset used

EMG Signals	Total
Normal	500
Myopathy	500
Neuropathy	500

B. WAVELET TRANSFORM

Wavelet transformis the representation of any signal in the time–frequency domain[10] simultaneously. It can provide time and frequency information at the same point of time, thus giving a time–frequency representation of the signal. It is an already known fact that the higher frequency elements are resolved, better, in time domain while the lower frequency components are resolved, better, in frequency domain. Hence, the wavelet transform can be defined as:

$$C(\alpha,\beta) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{\alpha}}\varphi\left(\frac{t-\beta}{\alpha}\right)dt \quad (1)$$

It can be seen from the above equation that the resultant signal obtained is a function of two variables, α and β. Here, φ is the transforming function called as the mother wavelet, α is the translation parameter and β is the scale parameter.

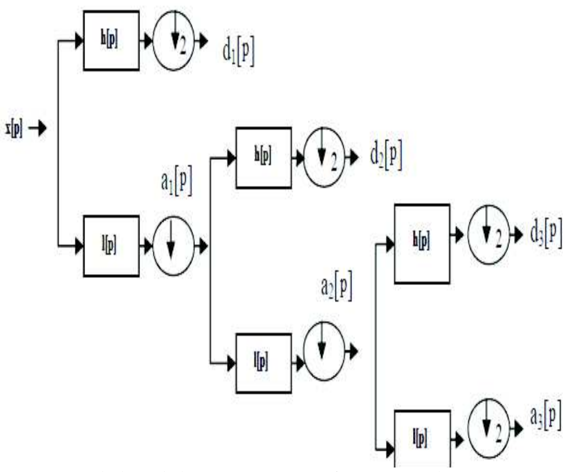

Fig. 3. Sub-band decomposition of DWT implementation; h[p] is the high pass filter, l[p] the low pass filter.

For this, the signal is passed through various high- and low-pass filters. This process is repeated for the either portion or both of the filter's output.

This process is known by the name decomposition. This constitutes one level of decomposition and can be expressed as:

$$y_{hi}(m)=\sum_{p} x(p).h(2m-p) \tag{2}$$

$$y_{lo}(m)=\sum_{p} x(p).l(2m-p) \tag{3}$$

Here, yhi[k] is the output from the high-pass filter and ylo[k] is the outputfrom the low-pass filter after sub-sampling by 2. It is shown in the Fig.3. Decomposition of any signal halves its time resolution, that is, only half the number of samples is required to describe the entire signal. However, this will also result in double the frequency resolution. The process shown in Fig.3 is known as the sub-band coding. This can be further repeated for more decomposition levels. In Fig.3 shows is the process of level decomposition. In the figure, x[n] represents the original signal that need to be decomposed.l[p] and h[p] are low- and high-pass filters, respectively. Thisdecomposition of the x[p] will give the detail and the approximation coefficients. The approximation coefficient may further be decomposed as the process is shown in Fig.4.For the EMG signal, these approximation and detail coefficients are calculated for the Coiflet 5 (coif5) wavelet transform.

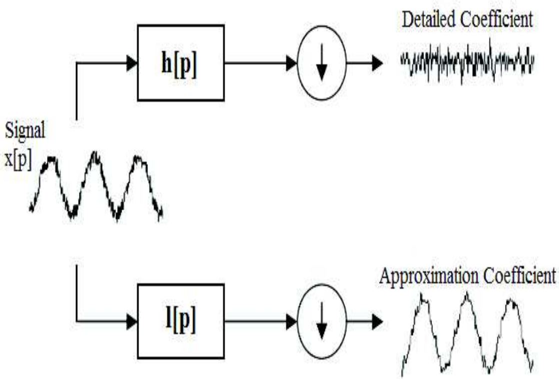

Fig. 4. EMG signal and its wavelet decomposition into Approximation and Detailed coefficients.

Wavelet coefficients extracted as detailed and approximation ones gives the representation of the distribution of EMG signal in time and frequency domain simultaneously.

Now, detail coefficients computed for the EMG signals are selected and the coefficient which highly resembles its original signal is taken out. Here, this coefficient is 4th one i.e. D4 coefficient. It is shown in the Fig. 5 that D4 coefficient resembles its original signal. Feature extraction of the EMG signals is now begins. Features that are going to be calculated for these signals D4 coefficient are mean, energy and standard deviation [11]. These are briefly described as follows:

(1) Mean of the absolute values of the coefficient 4 in each sub-band.

$$Mean=\frac{\sum_{w} z_w}{w} \tag{4}$$

(2) Energy of the wavelet coefficient 4 in each sub-band.Energy of the sub-signal xwk (t) is calculated by

$$Energy=\sum_{w}\sum_{j}\left|D_j^w\right|^2 \tag{5}$$

(3) Standard deviation of the coefficient 4 in each sub-band.

$$\text{Standard Deviation} = \sqrt{\frac{\sum_{w}(z_w - mean)^2}{w}} \tag{6}$$

The features extracted as mean, energy and standard deviation are now utilized to train and test on the classifiers which are going to be explained in the next sub-sections.

C. SVM

The Classifiers are now applied using the features computed in the previous sub-section that includes coiflet wavelet transform of the EMG signals and features like mean, energy and standard deviation for the D4 coefficient of the transform. These features are now utilized to train the SVM model and then test on the same trained SVM for the classification.

SVM (Support Vector Machine) is a classifier which requires training of the model for the testing of the samples and such technique in which training is given is called as supervised learning technique. In this, model is firstly trained to learn according to the features of the classes which need to be classified. Then that trained model is exploited in the classification process. Learning given to the classifier provides better results compared to the other classifiers in which unsupervised learning is used. This classifier is simple and easy to understand as it constructs a hyperplane between the different classes which need to be classified. The classifier used may be linear or non-linear. In linear SVM, training samples of the classes are linearly separable. But it is very difficult in practical situations that a straight line is sufficient to classify each and every sample. For such cases, non-linear classifier is exploited.

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In these, kernel functions may also be utilized to increase the dimensionality of the mapping. If the samples are not distinguishable in lower dimensional space, then kernel functions are used. In this, a non-linear operator maps the inputs to the classifier into a higher dimensional space so that samples can be classified easily.
If a linear function is given by the equation

$$g(z) = az + b \tag{7}$$

Then its dimensionality can be increased by using the equation as

$$g(z) = a.\phi(z) + b \tag{8}$$

In this, after plotting the samples in a space, a hyperplane is drawn according to the condition that margin between the support vectors and the hyperplane need to be maximized. It can be seen in [9].

However, classification skill of SVM is better as compared to the other methods, but, some complications still persists in its applications which includesclassifying accuracy as low in the complex applications. It is also difficultto choose the kernel function parameters. In an attempt to find solution for these problems, SVM is combined with k-nearest neighbour classifier (kNN). It will be seen in the results section that doing this is a good approach and better results are obtained using the SVM-kNN. This explained in the next sub-section.

D. SVM-kNN

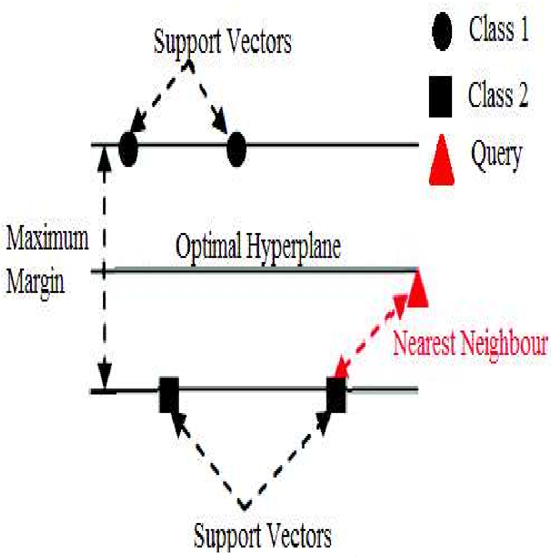

Fig.5. SVM-kNN Classification

SVM-kNN classifier is a hybrid of Support Vector Machine and k-Nearest Neighbour classifiers. In the previous section studied, SVM is a 1NN classifier [9]. That is, according to the nearest neighbour approach, SVM uses only a single representative point as support vectors for each class. But on combining the SVM with kNN, more than one points are chosen from the sample points i.e. say k-points are selected and accordingly, the class is decided for the tested sample.

It can be seen from the Fig.5 that this hybrid algorithm (SVM-KNN) considers more than one support vectors as the representative points of a class. This is much better than the SVM in which samples present nearest to the hyperplane represents the support vectors. In that, only one representative point is chosen for support vectors in each class and this representative point only represents the whole class which becomes quite complicated in the complex situations. In SVM-kNN, all support vectors are considered as representative points for the class and hence, maximum of information of a class is exploited in the classification process. In this classifier, radial basis kernel function is used with SVM to train the classifier. And, during the testing of the signals, nearest neighbour (that is, support vector) is computed as the query point using k-nearest neighbour algorithm. In the next section, the experimental point of view is shown.

IV. Experimental View

EMG Dataset: Data set of EMG signals is loaded from the MIT-BIH database. It is described in the table shown in Table II.

Table II
Description of dataset used

EMG Signals	Training	Testing	Total
Normal	350	150	500
Myopathy	350	150	500
Neuropathy	350	150	500

Computing the wavelet transform and their features: Discrete wavelet transform (DWT) of the EMG signals are computed using the coiflet wavelet transform of the order of 5. Then, Features such as Energy, Mean and Standard Deviation for the D4 coefficient are computed for each and every sample of dataset of the different types of EMG signals used during the research. These calculated features in the form of mean, energy and standard deviation serve as an input to train and test the various classifiers.

Classification: During the classification, computed features of the EMG signals in the second stage are

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exploited by the classifiers like SVM and SVM-kNN to determine the corresponding class of the samples. This feature set consists of mean, energy and standard deviation of the D4 coefficient of the

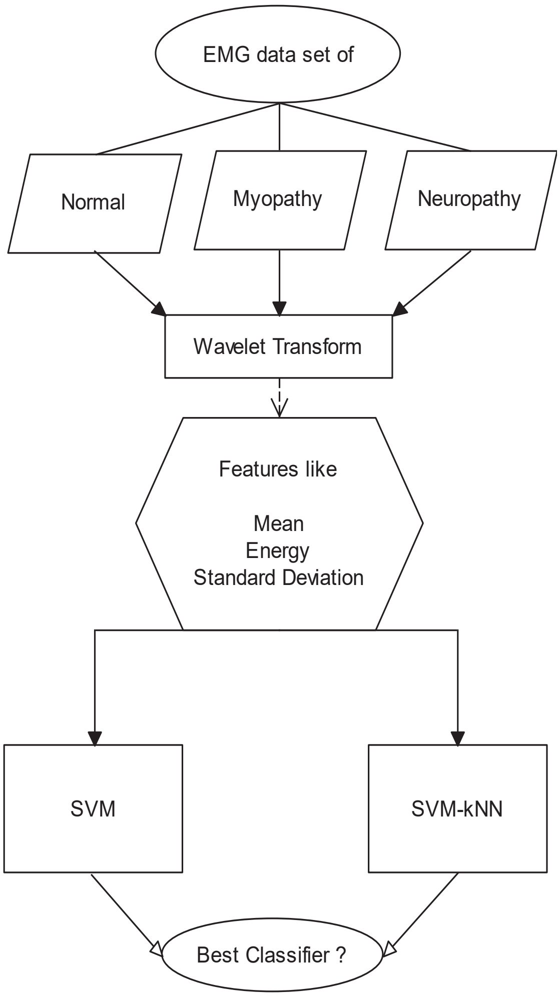

Fig.6. Block Diagram of EMG Signals Classification

coiflet wavelet transform that should efficiently characterize the variations in the input signals for accurate detection and classification of the EMG signals. The calculated features will be applied to the classifiers like SVM and SVM-kNN classifiers as training and testing data to classify the EMG signals in their corresponding classes.

V. Results

In this study, SVM and SVM-kNN classifiers are utilized for the classification of three different types of EMG signals (Normal, Myopathy and Neuropathy). As the features required to train the classifiers, D4 coefficient of the coiflet wavelettransform is used. Then, as the features, mean, energy and standard deviation is used.

Now, data set utilized for this research is shown in the Table I. For this data of the EMG signals, firstly, wavelet transform is applied. In the wavelet transform, coiflet family of order 5 is used. The results for each type of data set used is shown in the figures 7, 8 and 9.

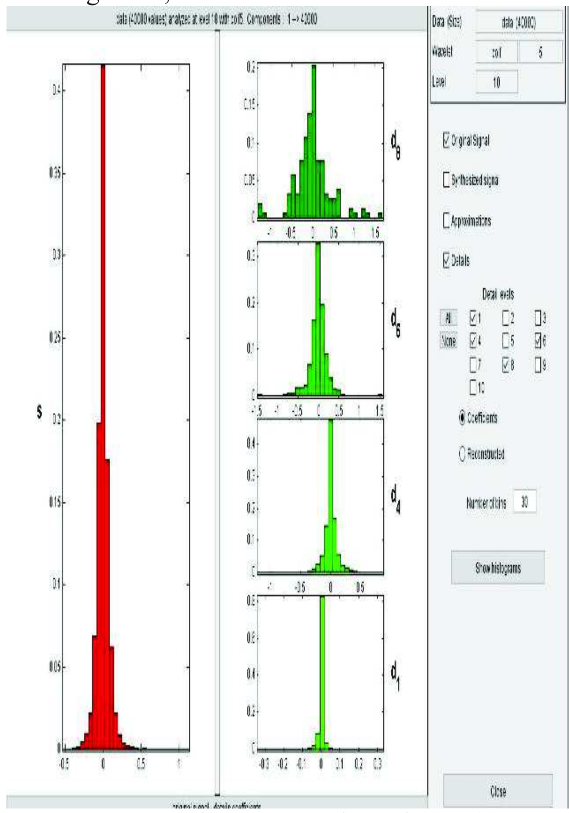

Fig.7. Histogram of wavelet transform of normal person EMG

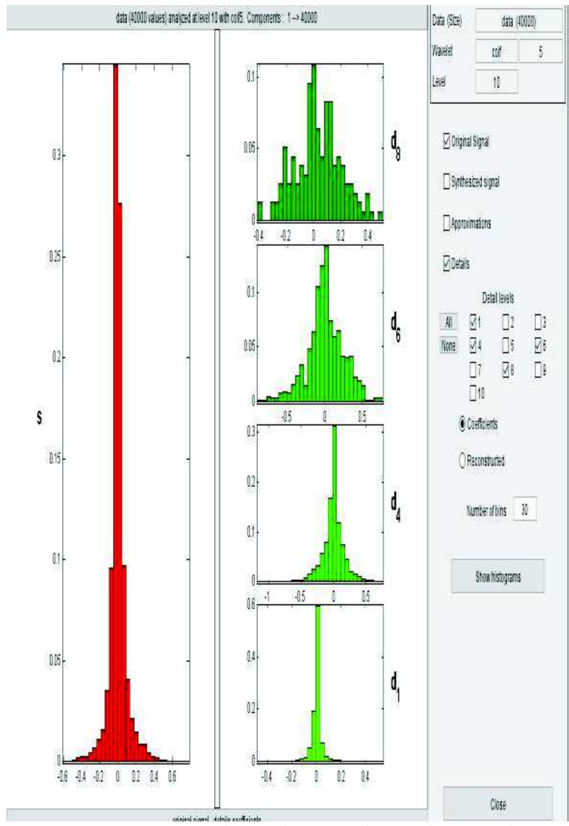

Fig.8. Histogram of wavelet transform of myopathy person EMG

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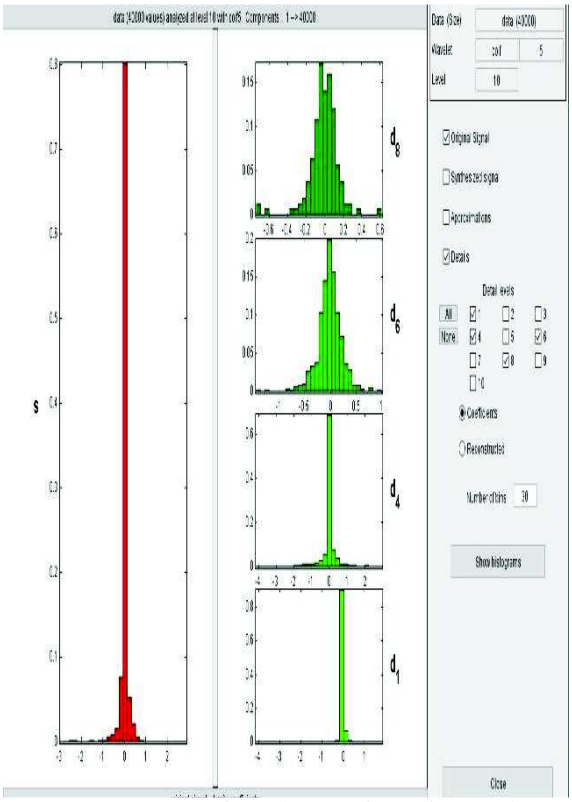

Fig.9. Histogram of wavelet transform of myopathy person EMG

These figures shows the EMG signals wavelet transform in the form of histograms. And it can be observed from the figures that histogram of D4 coefficient maximally resembles the original signals histogram. This implies that maximum information lies in that coefficient and hence, for further analysis, D4 coefficient is sufficient to give the maximum features alone. Therefore, mean, energy and standard deviation is computed for D4 coefficient only. Sample values for these features are shown in the Table III.

Table III. Sample values of features for EMG signals

EMG Signal	Mean	Energy	Standard Deviation
Normal	7.43	56.58	1.173
Myopathy	5.26	28.46	0.890
Neuropathy	9.48	85.34	1.212

In the Table III shown is the sample values for the features computed for the D4 coefficients of the coiflet of order 5. These features include mean, energy and standard deviation values of the signal. These features are calculated for each and every sample of data set of the three types of EMG signals used.

Now, from these features computed, features of 350 samples from each class are selected and used to train the SVM. After that, remaining 450 samples (Normal-150, Myopathy-150 and Neuropathy-150) are tested on the same trained SVM. Its classification results are in the Table IV in the form of a confusion matrix.

Table IV. SVM Classification

Targets→ Outputs↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	141/150	3/150	6/150	94%
Myopathy	11/150	134/150	5/150	89.33%
Neuropathy	7/150	4/150	139/150	92.67%

The confusion matrix shown in the Table IV shows a good result in terms of classifying the EMG signals into their respective classes. SVM gives 92% of accuracy in classifying these signals. This is quite good but SVM-kNN is utilized further to increase this percent of accuracy in classification of EMG signals.

Next, SVM-kNN classifier is used for the EMG signals classification. In this also, features of 1050 samples (Normal-350, Myopathy-350 and Neuropathy-350) are utilized to train the SVM-kNN. Then, the remaining samples are used to test on the same trained SVM-kNN.

Table V. SVM-kNN Classification

Targets→ Outputs↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	147/150	2/150	1/150	98%
Myopathy	8/150	137/150	5/150	91.33 %
Neuropathy	3/150	5/150	142/150	94.67 %

And, it can can be clearly seen from the Table V that increase in the accuracy of classification is observed. Table V shows the confusion matrix of SVM-kNN classification and from this classifier an accuracy of approximately 95% is observed.

VI. Conclusion

In the research, a method is presented for the classification of three different types of EMG signals (i.e. Normal, Myopathy and Neuropathy) using the classifier SVM-kNN. This method is based on the extraction of features like mean, energy and standard deviation for the coiflet family of wavelet transform of the order of 5. Results achieved from the classification show that the proposed method can beconsidered as an alternative approach, compared to the other methods, for extracting relevant features and classification for EMG signals.

This method exploits only three features of the EMG signals compared to other existing methods. And, hence, this also allows an efficient classification results with 95% accuracy with only a small number of features.Therefore, now,it can be concluded that,with some more efforts in achieving more accuracy in classification, the expensive tests of diagnosing the EMG can be replaced by this automatic techniques of classifying EMG signals.

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Dezert- Smarandache Theory based Classification of EMG Signals

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Abstract: This research paper proposes an intellectual method for the classification of different types of Electromyography (EMG) signals like normal, myopathy and neuropathy signals. Inside the human body, contraction of muscles and nerves occur at every second. And, EMG is a techniqueused to measure this electrical activity. For the analysis of EMG signals, so many methods have been already used.With this research, a new method is proposed in which Dezert-Smarandache Theory (DSmT) based classification technique is utilizedfor the EMG signals analysis. In this, discrete wavelet transform with some features likeenergy, mean and standard deviation are exploited for the features extraction of the EMG signals. After that, classifiers are used in the analysis for the modelling purpose. Then, using these classifiers, DSmT based technique helps in improving the accuracy of the results.It can be seen in the results that DSmT based classification gives the best accuracy (approximately 97%) in comparison to the other classifiers used during this research.

Keyword: DSmT, Electromyography, Wavelet Transform, SVM, SVM-kNN.

I. INTRODUCTION

For the analysis of Electromyography (EMG), it should be a well-known fact that muscles and nerves exists in the human body and contraction of these two may cause pain in the body. EMG is utilized to record these changes in the form of a graph occurred due to contraction of musclesEarly diagnosis is required for dealingwith such diseases. Classification of EMG signals is a vitalexploration. Asystematizedstudy on their classification is required for the proper analysis of the diseases.Hence, a number of methods, most ofthem were computer based, have been proposed. Amongst these EMG analysis algorithms, features of the EMG were extracted using the techniques like Discrete wavelet transform (Daubechies-6) [2], AR modelling [3], autoregressive cepstral analysis [4], PSO [5], wavelet packet energy [6] etc. With these feature extraction techniques, training of different classifiers are done for their modeling.

Classifiers already utilized in the classification of EMG signals are as follows: Fuzzy [6], Artificial neural networks (ANN) [7], Fuzzy-genetic [8], Neuro-fuzzy [9], Deep fuzzy neural network [2], SVM [10], SVM-kNN [1]etc. Using these methods of features extraction and classifiers for classification, good results were obtained in the EMG classification. Nevertheless, performance of these results can be enhanced using a technique called as Dezert-Smarandache Theory (DSmT) [14] for the much better accuracy in terms of results.

In the research paper, a new method for the classification of EMG signals is proposed. The brief outline for the method is represented in the block diagram in Fig.1. From the block diagram, it is seen that firstly, EMG signals are taken as the dataset. Then wavelet transform for these signals are computed as Detail coefficients. For the D_4 coefficient only, features like energy, mean and standard deviation are found out. Later, classification of these signals is performed based on the calculated feature values.

This research paper is organized in different sections which are as follows: Section II gives an overview for the method proposed as a block diagram. Section III gives a detailedview of the dataset used and explanations for the methods and classifiers used. Section IV provides the idea about the overall simulation technique explained using the block diagram for the proposed method. Section Vcomprisesof the classification results trailed by conclusion in Section VI.

II. BLOCK DIAGRAM

The brief outline for the method is represented in the block diagram in Fig.1.In this, anovelmethod is proposed for the classification of EMG signals.

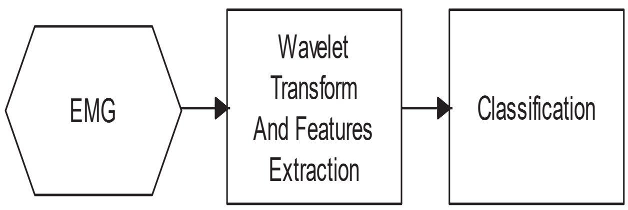

FIG.1.EMG SIGNALS CLASSIFICATION

From the block diagram, it is seen that firstly, EMG signals are taken as the dataset. Then wavelet transform for these signals are computed as Detail coefficients. For the D_4 coefficient only, features like energy, mean and standard deviation are found out. Later, classification of these signals is performed based on the calculated feature values.

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III. PROPOSED METHOD

A. Data Set Used

MIT-BIH database is used to load the Data set of EMG signals. A description of the data set is shown in the Table I.

TABLE I
DESCRIPTION OF DATASET USED

EMG Signals	Total
Normal	500
Myopathy	500
Neuropathy	500

From the sample of dataset used, waveforms of three types of EMG signals are taken and shown in the Fig. 2. These waveforms represent the normal, myopathy and neuropathy signals.

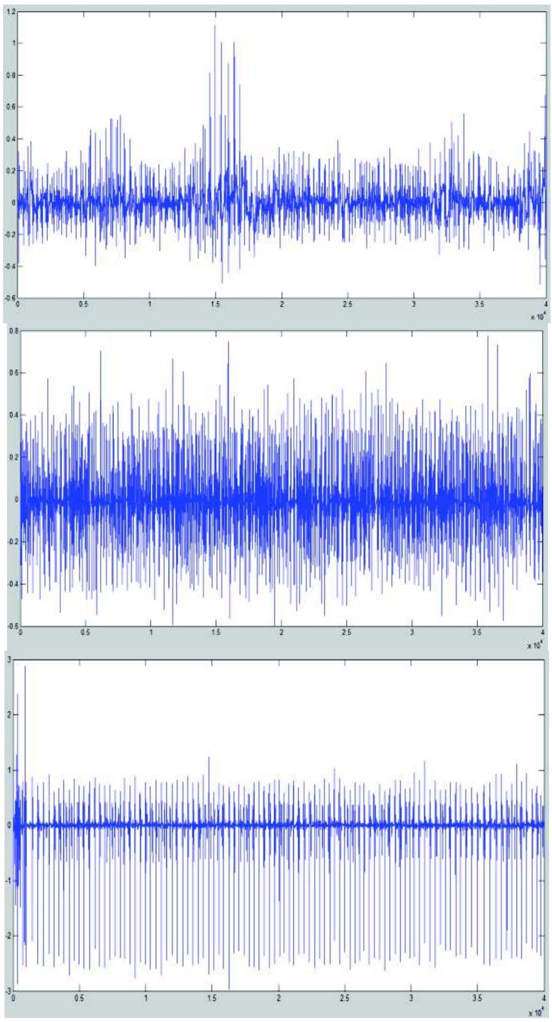

FIG.2. EMG SIGNALS – NORMAL, MYOPATHY AND NEUROPATHY

B. Wavelet Transform

Wavelet transformis the simultaneous representation of the signal in real-time and frequency domain[10]. Hence, it cangive time and frequency information of the signal at the same point of time. Hence, the wavelet transform can be defined as:

$$T(m,n) = \int_{-\infty}^{\infty} x(\tau) \frac{1}{\sqrt{m}} \psi\left(\frac{\tau - n}{m}\right) d\tau \quad (1)$$

Here, ψ representsthe transforming function known as the mother wavelet function. It can be observed from the equation that the transformation is a function of the variables, m and n, wherem is the translation parameter and n is the scale parameter.

For such transformation, signal is distributed from various high-pass h[p] and low-pass l[p] filters. For the proper decomposition of the signal, process is made repetitive for the either h[p] output or l[p] output or for both of the outputs.Such decomposition's first level establishes one level of decomposition and it can be given as:

$$y_{hi}(r) = \sum_{p} x(p).h(2r - p) \quad (2)$$

$$y_{lo}(r) = \sum_{p} x(p).l(2r - p) \quad (3)$$

Here,$y_{hi}[r]$ is the output from the high-pass filter and $y_{lo}[r]$ is the outputfrom the low-pass filter after sub-sampling by 2. It is shown in the Fig.3.

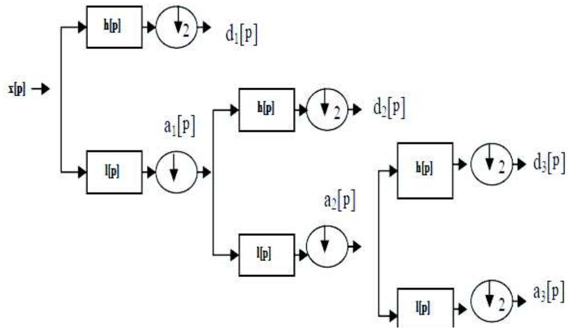

FIG. 3. SUB-BAND DECOMPOSITION OF DWT IMPLEMENTATION;
H[P] IS THE HIGH PASS FILTER, l[P] THE LOW PASS FILTER.

In the Fig.3 shown is the Sub-band decomposition of DWT in which x[p] is the original signal that needs to be decomposed,l[p] and h[p] are low-pass and high-pass filters, respectively. Thisdecomposition of the x[p] will results in the detail and the approximation coefficients. The approximationor the detail coefficients may further be decomposedby sub-level of decomposition as shown in the process Fig.4.

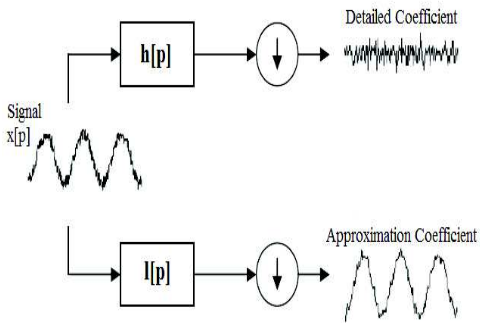

FIG. 4. EMG SIGNAL AND ITS WAVELET DECOMPOSITION INTO APPROXIMATION AND DETAILED COEFFICIENTS.

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For the EMG signal, Coiflet 5 (coif5) wavelet transform is utilized to compute the approximation and detail coefficients.These wavelet coefficients computed gives the EMG signal's representation in time and frequency domain simultaneously.
Now, from the computed detail coefficients of the EMG signals, the coefficient which highly in resemblance with its original signal is selected. From the results, it will be shown that this coefficient is the D_4 coefficient. And in the Fig. 5, it can be observed that D_4 coefficient resembles its original signal.

C. Features Extraction

Now, features are extractedfor the EMG signals. As from the wavelet transform of the EMG signal, D_4 coefficient is already computed and it contains the maximum information of the original signal. Hence, D_4 coefficient is utilized to extract the features for the EMG signals and that areenergy, mean and standard deviation [13]. These feature are briefly discussed:

(a) Mean of the absolute values of the D_4 coefficient in each sub-band.

$$Mean = \frac{\sum_q y_q}{q} = \mu \qquad (4)$$

(b) Energy of the wavelet coefficient 4 in each sub-band.Energy of the sub-signal y_{qv} (τ) is calculated by

$$Energy = \sum_q \sum_k \left| D_k^q \right|^2 \qquad (5)$$

(c) Standard deviation of the D_4 coefficient in each sub-band of the signal.

$$\text{Standard\_Deviation} = \sqrt{\frac{\sum_q (y_q - \mu)^2}{q}} \qquad (6)$$

The features extracted as energy,mean and standard deviation are now exploited to train and test on the classifiers.

D. SVM

Now, the Classifiers are used which are trained using the computed features.In the previous sub-section that coiflet wavelet transform's D_4 coefficient of the EMG signals and features like energy,mean and standard deviation were collected. Here, the SVM model is trained using these features and then the same trained model is utilized to test for the classification of the EMG signals. Support Vector Machine is a classifier in which supervised learning technique is used whichincludes training is provided to the model and then samples are tested on that model. This technique providesmuch efficient results compared to theunsupervised learning based classifiers. This classifier is modest and informal to recognize. This is because it builds a hyperplane between the different classes which need to be classified using the classifier.In this, after plotting the samples in a space, a hyperplane is drawn according to the condition that margin between the support vectors and the hyperplane need to be maximized. It can be seen in [10].For this,the classifier used may be linear or non-linear. Samples which are able to classify only using a straight line are the linearly separable or linear SVM. But in practical situations, it is very difficult for a straight line hyperplaneto classify each and every sample. For such cases, non-linear classifier is used.In this, a non-linear operator maps the inputs to the classifier into a higher dimensional space so that samples can be classified easily.
If a linear function is given by the equation

$$h(y) = cy + d \qquad (7)$$

Then its dimensionality can be increased by using the equation as

$$h(y) = c.\psi(y) + d \qquad (8)$$

In (8), kernel functionis used to raise the dimensionality of the mapping. If the samples are not distinguishable in lower dimensional space, then kernel functions are used.
Though, the classification using SVM faces some complications in the complex applications which lowers its classification accuracy. It is also difficultto choose the kernel function parameters. So, for better classification results, SVM-kNN is used.

E. SVM-KNN

SVM-kNN is a hybrid classifier. It is the hybrid of Support Vector Machine and k-Nearest Neighbour classifiers. In the previous section studies, it was observed that SVM is a 1NN classifier [10] because SVM utilizes only a single representative point for each classaccording to the nearest neighbour approach. Nevertheless in the combination of the SVM andkNN, more than one vector points are preferred from the sample points. Say k-points are chosen and hence, the class is decided for the tested samples.

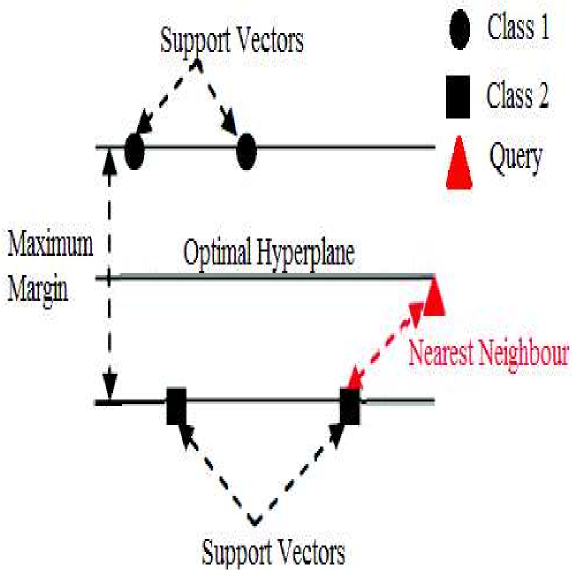

FIG.5. SVM-KNN CLASSIFICATION

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In the Fig.5 it can be observed that this hybrid algorithm of SVM-KNNconsiders more than one support vectors as the representative vector points for a class. This is a much better classifier than the SVM as in that only sample pointthat is present nearest to the hyperplane represents the support vector. In SVM-kNN, all support vectors are considered as representative vector points for the class and hence, maximum of information of a class is utilized in the classification process.During thismodel approach of the signals, nearest neighbour (that is, support vector) is computed as the query point using k-nearest neighbour algorithm. In the next sub-section, DSmT is explained.

F. DSMT

For the classification purpose, more than two classes classification problem is formulated as a m-class problem in which classes are associated to pattern classes such as ψ_0, ψ_2,ψ_3........., ψ_m.In this, parallel combination of two classifiers, which will be treated as the information sources, are formulated through Dezert-Smarandache Theory (DSmT) using the PCR6 combination rule.

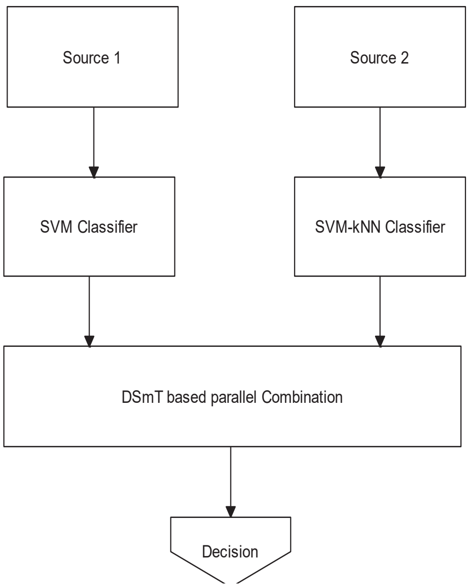

FIG.6. STRUCTURE OF THE COMBINATION SCHEME USING DSMT

DSMT is a fusion process of which allows to combine independent sources of information which are formulated as the belief functions. It is able to solve complex and multi-class problems with efficient results.

IV. EXPERIMENTAL VIEW

EMG Dataset:MIT-BIH Database is loaded as the Data set of EMG signals. It is shown in the tableshown in Table II.

TABLE II
DESCRIPTION OF DATASET USED

EMG Signals	Training	Testing	Total
Normal	350	150	500
Myopathy	350	150	500
Neuropathy	350	150	500

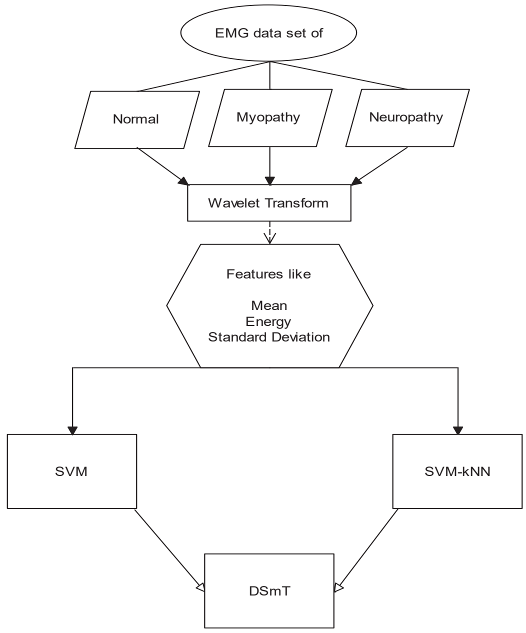

FIG.7. BLOCK DIAGRAM OF EMG SIGNALS CLASSIFICATION

Computing the wavelet transform and their features:Discrete wavelet transform (DWT) of the EMG signals are computed using the coiflet wavelet transform of the order of 5. Then, Features such as Energy, Mean and Standard Deviation for the D_4 coefficient are computed for each and every sample of data set of the different types of EMG signals used during the research. These calculated features in the form of energy, mean and standard deviation serve as an input to train and test the various classifiers.

Classification: During the classification, computed features of the EMG signals in the second stage are exploited by the classifiers like SVM, SVM-kNNand DSmTto determine the corresponding class of the samples. This feature set consists of mean, energy and standard deviation of the D_4 coefficient of the coiflet wavelet transform that should efficiently characterize the variations in the input signals for accurate detection and classification of the EMG signals. The calculated features will be applied to the classifiers like SVM, SVM-kNN and DSmT classifiers as training and testing data to classify the EMG signals in their corresponding classes.

V. RESULTS

In this study, SVM, SVM-kNNand DSmTclassifiers are used for the classification of the different types of EMG (Normal, Myopathy and Neuropathy)signals. As the features required to train the classifiers, D4 coefficient of the coiflet wavelettransform is used. Then, as the features, energy, mean and standard deviation is used.

Now, data set utilized for this research is shown in the Table II. Firstly, onthis data set of the EMG signals, wavelet transform is applied. Coiflet family of order 5 is used in the wavelet transform. The results for the wavelet transform of each type of data set used is represented in the figures 8, 9 and 10.

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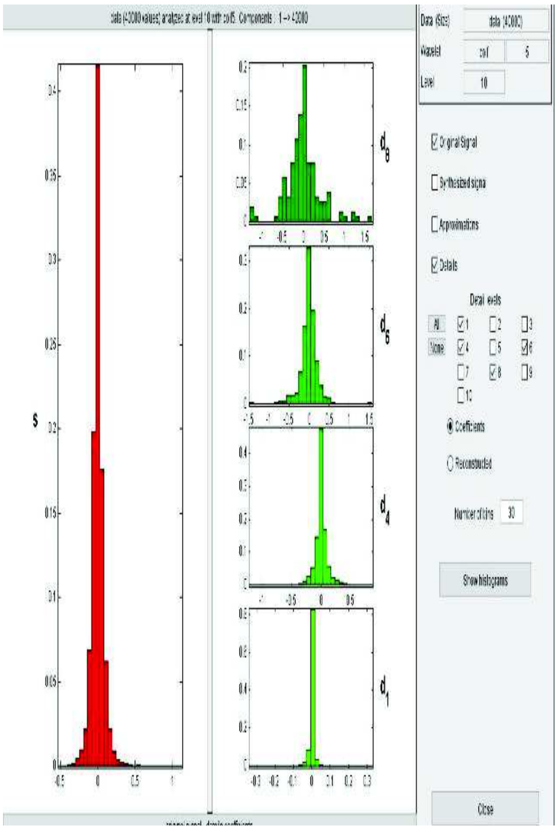

FIG.8. HISTOGRAM OF WAVELET TRANSFORM OF NORMAL PERSON EMG

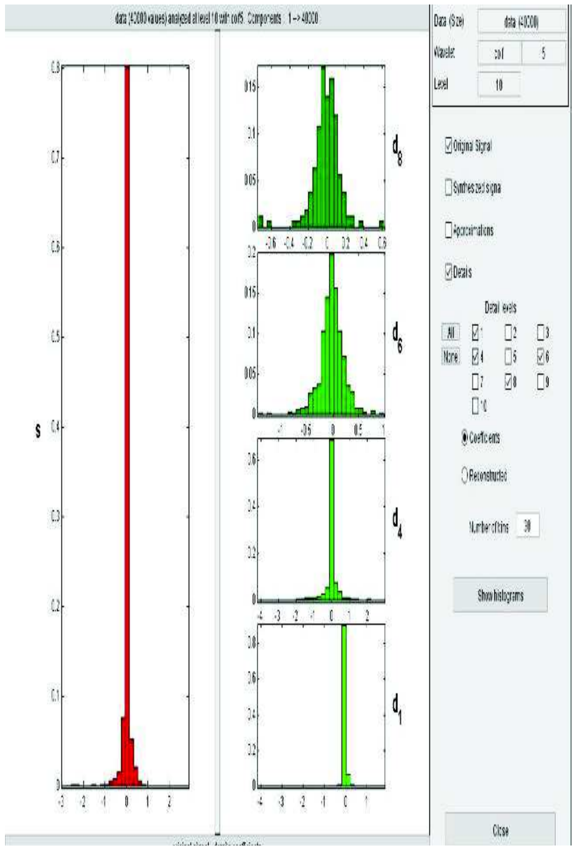

FIG 10. HISTOGRAM OF WAVELET TRANSFORM OF MYOPATHY PERSON EMG

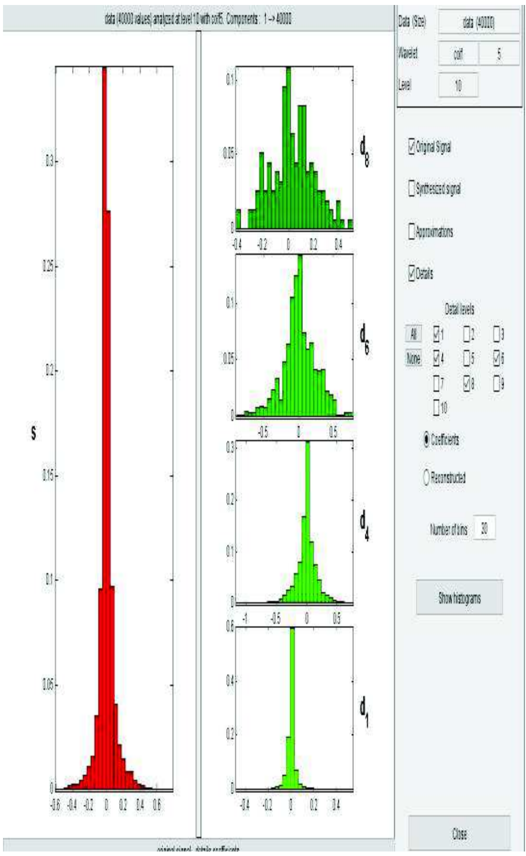

FIG.9. HISTOGRAM OF WAVELET TRANSFORM OF MYOPATHY PERSON EMG

In these figures, wavelet transformof the EMG signals is represented in the form of histograms. And it can be seen from the figures that histogram of D_4 coefficient greatly resembles its original signal's histogram. This implies D4 coefficient is sufficient to give the maximum features alone. Therefore, energy, mean and standard deviation is computed for D_4 coefficient only. Sample values for these features are shown in the Table III.

TABLE III
SAMPLE VALUES OF FEATURES FOR EMG SIGNALS

EMG Signal	Mean	Energy	Standard Deviation
Normal	6.85	46.55	2.173
Myopathy	4.97	24.49	0.574
Neuropathy	8.85	75.35	5.546

Table III shows the sample values for the EMG signals as the features computed (like energy, mean and standard deviation) for the D_4 coefficients of the coiflet of order 5. These features are computed for each and every sample of data set for the thre types of EMG signals exploited.
Hence, from these EMG features computed, features of 1050 samples (Normal-350, Myopathy-350 and Neuropathy-350)are chosenfrom each class and utilized to train the SVM. After that, remaining 450 samples (Normal-150, Myopathy-150 and Neuropathy-150) are tested on the same trained SVM. Its classification results are shown in the Table IV in the form of a confusion matrix.

TABLE IV
CONFUSION MATRIX OF SVM CLASSIFICATION

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	141/150	3/150	6/150	94%
Myopathy	11/150	134/150	5/150	89.33%
Neuropathy	7/150	4/150	139/150	92.67%

The confusion matrix shown in the Table IV shows a good result in terms of classifying the EMG signals into their respective classes. SVM gives 92% of accuracy in classifying these signals. This is quite good but SVM-kNNis utilized further to increase this percent of accuracy in classification of EMG signals.

Next, SVM-kNN classifier is used for the EMG signals classification. In this also, features of 1050 samples (Normal-350, Myopathy-350 and Neuropathy-350) are utilized to train the SVM-kNN. Then, the remaining samples are used to test on the same trained SVM-kNN.

TABLE V
CONFUSION MATRIX OF SVM-KNN CLASSIFICATION

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	147/150	2/150	1/150	98%
Myopathy	8/150	137/150	5/150	91.33%
Neuropathy	3/150	5/150	142/150	94.67%

And, this can be observed from the Table V that increase in the accuracy of classification is observed. Table V shows the confusion matrix of SVM-kNN classification and from this classifier an accuracy of approximately 95% is observed.

However, these results are improved using a technique known as DSmT technique. This technique utilizes features of both the classifiers used i.e. SVM and SVM-kNN. And, raise the accuracy of classifying the EMG signals.

TABLE VI
CONFUSION MATRIX OF DSMT BASED CLASSIFICATION

Targets → / Outputs ↓	Normal	Myopathy	Neuropathy	Accuracy
Normal	148/150	2/150	0/150	98.67%
Myopathy	3/150	144/150	4/150	96%
Neuropathy	2/150	3/150	146/150	97.33%

Here also, it can be clearly seen in the confusion matrix shown in the Table VI that an accuracy of 97.33% is reached using the DSmT in this classification compared to the other classifiers results.

VI. CONCLUSION

It can be conclude from the research that themethodpresented is a novel and very efficient method for the classification of the three different types of EMG signals (i.e. Normal, Myopathy and Neuropathy) using theDSmT based classifier.In this method, the extraction of features like energy, mean and standard deviation is done for the coiflet family of wavelet transform of the order of 5 for the EMG signals. Results achieved from the classification showsan alternative approach, which when compared to the other methods, for extracting relevant features and classification for EMG signals shows results with higher accuracy.

Classification results with accuracy of 97.33% with only a small number of features is only possible because of the use of DSmT based technique.Therefore, now,it can be concluded thatthe costly tests of diagnosing the EMG diseasescan beswitched by this automatic technique of classifying EMG signals.

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