An EMG based Expert System for Detection of Wrist Flexion and Extension

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ABSTRACT

This paper presents an electromyography (EMG) based system for classification and detection of wrist movement by carrying four different sets of movements. The experiment involved eight healthy subjects. The subjects were asked to put their hands in a horizontal plane. The subject then flexed their wrist from middle position to maximum flexion position and extended wrist to maximum extension position. The activities were performed in pronated as well as in supinated form. Notch filters and Band-pass filters were used in order to eliminate noise and preserve the features. The low and high cut-off frequency for notch and band-pass filter were 10Hz-80Hz with a sample rate of 512Hz. Discrete Wavelet Transform (DWT) was used to extract the features from EMG signals. Classification was carried out using machine learning techniques namely Decision Tree, Random Forest and Optimum Random Forest. Optimum Random Forest provided a testing accuracy of 89.38%.
Keyword: Electromyography, Prosthetic Wrist, Wrist Flexion, Wrist Extension.

I. INTRODUCTION

Electromyography is a biological signal representing neuromuscular activities [1] by measuring electrical currents generated in muscles during contraction. The neurological system always controls muscle contraction and relaxation. Electromyography (EMG) signals can help clinical/biomedical applications, Evolvable Hardware Chip (EHW) development, and current human-computer interfaces. In terms of operationality, a wristwatch [2] is now the preferred option. As a result, investigation showed Electromyogram (EMG), is a signal created by a live body in response to movement. Various studies use surface electromyography [3] to classify hand movements. Wearable surface electromyography (sEMG) devices can help people with sarcopenia and reduced muscle mass.

II. LITERATURE SURVEY

Five channel surface EMG signals [1] were obtained using the following muscles: i.) Flexor carpi ulnaris, ii.) Flexor carpi radialis, iii.) Extensor carpi radialis longus, iv.) Extensor carpi ulnaris and v.) Extensor Department of Artificial Intelligence and Data Science, AISSMS IOIT Pune Department of Artificial Intelligence and Data Science, AISSMS IOIT Pune Department of Artificial Intelligence and Data Science, AISSMS IOIT Pune Department of Artificial Intelligence and Data Science, AISSMS IOIT Pune All India Shri Shivaji Memorial Society's Institute of Information Technology digitorum. Five people participated in dataset collection. The research explored pattern recognition for myo-control prosthesis by employing feature extraction techniques like Mean absolute value (MAV), Root mean square (RMS), and Variance (var). Independent Component Analysis (ICA) was used as pre-processing technique [4] and

Common spatial pattern (CSP) was employed as dimensionality reduction. EMG challenges and prospective solutions were also included in the research. The pilot study included a 30-year man. Four superficial forearm muscles were used to record EMG signals using bipolar electrodes. EMG data was processed with cut-off frequency [5] of 6Hz40Hz (low and high frequency) using 4th order butterworth zero-phase filter. EMG signals were used to drive a prosthetic hand. The patient's forearm can be used to replace the prosthetic hand. Five servomotors power the prosthetic hand [6] and the system had taken visual and gesture controls. Four people were taken as subjects for dataset collection. A method was used to discriminate between EMG signals of wrist and fingers [7] using single surface electrode. Raw sEMG signals were digitised using the PCI1716, while Myoscan amplified them at 1kHz. SEMG signals were measured with three surface electrodes [8] using Extensor digitorum, Flexor carpi radialis, and Biceps brachii. Noise in raw data having 50/60 Hz notch filters was minimised in power lines. Band-pass filters with frequencies between 10/20Hz and 500Hz were routinely applied to EMG signals [9] in addition to notch filters. Ten volunteers provided the data. Five SEMG recordings were made for each subject using Ag-AgCl electrodes [10] placed on the forearm. Three men and three women, with unilateral transradial amputations participated in the experiment. All subjects had seven pairs of AgAgCL electrodes implanted in their forearms. The complete forearm's thickest portion was surrounded by electrode pairs [11]. Various muscles [12] were evaluated in the experiment in order to capture EMG signals. Six transforearm amputees without neurological illness participated in the tests. EMG data from four muscles of both arms were sampled at 500Hz [13] to determine wrist and hand movements. Two subjects participated in the dataset collection. Electromyogram (EMG) data was used to predict three shoulder movements (horizontal flexion extension, internal and external rotation), elbow flexion-extension [14] and forearm pronation/supination. The Time-delayed artificial neural network (TDANN) was used to forecast these motions. For EMG-based interfaces, wrist and hand movements were predicted using a musculoskeletal model (MM) and linear regression (LR). Wrist flexion/extension and metacarpophalangeal was performed by six people and one transradial amputee patient. The model’s performance was assessed using Pearson's correlation coefficient (r) [15] and feature extraction made use of normalised root mean square error (NRMSE). Extensor digitorum, Flexor Digitorum, Extensor Carpi Radialis Longus, and Flexor Carpi Radialis were used to record surface EMG signals. Using a 4th-order butterworth high pass filter, EMG signals were filtered at 40 Hz, rectified, and then filtered once more at 6 Hz. EMG patterns are distinguished by the log-linearized Gaussian mixture network (LLGMN), [16] a statistical neural network. New technology was tested on eight participants, including two amputees. Triceps Brachii, Flexor Carpi Ulnaris, Brachioradialis and Triceps Brachii were consulted. Feature extraction using quadratic polynomials was proposed [17] to improve the accuracy of conic models. The experimental setup was performed on five subjects. Each participant repeated the motion five times to get a learning parameter for quadratic polynomials. A 3D hand model was used to test these strategies. A Genetic algorithm (GA) was used for classifying hand movements using electromyography (EMG) signals. The Wavelet Transform (WT) was utilized to extract data signal features and the qualities were given in a hybrid intelligent system (HIS) made of artificial neural networks (ANNs) and GA. The categorization findings were promising, with 90% accuracy and 98% reliability. For dataset collection [18] ten volunteers were taken as subjects. Using the Nyquist theorem, noise was cut down by using band-pass filtering [19] on digital signals that had been sampled at 1 kHz. The investigation's data segmentation took 128ms. A number of feature extraction methods and time-delayed artificial neural networks (TDANN) were used to train and test raw EMG input signals. A hybrid EMG-to-motion model was built using a latent Dirichlet allocation model (LDA). With the help of a Feed forward neural network (FNN) model, researchers were able to calculate the continuous joint movement [20] and the model recognized tiny joint motion modes. A context-based task model was created to improve the hybrid model's estimation.

III. METHODOLOGY

The proposed system is built to control prosthetic wrist using EMG signal. Fig.1. demonstrates the System block diagram employed in this research.

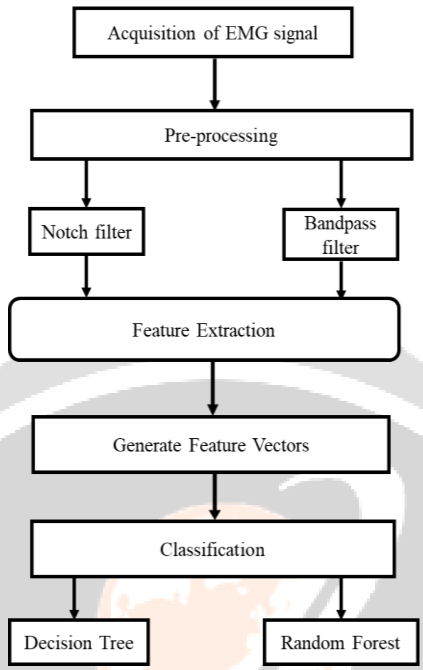

Fig.1. System Block Diagram

A. Dataset and pre-processing

Surface EMG signals were recorded with 512Hz sampling. All subjects participating in the signal acquisition were given instructions to familiarize themselves with the technique. The experiment included eight healthy subjects. The activities included in the experiment for dataset acquisition included wrist Flexion and Extension. The subjects were asked to put their hands in a horizontal plane in order to flex their wrist from middle position to maximum flexion position and extend their wrist to maximum extension position. The activities were performed in pronated as well as in supinated form. Fig.1. demonstrates the activities performed for dataset collection. The EMG signal was recorded using four channel electrodes. The muscles employed to record EMG signals were: (i)Flexor carpi radialis, (ii)Flexor carpi ulnaris, (iii)Extensor carpi radialis longus, and (iv)Extensor carpi radialis longus. Fig.2. demonstrates the montage used for the electrode placement during dataset collection. Channel 1 electrode was positioned at Flexor Carpi Radialis, Channel 2 electrode was positioned at Flexor Carpi Ulnaris, Channel 3 electrode was positioned at Extensor Carpi Radialis Longus, and Channel 4 electrode was positioned at Extensor Carpi Ulnaris. Each activity performed for Dataset collection lasted between 3-4 seconds. Each activity was performed multiple times and the signals were recorded. The EMG signal data for all the subjects were converted into CSV files. CSV file consists of 5 columns where first column indicates index and remaining columns represents the channels used for data acquisition. Each CSV file contains 5 columns and 6000-8000 rows. The dataset was further split into two groups: Training and testing. For Training purpose data of 6 subjects was used and remaining data of 2 subjects was used for testing.

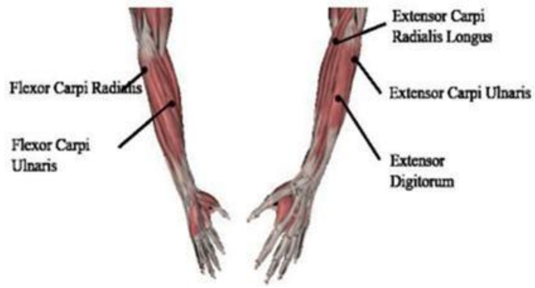

Fig.2. Montage used for electrode placement [1]

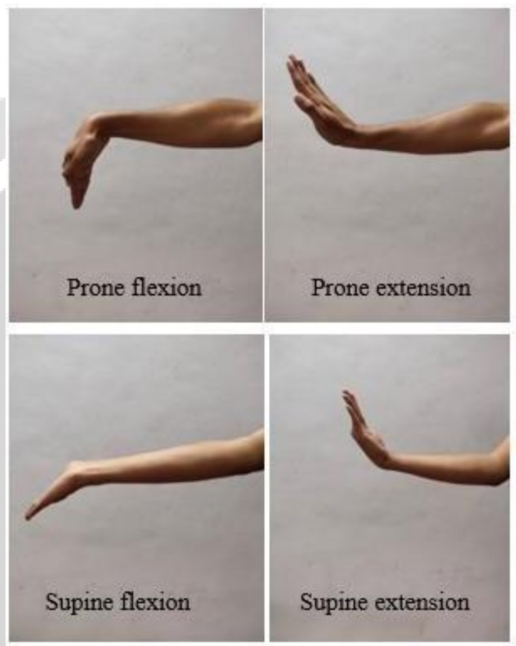

Fig.1. Activities performed for Dataset collection

The approach employed for filtering techniques are the notch filter and the band pass filter (BP). Bandpass filters, such as notch filters, only affect frequencies within a specific range and leave the rest untouched. Fig.3. demonstrates the graph plotted for notch filter for band reject frequency range as 49Hz to 50Hz to remove supply frequency artifacts. The plot shows original waveform vs filtered waveform. Wrist action presented in the graph is for Normal extension. Band-pass filter permits signals within a specified frequency range to be received or decoded, while inhibiting the collection of signals at other frequencies.

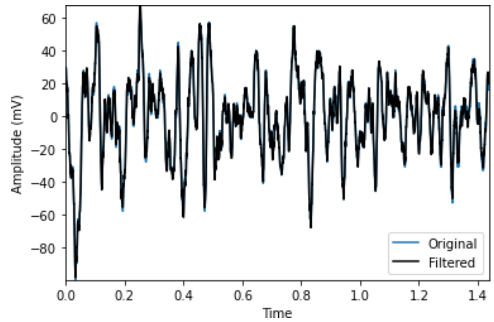

Fig.3. Waveform of Notch Filter output

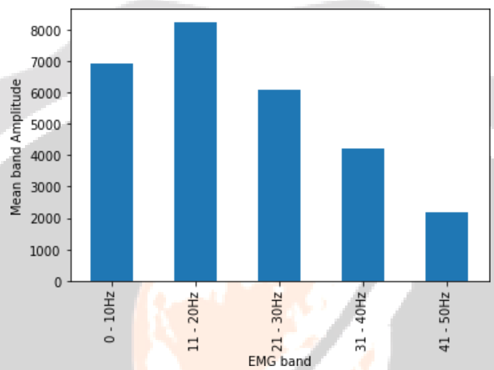

Fig.4. Mean band Amplitude of notch filter output

The bandpass filter of lower cutoff frequency 10Hz and higher cutoff frequency 80Hz is used to remove the remaining frequencies. The following plot shows original waveform vs filtered waveform.

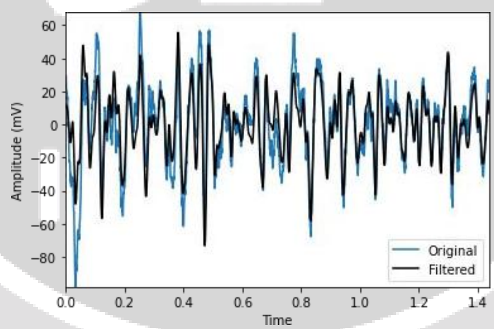

Fig.5. Graph for Band-pass Filter

Filtered signals in Fig.5. show that the frequency in the range of 10Hz to 80Hz are retained and the rest are removed. Fig.6. shows the Mean band amplitude of the filtered signal.

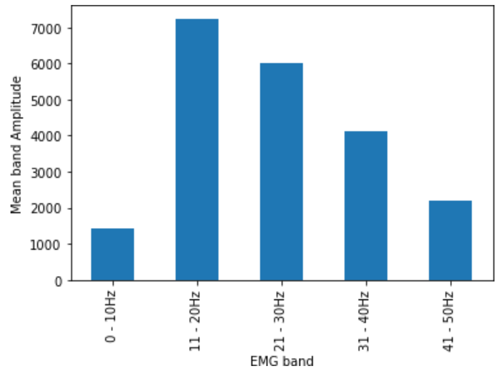

Fig.6. Mean band amplitude for bandpass filter

PSD (Power Spectral density for filtered signal can be calculated with given equation:

$Sp\ (f) = Ts\ N\ (\sum x[n] * e\ N\ -j2\pi fnT\ n{=}1\ )\ 2$

$Pm = \sum S(k)\ k{=}f2\ k{=}f1$ (2)

Following signal shows the PSD of filtered output signal:

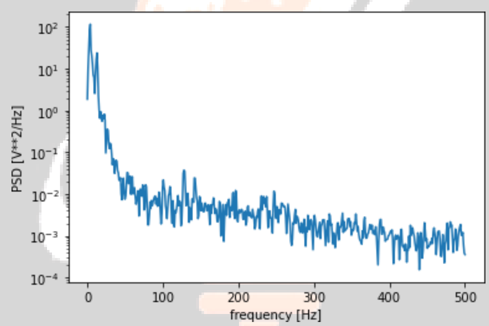

Fig.7. PSD of filtered signal

It can be observed that majority portion of signal power is distributed at lower range of frequency.

B. Feature Extraction

Classification relies on a variety of digital-signal processing methods. Pre-processing the signals, removing noise, and obtaining clearer information are some of the benefits of these procedures. Fast Fourier transform and Wavelet Transform are examples of some of the techniques. In contrast to the other methods, the Wavelet transform retrieves data in time-frequency domains whereas other techniques extract information only in frequency domain. The signals were put through a Discrete Wavelet Transform (DWT) dB2 with the decomposition of 3 level. Energy, entropy, and standard deviation of the wavelet coefficients was calculated to describe the feature. Each wave segment was analyzed to calculate time domain features and variation over the time in terms amplitude and frequency. Various time domain properties are described in the following equations given below. The average corrected value (ACV) is the same as the mean absolute value (MAV). MAV helps in detecting and gauging muscle contraction levels. MAV is represented in Eq. 3. In E.q. 3,4,5, 6, 7, and 8 xn represents the sEMG signal and N represents length of the signal.

$MAV = 1\ N \sum |xn\ |\ N\ n=1$ (3)

The time-domain feature extractor variance is used to extract the information of the power of EMG. The variance is typically equal to the mean of the square of the variable's deviation. The mean of the EMG signal, on the other hand, is near to zero. VAR is represented in E.q. 4.

$VAR = 1\ N-1 \sum xn\ N\ 2\ n=1$ (4)

The frequency information in the EMG segment is measured using Willison Amplitude (WAMP). It keeps track of how frequently the difference between two successive amplitudes exceeds a set threshold. It is equivalent to Slope Sign change (SSC)and Zero crossing (ZC), which are used to reduce noise effects. WAMP is represented in E.q. 5

$WAMP = \sum f(|xn - xn+1\ |)\ N-1\ n=1$ (5)

The amplitude modulated gaussian random process is known as root mean square. It is associated with consistent force and non-fatiguing muscle contractions. Feature Extraction using RMS is quite popular because it is computationally efficient and speedy. RMS is stated in E.q. 6.

$RMS = \sqrt{}\ 1\ N \sum x\ 2n\ N\ N=1$ (6)

Integrated EMG gives the absolute value of all the amplitudes. When the signal's absolute value is calculated, noise causes the mathematical integral to grow at a constant rate. IEMG is stated in E.q. 7.

$IEMG = \sum |xn\ |\ N\ n=1$ (7)

The overall length of a waveform during a certain period is referred to as its Waveform length (WL). It provides comprehensive information about frequency, amplitude, and duration of the input signal. Equation for WL is stated in E.q. 8.

$WL = \sum |xn+1 - xn\ |\ N-1\ n=1$ (8)

Various Frequency domain features are included in this research. The amplitude spectrum multiplied by the frequency spectrum divided by the sum of total intensity of the spectrum is used to compute mean frequency.

$MNF = \sum fjAj\ m\ j=1 \sum Aj\ m\ j=1$ (9)

Equation for mean frequency is mentioned in E.q. 9 where Aj is the Power spectral density. Median Frequency (MFD) is a technique for extracting features based on Power spectral density (PSD). When it comes to PSD signals there are generally two types: Parametric and non-parametric. MFD is the frequency whose spectrum is divided into two equal parts. Equation for median frequency is mentioned in E.q. 10.

$\sum Aj\ MF\ J=1 = \sum Aj\ M\ J=MF = 1\ 2 \sum Aj\ M\ J=1$ (10)

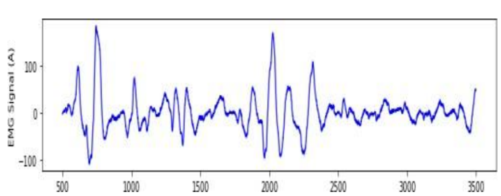

Fig.a. Normal Flexion

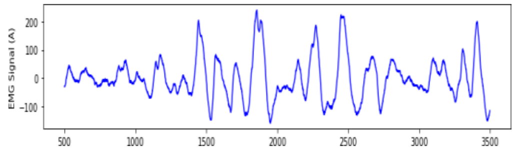

Fig.b. Inverted Extension

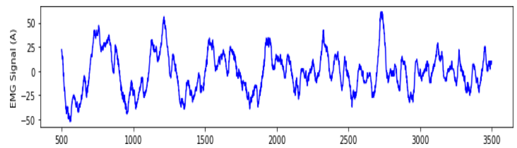

Fig.c. Inverted Flexion

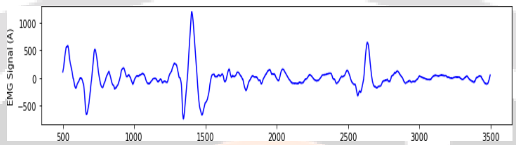

Fig.d. Normal Extension

Fig a, b, c, and d shows the EMG signals generated during different wrist actions. Fig a. describes about Normal Flexion. Fig b. describes about Inverted Extension. Fig c. describes about Inverted Flexion and Fig d. describes about Normal Extension. The EMG signals plotted were generated for channel-4 which acquired the signal generated by Extensor Carpi Ulnaris muscle.

Windowing of the signal is a process where we select a small segment of the waveform to perform further analysis and operation on the signal. For performing windowing of the signal, data length of 250, 500 and 1000 were analysed. Fig.8. describes about the windowing of the signal with 3 different lengths of data points taken into consideration. It was observed that the window length of 500 extracts features discriminative towards class and supports dataset consistency.

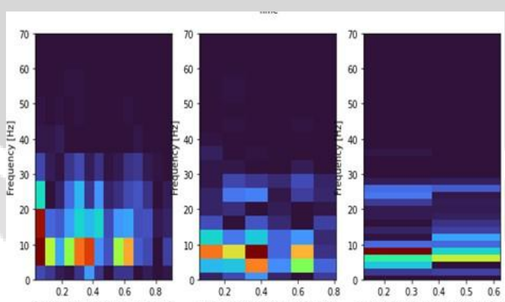

Fig.8. Windowing of signal

Boxplot for all the feature vectors were plotted to observe the variations. Fig.9. shows the boxplot for mean features.

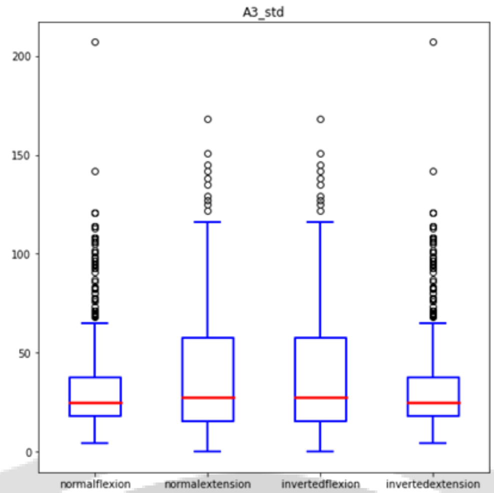

Fig.9. Standard deviation Boxplot

The variance or dispersion of a group of values is quantified by the standard deviation. Data tends to get scattered more closely around the mean in low standard deviation, whereas data disperses away from the mean in high standard deviation. Fig.9. describes the boxplot where the mean value for the feature vector is calculated. For all the four actions the mean value is observed to be between 10-40.

Algorithm 1 provides a mechanism for feature extraction. The algorithm takes raw EMG signals as input and trains the model with extracted features. Bandpass and notch filters are used to filter the signals for a particular frequency. Bandpass filters are provided a frequency range of 10Hz-80Hz and notch filters with 49Hz-51Hz. Thus, the feature vectors are generated as output.

Algorithm 1: Feature Extraction

Input: Raw EMG Signals

Output: Feature Vector

Initialization:

LOOP Process

1.for filename in folder:
2.Filter using bandstop/notch to remove noise
3. Bandpass filter to preserve signals within a particular frequency range

4. Select the frequency range using the filter Sample rate = 512Hz Bandpass filter = 10Hz-80Hz

Notch filter= 49Hz-51Hz

5. Windowing technique to generate features Datapoints of 250, 500 and 1000

6. for each window:

7. Extract time domain, frequency domain and time-frequency domain features

8. end for

9. concatenate features in matrix

10. end for

C. Classification and evaluation of wrist movements

The solution explored two supervised machine learning algorithms for binary classification between wrist flexion and extension in pronated as well as in supinated form. Following classifiers were evaluated for their performance to classify these activities: i. Decision Tree Classifier ii. Random Forest Classifier. Decision tree is a tree-based supervised learning technique where root node represents the features and leaf node represents the output. There is a need of choosing suitable attribute so that the desired output is acquired by splitting the root node. Attribute selection measurement can be performed by obtaining Information gain and Gini Impurity index. In this model an entropy attribute is used with optimum depth of 3. The biggest advantage of decision tree is that it is exhaustive in terms of possibility. Entropy is given in E.q. 11. $E(S) = \sum -Pi\ log2\ pi\ c\ i=1$ (11) Where pi is the probability of class i. This entropy determines the information gain in each node of the decision tree. The second classifier investigated was the Random Forest Classifier. The algorithm consists of many decision trees that are used on different subsets of the dataset. The system then combines the results of all decision trees to establish the object's ultimate class. Mean Squared Error (MSE) is utilised to branch data from each node. Therefore, the greater number of trees there are in the forest, the more accurate it is. This avoids the problem of overfitting. MSE is given in E.q. 12. $MSE = 1\ n\sum\ (yi - \hat{yi})\ 2\ n\ i=1$ (12) Where n is the number of data points, yi represents observed values and $\hat{yi}$ represents predicted values.

IV. RESULT AND DISCUSSION

Table 1. Shows the training and testing accuracy obtained. A promising accuracy has been found with the use of decision trees, random forests, and optimum random forest. Optimum Random Forest has the maximum training and testing accuracy of all classifiers used. The random forest has been optimized by searching optimum parameter of maximum depth and number of estimators using grid search technique. Grid search was conducted for maximum depth from 2 to 24 and estimators values from 32 to 256 with suitable increment. The search technique extracted the best forest among these which resulted in high accuracy of 89.38%. Decision trees and Random Forest also offer promising results in terms of training and testing accuracy. Table 2. shows the comparison of the classifiers based on precision, recall and F1-score.

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Table 1. Performance analysis of wrist movements

	Training accuracy	Testing accuracy
Decision Tree	79.95%	80.42%
Random Forest	93.35%	88.67%
Optimum Random Forest	93.35%	89.38%

Table 2. Performance parameters

	Precision	Recall	F1 - Score
Decision Tree	89.40%	76.37%	82.37%
Random Forest	94.01%	86.61%	90.16%
Optimum Random Forest	93.36%	88.58%	90.90%

V. CONCLUSION

This paper presented an electromyography (EMG) based system for classification and detection of wrist movement. A 4-channel EMG setup is used for data acquisition of wrist flexion and extension. For each muscle group, electrodes were attached to one of four muscles: Flexor carpi radialis (channel 1), Flexor carpi ulnaris (channel 2), Extensor carpi radialis longus (channel 3), and Flexor carpi ulnaris (channel 4). Experimental results suggested that the model recognized wrist flexion and extension in pronated as well as in supinated form. Optimum Random Forest classifier provided a training accuracy of 93.35% and a testing accuracy of 89.38%.

The results indicated that the muscle activity measured at each electrode placement offer sufficient information for classifying pronated and supinated wrist flexion and extension. Authors integrate and analyse different wrist movements which is supported by the test and train subjects' accuracies.

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