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Time Frequency Feature Extraction Scheme based on MUAP for classification of Neuromuscular Disorders using EMG signals.

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Abstract—The features of motor unit action potentials(MUAPs) are extracted from electromyographic (EMG) signals which provide information for diagnosis of neuromuscular disorders. Neuromuscular Disorders are classified into two categories Myopathic and Amyotrophic Lateral Sclerosis(ALS). ALS is a progressive neurodegenerative disease that affects nerve cells in the brain and the spinal cord. The progressive degeneration of the motor neurons in ALS eventually leads to their demise. When the motor neurons die, the ability of the brain to initiate and control muscle movement is lost hence the EMG signals of the patient of this disease are characterized by signals that have a increased value of amplitude , thereby increasing the peak to peak value of the signal. On the other hand Myopathies are a group of disorders characterized by a primary structural or functional impairment of skeletal muscle. They usually affect muscle without involving the nervous system, resulting in muscular weakness hence the EMG signals of the patients of this group of disorder are characterized by signals of shorter duration and smaller amplitude.

The aim of this study, is to design a automated system which can classify the signals as ALS , Myopathic and Normal.The proposed scheme employs extracting both time and time–frequency features of a MUAP and then providing it to classifier which can classify the signals as ALS, myopathic and normal.In the proposed system, three classifiers are implemented and their results are evaluated out of which Random Forest classification technique provides the highest accuracy of 97.85%.

Keywords- *MUAP's ,EMG ; Feature Extraction;Neuromuscular Disorders , SVM, ANN, Random Forest;*

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I. INTRODUCTION

Electromyographic (EMG) signals demonstrate the electrical activity of muscles during voluntary contraction. Each muscle consists of many muscle fibers which are organized into groups for the control of muscle force with each muscle fiber of a group being connected to a motor neuron. Each muscle fiber of a group is activated concurrently by the motor neuron to which they are connected. Each muscle consists of small muscle fibers which are controlled by different α-motoneurons via the connected axons motor neuron, its axon and the set of connected muscle fibers are called a motor unit (MU) [1]. The summation of the muscle fiber potentials created by the spatially and temporally disperse depolarization and repolarization of all of the excited fibers of a single MU is known as motor unit action potential (MAUP). During a muscle contraction, several MUs may be activated each of which fire repetitively to maintain the force of the muscle contraction. Therefore, each activated MU generated a train of MUAP known motor unit action potential train (MUAPT). EMG signal acquired from a contracted muscle is the summation of MUAPTs and background noise [1]. The smallest functional unit to describe the neural control of the muscular contraction process is called a Motor Unit**.** It is defined as "the cell body and dendrites of a motor neuron, the multiple branches of its axon, and the muscle fibers that innervates it. The term *units* outlines the behavior, that all muscle fibers of a given motor unit act **"**as one**"** within the innervation process.

Neuromuscular diseases change the morphology and physiology of motor units (MUs) of a muscle. Two main groups of neuromuscular disorders are myopathic and neuropathic. The former disorder is caused by the death or atrophy of motor fibers and the latter is caused by the death or damage of motor neurons. As the results of these changes, the shape and characteristics of the motor unit action potentials (MUAPs) and firing patterns of the MUs are affected. MUAPs detected from myopathic patients are characterized by high frequency contents, low peak-to-peak amplitude, and short duration that consequently are smaller and more complex than the normal MUAPs. In contrast, the extracted MUAPs from neuropathic patients are poly-phasic, have high peak-to-peak amplitude, long duration, and consequently are larger and more complex than the MUAPs of normal ones. Therefore, analyzing the MUAPs created by the MUs of a muscle can

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help clinicians to infer the degree and type of disorder that may have affected the muscle.

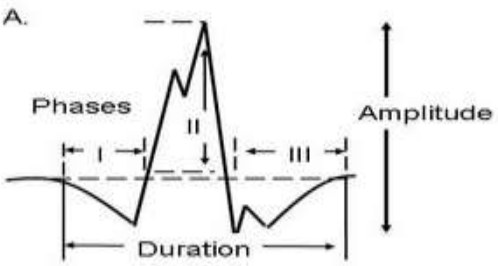

Fig.1(a)Characteristics for Healthy Muscles

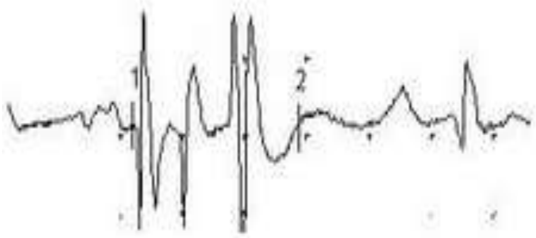

Fig.1(b) Characteristics for Myopathy

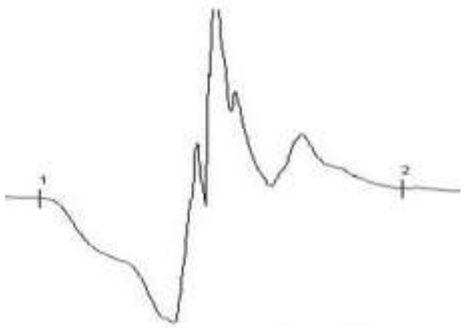

Fig.1(c) Characteristics for ALS

EMG can be detected using either needle electrodes or surface electrodes each of which has its own advantages, disadvantages and usages. Surface electrodes record the summation of activities from many motor units and even thenactivity of adjacent muscles.On the other hand, needle electrodes permit recording of individual motor unit potentials and provide much information about deep muscles. For diagnostic applications it is desired to get detailed temporal and spatial information about the muscle fibers of a MU; therefore EMG signals detected directly from the muscles by needle electrodes are used for clinical use [2].

MUAPs detected from neuropathic patients are polyphasic (number of baseline crossings are increased), have long peak to peak amplitude, long duration and consequently are larger and more complex than normal cases. Consequently, analyzing MUAPs created by the MUs of a contracting muscle can assist with identifying its state of health [3]. In traditional clinical practice, neurologists assess individual MUAPs visually and auditory to diagnose disorders. In visually assessment of MUAPs, neurologists analyze isolated MUAP morphology and MU firing patterns. These features demonstrate MUAP shape and MU firing patterns which are representative for the underlying diseases. In auditory assessment neurologists investigate frequency and amplitude of the clicks and crackles made by amplified EMG signals. In general, both visual and auditory assessments of MUAP are performed simultaneously and the one with better discriminative information is considered as a reference for decision. MU firing pattern are considered as a supplementary source of information. Although such a qualitative analysis can assist with diagnosing neuromuscular disorders, there are several limitations with these techniques [4].

II. METHODOLOGY

The block diagram is shown in the figure below.

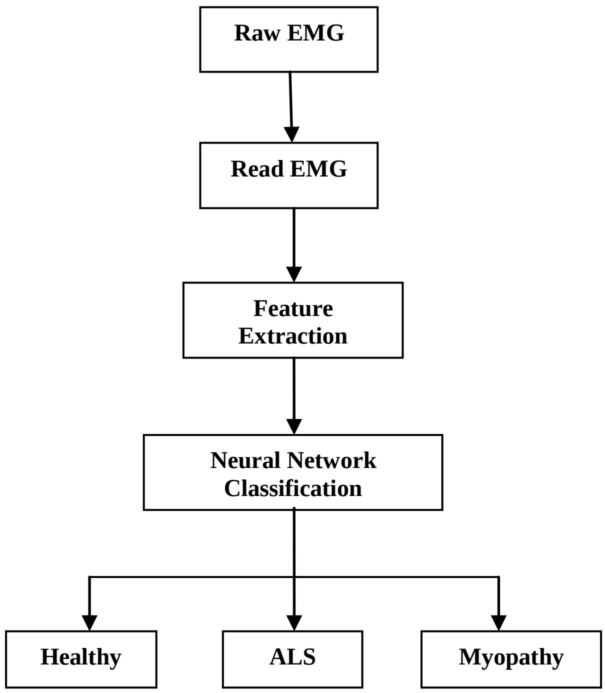

Fig.2. block diagram

The first step is data acquisition. It involves recording and reading of the emg signals. The input signal is processed and features are extracted. six features were extracted i.e. root mean square, mean, standard deviation, variance, maximum and minimum values of the given EMG signals. The feature vector is then given to the classifier.In this system, we have evaluated accuracies of three classifiers namely Random Forest,Artificial Neural Network(ANN),Support Vector Machine(SVM)

III. DATA ACQUISITION

[1] The following data was taken for the proposed system. Healthy:10 normal subjects aged 21-37 years, 4 females and 6 males. None in this group had any history of neuromuscular

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disorders.ALS: 8 patients;4 females and 4 males aged 35-67 years MYOPATHY: 7 patients; 2 females and 5 males aged 19-63 years. The EMG tests were conducted using different muscles of human body.The muscles that were used are :

(i)Biceps brachii: is a two-headed muscle that lies on the upper arm between the shoulder and the elbow. Both heads arise on the scapula and join to form a single muscle belly which is attached to the upper forearm.It is of two types short head and Long head.

(ii)vastus medialis: The vastus medialis is a muscle present in the anterior compartment of thigh, and is one of the four muscles that make up the quadriceps muscle. The others being the vastus lateralis, vastus intermedius and rectus femoris. It is the most medial of the "vastus" group of muscles. The vastus medialis arises medially along the entire length of the femur, and attaches with the other muscles of the quadriceps in the quadriceps tendon.

(iii)Vastus laterals: The vastus lateralis arises from the several areas of the femur, including the upper part of the intertrochanteric line; the lower, anterior borders of the greater trochanter, to the outer border of the gluteal tuberosity, and the upper half of the outer border of the linea aspera. These form an aponeurosis, a broad flat tendon which covers the upper three-quarters of the muscle. From the inner surface of the aponeurosis, many muscle fibres originate. Some additional fibres arise from the tendon of the gluteus maximus muscle, and from the septum between the vastus lateralis and short head of the biceps femoris.

(iv)Deltoideus muscle: the deltoid muscle is the muscle forming the rounded contour of the shoulder. Anatomically, it appears to be made up of three distinct sets of fibers though electromyography suggests that it consists of at least seven groups that can be independently coordinated by the nervous system

(v)Tibialis anterior: is a muscle that originates in the upper two-thirds of the lateral (outside) surface of the tibia and inserts into the medial cuneiform and first metatarsal bones of the foot. It acts to dorsiflex and invert the foot. This muscle is mostly located near the shin.

(vi) Abductor pollicis brewis: The abductor pollicis brevis is a flat, thin muscle located just under the skin. It is a thenar muscle, and therefore contributes to the bulk of the palm's thenar eminence.It originates from the flexor retinaculum of the hand, the tubercle of the scaphoid bone, and additionally sometimes from the tubercle of the trapezium.Running lateralward and downward, it is inserted by a thin, flat tendon into the lateral side of the base of the first phalanx of the thumb and the capsule of the metacarpophalangeal joint Innervation

Fig3.1Biceps Brachii

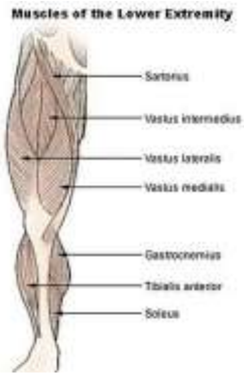

Fig3.2Vastus Medias and Vastus Laterals

Fig3.3 Deltoideus

Fig3.4 Tibialis Anterior

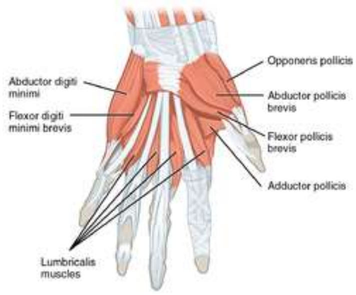

Fig3.5Abductor Pollicis Brewis

Fig3.6(a)EMG test being conducted

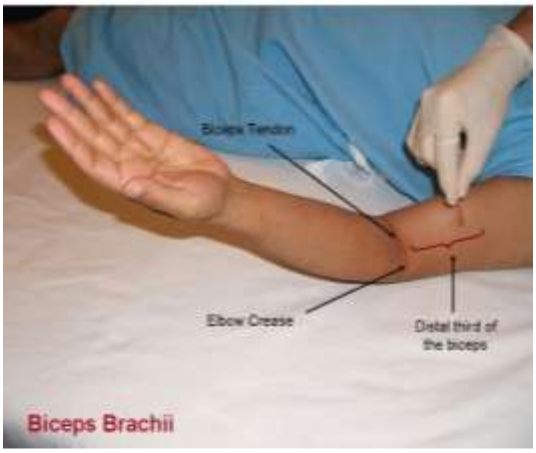

Fig3.6(b)EMG test being conducted

The EMG signals were recorded under usual conditions: The recordings were made at low (just above threshold) voluntary and constant level of contraction.Visual and audio feedback was used to monitor the signal quality. A standard concentric needle electrode was used.The EMG signals were recorded from five places in the muscle at three levels of insertion (deep, medium, low).The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz.

Fig.4. placement of the electrodes

IV. FEATURE EXTRACTION

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.The myo-signals generated by the body have to be acquired into the system for processing and classification.six features were extracted i.e. root mean square, mean, standard deviation, variance, maximum and minimum values of the given EMG signals.

A. Root mean square: Root mean square (RMS) is another popular feature in analysis of the EMG signal (e.g. Boostani & Moradi, 2003; Kim et al., 2011). It is modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction. It is also similar to standard deviation methodthe root mean square (abbreviated RMS) is defined as the square root of mean square (the arithmetic mean of the squares of a set of numbers). The RMS is also known as the quadratic mean.For a set of n numbers or values of a discrete distribution x_i , ..., x_n , the root-mean-square (abbreviated "RMS" and sometimes called the quadratic mean), is the square root of mean of the values x_i^2 , namely

$$x_{\mathrm{RMS}} \sqrt{\frac{x_1^2 + x_2^2 + \ldots + x_n^2}{n}}$$

$$\sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}}$$

$$\sqrt{\langle x^2 \rangle},$$

where $\langle x^2 \rangle$ denotes the mean of the values x_i^2 .

B. **Rise Time:** The time between the initial positive to the next negative peak within the main spike.
C. **Peak to Peak Value**: VALUE:**Peak-to-peak** (pk-pk) is the difference between the maximum positive and the maximum negative amplitudes of a waveform
D. **Thickness**: The ratio of the area to the peak to peak amplitude.
E. **Maximum:**The value of the function at a maximum point is called the maximum value of the function.

F. **Minimum:**The value of the function at a minimum point is called the minimum value of the function.
G. **PH Difference:**It is the ratio of maximum value of signal to the rms value of the signal

V. CLASSIFICATION

A] Support Vector Machine

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are not labelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering and is often used in industrial applications either when data are not labeled or when only some data are labelled as a pre-processing for a classification pass.

Support vector machine basically deals with pattern classification which means that this algorithm is mainly used for classifying the different types of patterns. The main aim of SVM is to maximize the margin hence the SVM can correctly classify the given patterns.

B]Artificial Neural Network [ANN]:

Connectionist **systems** are a computational model used in computer science and other research disciplines, which is based on a large collection of simple neural units (artificial neurons), loosely analogous to the observed behavior of a biological brain's axons. Each neural unit is connected with many others, and links can enhance or inhibit the activation state of adjoining neural units. Each individual neural unit computes using summation function. There may be a threshold function or limiting function on each connection and on the unit itself, such that the signal must surpass the limit before propagating to other neurons. These systems are self-learning and trained, rather than explicitly programmed, and excel in areas where the solution or feature detection is difficult to express in a traditional computer program.

Neural networks typically consist of multiple layers or a cube design, and the signal path traverses from the first (input), to the last (output) layer of neural units. Back propagation is the use of forward stimulation to reset weights on the "front" neural units and this is sometimes done in combination with training where the correct result is known. More modern networks are a bit more free flowing in terms of stimulation and inhibition with connections interacting in a much more chaotic and complex fashion. [Dynamic neural networks are the most advanced, in that they dynamically can, based on rules, form new connections and even new neural units while disabling others

The goal of the neural network is to solve problems in the same way that the human brain would, although several neural networks are more abstract. Modern neural network projects typically work with a few thousand to a few million neural units and millions of connections, which is still several orders of magnitude less complex than the human brain and closer to the computing power of a worm.

New brain research often stimulates new patterns in neural networks. One new approach is using connections which span much further and link processing layers rather than always being localized to adjacent neurons. Other research being explored with the different types of signal over time that axons propagate, such as Deep Learning, interpolates greater complexity than a set of boolean variables being simply on or off.

Neural networks are based on real numbers, with the value of the core and of the axon typically being a representation between 0.0 and 1.

An interesting facet of these systems is that they are unpredictable in their success with self-learning. After training, some become great problem solvers and others don't perform as well. In order to train them, several thousand cycles of interaction typically occur.

Like other machine learning methods – systems that learn from data – neural networks have been used to solve a wide variety of tasks, like computer vision and speech recognition, that are hard to solve using ordinary rule-based programming.

Historically, the use of neural network models marked a directional shift in the late eighties from high-level (symbolic) artificial intelligence, characterized by expert systems with knowledge embodied in *if-then* rules, to low-level (sub-symbolic) machine learning, characterized by knowledge

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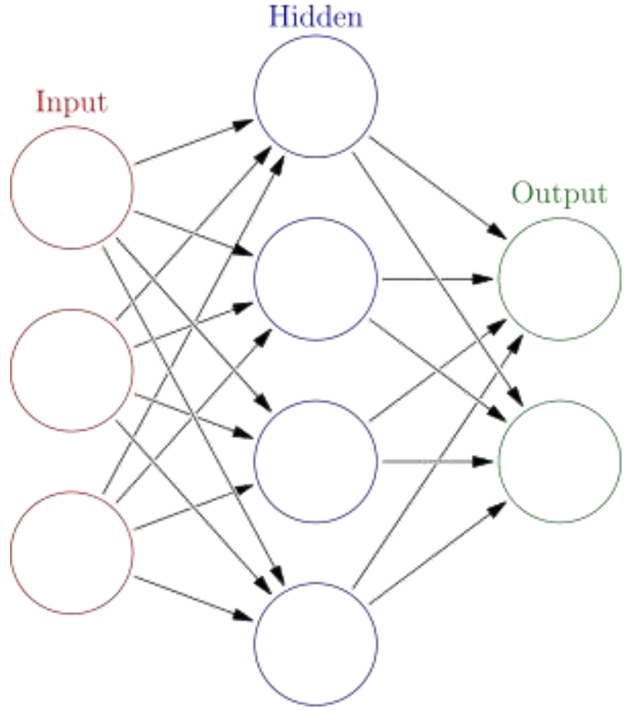
embodied in the parameters of a cognitive model with some dynamical system.

Representation of Neural Network:

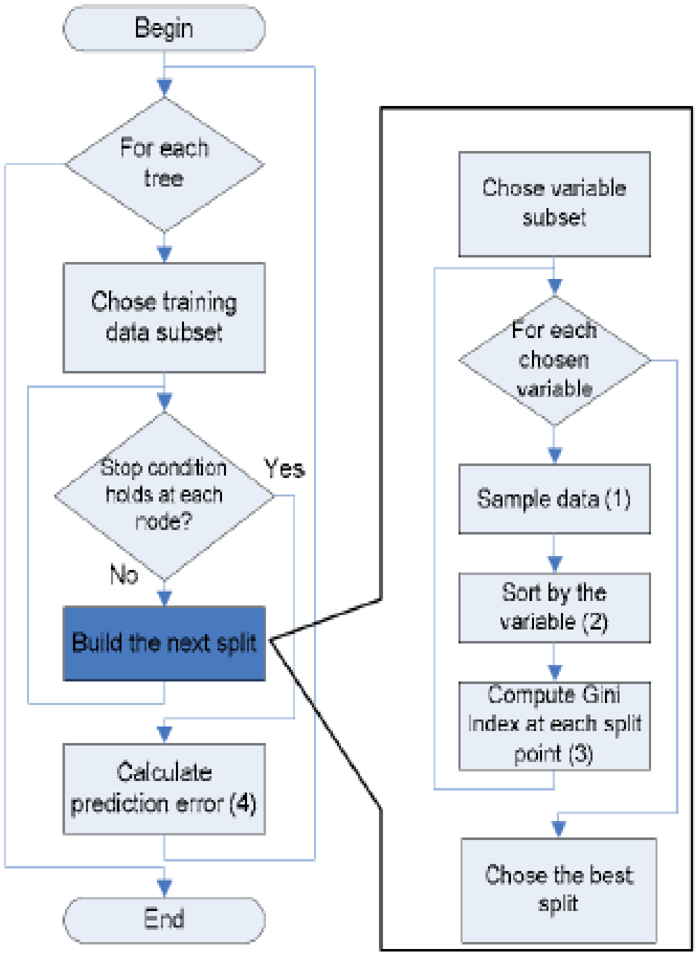


C]Random Forest:

RandomForest is one of the most popular and most powerful machine learning algorithms. It is a type of ensemble machine learning algorithm called Bootstrap Aggregation or bagging.The bootstrap is a powerful statistical method for estimating a quantity from a data sample. Such as a mean. You take lots of samples of your data, calculate the mean, then average all of your mean values to give you a better estimation of the true mean value.In bagging, the same approach is used, but instead for estimating entire statistical models, most commonly decision trees.Multiple samples of your training data are taken then models are constructed for each data sample. When you need to make a prediction for new data, each model makes a prediction and the predictions are averaged to give a better estimate of the true output value.

Random forest is a tweak on this approach where decision trees are created so that rather than selecting optimal split points, suboptimal splits are made by introducing randomness.

The models created for each sample of the data are therefore more different than they otherwise would be, but still accurate in their unique and different ways. Combining their predictions results in a better estimate of the true underlying output value



VI. RESULTS AND CONCLUSION

The scatter plot for the six features are shown.

Where X- axis denotes the category of finger movement and Y- axis denotes the features.

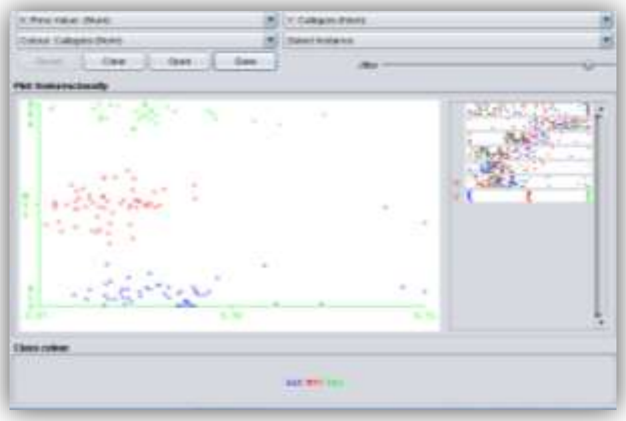


Fig.5. scatter plot for root mean square

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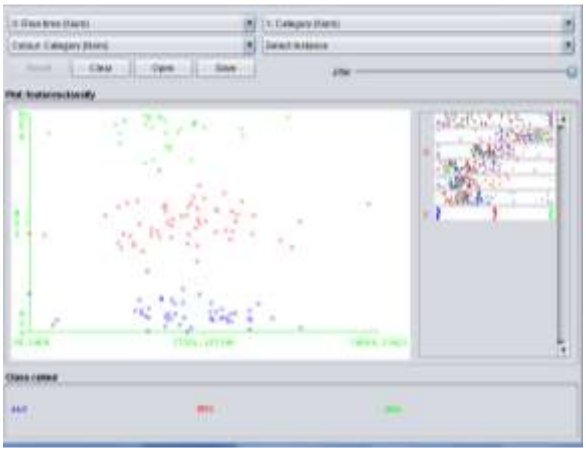

Fig.6. scatter plot for rise time

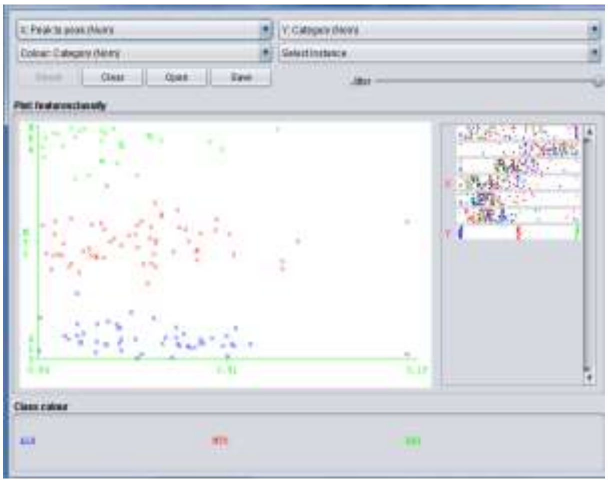

Fig.7. scatter plot for peak to peak value

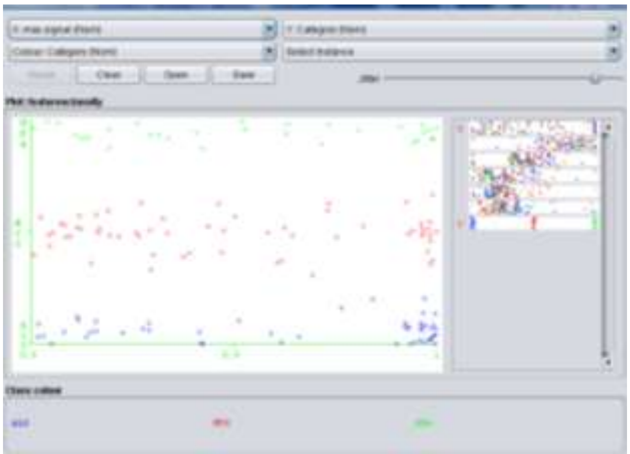

Fig.8. scatter plot for maxima

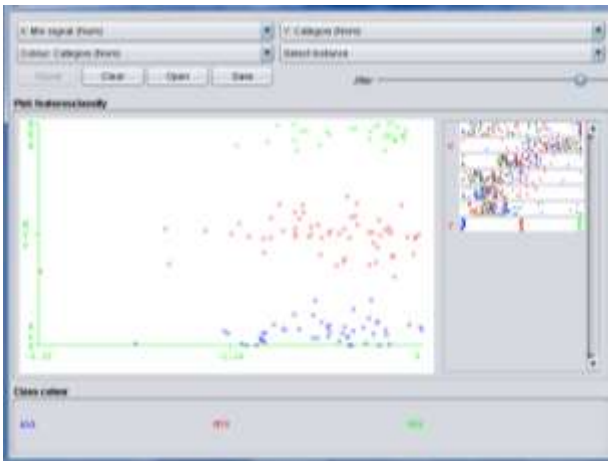

Fig.9. scatter plot for minima

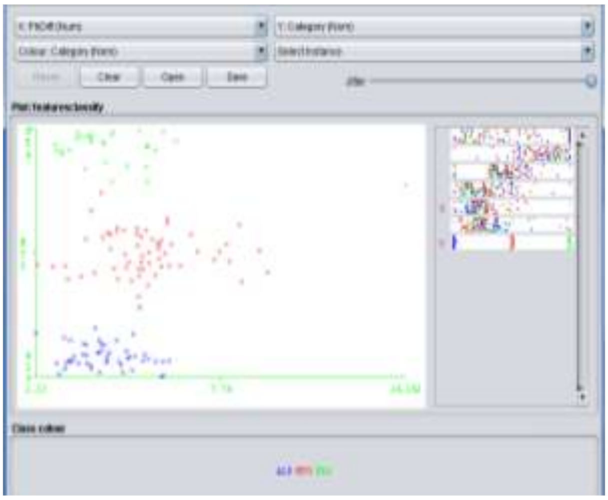

Fig.10. scatter plot for Peak to height Difference

A]**Result for svm classifier**

The confusion matrix for svm classifier is given in figure below. The confusion matrix for the SVM classifier shows that it gives an accuracy of around 95.71%. The values have been taken for 140 training samples**.**

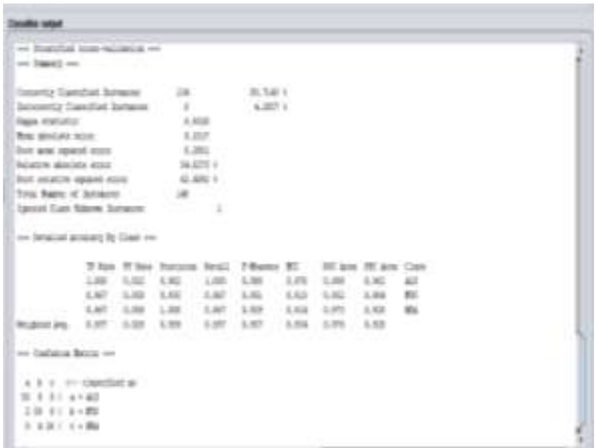

Fig.11. Confusion matrix for svm classifier

B]Result for ANN

The confusion matrix for Sann classifier is given in figure below. The confusion matrix for the classifier shows that it gives an accuracy of around 95.71%. The values have been taken for 140 training samples**.**

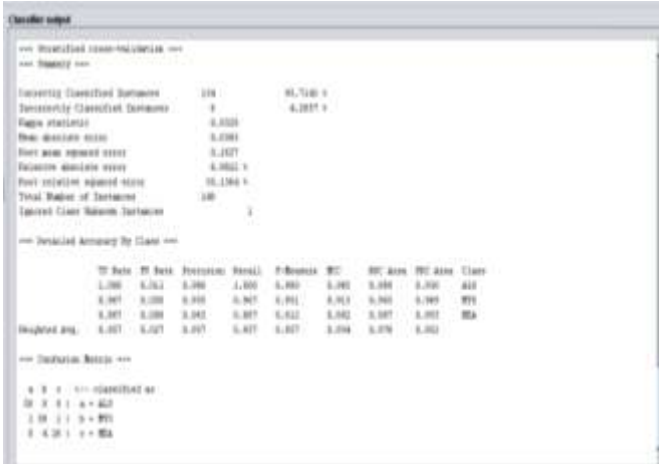

Fig.12. Confusion matrix for ANNclassifier

C]Result for Random Forest

The confusion matrix for Random Forest classifier is given in figure below. The confusion matrix for the classifier shows that it gives an accuracy of around 97.85%. The values have been taken for 140 training samples

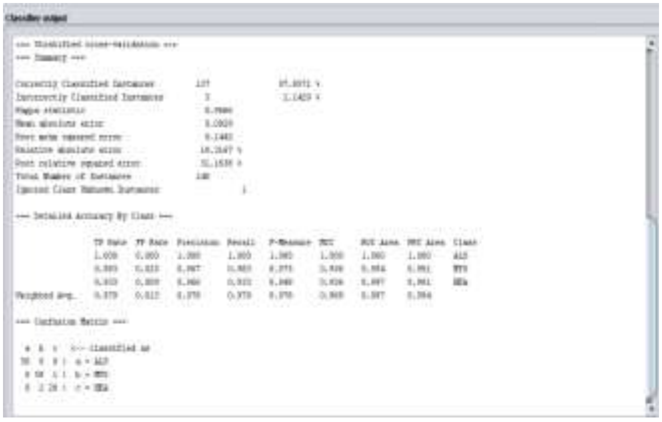

Fig.13. Confusion matrix for Random Forest classifier

It can be seen from the above classifiers output that out of the three classifier the best results were obtained from the Random Forest Classification Technique. An accuracy of 97.85% was obtained with this technique. The kappa statistic of this classifier is 0.966 which is close to 1.

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REFERENCES

[1] Merletti R, Parker P. Electromyography: Physiology Engineering and Non- invasive Applications.New Jersey: Wiley-IEEE Press; 2004. 520 p.

[2] DeLuca CJ. Towards Understanding the EMG Signal.In: Basmajian JV, DeLuca CJ, editors. Muscles alive: their functions revealed by electromyography. 5th ed. Baltimore: Williams & Wilkins; 1985.p. 53-78.

[3] Krarup C. Pitfalls in electrodiagnosis. *J Neurol.*1999;**246**:1115-26. Review. PubMed PMID:10653302.

[4] McGill KC. Optimal resolution of superimposed action potentials. *IEEE Trans BiomedEng* 2002;**49**:640-50. PubMed PMID: 12083298

[5] Tahereh Kamali ,Reza Boostani,and Hoossein Parsaei "A Multi-Classifier Approach to MUAP Classification of Neuromuscular Disorders" *IEEE Transaction on Neural Systems and Rehabilitation vol22 no1 January 2014*

[6] Hoosien Parsaei and Daniel .W.Stashul "EMG Signal Decomposition Using Motor Unit Potential Train Validity" *IEEE Transaction on Neural Systems and Rehabilitation vol21 no2 Marchry 2013*

[7] Miki Nikolic and Christian Krarup "ENGTools ,an Adaptive and Versitile Tool For Detailed EMG Analaysis" *IEEE Transaction on Biomedical Engineering vol 58 No10 October 2010.*

[8] Paulito Palmes∗, Wei Tech Ang, Ferdinan Widjaja, Louis CS Tan, and Wing Lok Au "Pattern Mining of Multichannel sEMG for Tremor Classification" *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 57, NO. 12, DECEMBER 2010.*

[9] SHANG Xiaojing, TIAN Yantao and LI Yang "Feature Extraction and Classification of sEMG Based on ICA and EMD Decomposition of AR Model*"IEEE Conference on Biomedical Engineering 2011 ISN 978-1-4577-0321-8/11*

[10] Aaron J. Young∗*, Student* . Lauren H and Smith, Elliott . "Classification of Simultaneous Movements Using Surface EMG Pattern Recognition" *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 60, NO. 5, MAY 2013*

[11] Sarbast Rasheed,, Daniel W. Stashuk and Mohamed S. Kamel. "Integrating Heterogeneous Classifier Ensembles for EMG Signal Decomposition Based on Classifier Agreement" *IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 14, NO. 3, MAY 2010*

[12] Rami N. Khushaba ."Correlation Analysis of Electromyogram (EMG) Signals for Multi-User Myoelectric Interfaces". *IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 11, NO. 1, JANUARY 2014*

[13] Saara M. Rissanen , Markku Kankaanp and Mika P. Tarvainen ." Analysis of EMG and Acceleration Signals for Quantifying the Effects of Deep Brain Stimulation in Parkinson's Disease" *.IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 58, NO. 9, SEPTEMBER 2011*

[14] A Dictionary of Physics (6 ed.). Oxford University Press. 2009. ISBN 9780199233991.

[15] Bland, J.M.; Altman, D.G. (1996). "Statistics notes: measurement error". BMJ. 312(7047): 1654. PMC 2351401. PMID 8664723. doi:10.1136/bmj.312.7047.1654.

[16] Simone Benatti, *et al.*: "A Versatile Embedded Platform for EMG Acquisition and Gesture Recognition", IEEE Transactions on Biomedical Circuits and Systems, Vol. 9, No. 5, October 2015.

[17] Mohd Haris, et al, "EMG Signal Based Finger Movement Recognition for Prosthetic Hand Control", 2015 International Conference on Communication, Control and Intelligent System(CCIS).

[18] Ganesh R. Naik, Ali H. Al-Timemy, and Hung T. Nguyen, "Transradial Amputee Gesture Classification using an Optimal Number of Semg Sensors: An Approach Using ICA Clustering", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 24, No. 8, August 2016.

[19] Xiang Chen, et al., "Multiple Hand Gesture Recognition based on Surface EMG Signal", 1-4244-1120-3/07 ©2007 IEEE.

[20] Ganesh R Naik, et al., "Multi run ICA and surface EMG based signal processing system for recognizing hand gestures", 978-1-4244-2358-3/08 © 2008 IEEE..

[21] R. H. Chowdhury, M. B. Reaz, M. A. B. M. Ali, A. A. Bakar, K.Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," *Sensors*, vol. 13, no. 9, pp.12431–12466, 2013.

[22] S. Benatti, E. Farella, L. Benini, and E. Gruppioni, "Analysis of robust implementation of an EMG pattern recognition based control," in *Proc. Int. Conf. Bio-Inspired Systems and Signal Processing*, 2014, pp. 45–54.

[23] [L. Hargrove, K. Englehart and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.

[24] K. Nagata, K. Adno, K. Magatani, M. Yamada, "A classification method of hand movements using multi channel electrode," Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society, Shanghai, China, 2005, pp. 2375-2378