EMG Signal Classification and Feature Extraction using Machine Learning and DWT Technique

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Abstract-

In this paper, a classifier has been designed using Support Vector Machine (SVM) to classify Electromyography (EMG) signals. Given the EMG signals, the SVM-based classifier aims to classify ten individual and combined fingers motion command into one of the predefined set of movements. Prior to classification, EMG data is segmented with a DWT such as Mean Absolute Value (MAV), Root Mean Square (RMS) and SD are extracted for each window and combined to a feature set. Extracted features are used as inputs to the classification system. A linear SVM (one-against-one method) is used for the multiclass classification of EMG signals. DWT sizes that affect the classification performance have been reported. The best feature set that ensures maximum discrimination between the finger movements has also been reported. Validation shows that support vector machine can classify EMG signals correctly with a higher classification accuracy at 91.7% suitable for designing for proposed method.

Keywords: *Classification, Electromyography, Feature Extraction, Support Vector Machine.*

I. Introduction

The EMG signals are highly complex and non-linear signal. These signals are widely used in clinical trials for the diagnosis of neurological and neuromuscular problems [1]. Because of the complexity of EMG signals many times even experienced researchers are fail to provide enough information about these signals. EMG signals involve a great deal of information about the nervous system with anatomical and psychological properties of fingers. It is a record of electrical potentials generated by fingers [2]. The changes in the voltage difference between electrodes are sensed and amplified before it is transmitted to a computer program to display the tracing of the voltage potential recordings [3].

There are numerous neuromuscular disorders that influence the spinal cord, nerves or fingers. Early finding and diagnosis of these diseases by clinical examination is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling. This information’s are also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases [4].

Ii. Research Motivation

EMG signals are very complex and inherit several types of noises that pose greater challenges to the medical community. It has been widely used as a diagnostic technique to access muscular health and related disorders. The technique involves the placement of electrodes over the muscle to monitor its muscular activity via electrical signals. It is practiced as a popular clinical application for human computer interface involved in the diagnosis of myopathy that involves muscle cramps, spasm, stiffness, and dysfunction. The skeletal fingers represent the largest group of fingers that manages body posture, motion, heat generation, and directly controlled by the brain in decision making. Also, growing awareness and concerns about physiological and psychological health significantly lead to a rise in the EMG device market over the globe.

Since the beginning of the development of computer technology, the main interface of human-computer interaction has been dialog boxes controlled by keyboard and mouse. However, with the development of hardware and software, for example, with the advent of mobile phones, augmented reality helmets, IoT, more intelligent interaction interfaces were required, which can be classified as follows:

(1) Voice control [1, 2];

(2) Control gestures (with video cameras [3], special gloves [4] or special sensors, such as Kinect);

(3) The brain-computer interface [5,6].

The use of these interfaces provides convenience in situations where there is no possibility or need to interact with external physical devices. One of the most accurate and effective ways to control gestures is to control muscle activity, which occurs with any movement. Therefore, the use of signals of bioelectrical activity of fingers to control a device is an urgent task for today. Electromyography (EMG) is used to record this activity. In addition, the scope of EMG signals is very wide: they can be used in medicine to study muscle activity abnormalities; when evaluating the effectiveness of rehabilitation measures; for monitoring the human condition, etc. When analyzing the bioelectrical activity of different fingers, one can understand which fingers were involved, and, therefore, with the best classification method, determine the movement that is made with their help.

Iii. Problem Statement

For people with hand fingers disabilities, independently performing daily tasks that require hand function such as holding objects, opening/closing doors and eating meals is a major challenge. For this population, the use of an assistive device targeting in particular the hand could be beneficial. According to the type of disability, this device can be a prosthesis or an orthosis. Among different kinds of hand prosthesis, micro-controlled hand prosthesis has gained rising interest among researchers. Micro-controlled technique uses signals acquired from finger to control the assistive device [5]. In micro-controlled hand prostheses, the signals acquired from users' fingers is classified to predict hand movement intention. Then the predicted movement will be used to control the artificial hand. Although micro controlled devices have been introduced for many years, due to their insufficient classification accuracy and robustness, they have not yet been accepted by a considerable portion of the targeted population [2]. Traditionally, EMG signals were pre-processed to remove unwanted signals. Then signal is segmented into windows and signal features were calculated over each window. Signal features would then be fed to a classifier to be classified [6]. One significant challenge, which is present to this day, is choosing the right combination of features. Many researchers have tackled this issue by analyzing different feature combinations and evaluating their performance in terms of accuracy, time efficiency and robustness [3].

Iv. Feature Extraction

The benefit the feature extraction is to avoid extensive data and time consuming for signal processing. Therefore, many feature extraction types are used to reduce the raw data dimensions and produce new vectors that will enter the classification stage instead of the raw data. So, the new vectors must contain all the required information to obtain fast training [6,7]. In this work, the EMG signals are analysed in offline mode using MATLAB 2015a. The recoded signals are then segmented in a window size of 200ms and an increment of 150ms. The window is analysed using Root Mean Square (RMS), Difference Absolute Standard Deviation Value (DASDV), Mean Absolute Value (MAV), Standard deviation (SD) and Principal Component Analysis (PCA) is used for dimension reduction because of reduction in time and space complexities. The dimensions of the new components will be uncorrelated and orthogonal to each other [8,9,10].

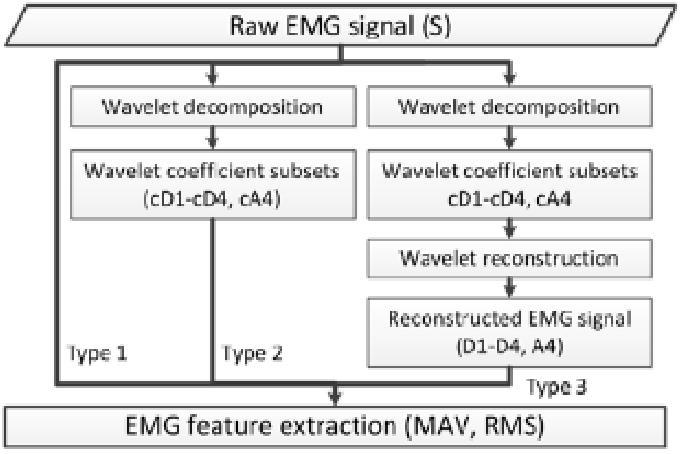

Fig 1. DWT Method.

V. Wavelet Analysis

A transform can be thought of as a remapping of a signal that provides more information than the original. The Fourier transform fits this definition quite well because the frequency information it provides often leads to new insights about the original signal. Fourier analysis provides a good description of the frequencies in a waveform, but not their timing. However, the inability of the Fourier transform to describe both time and frequency characteristics of the waveform led to a number of different approaches. None of these approaches was able to completely solve the time–frequency problem. Timing information is often of primary interest in many biomedical signals. A wide range of approaches have been developed to try to extract both time and frequency information from a waveform. Basically they can be divided into two groups: time–frequency methods and time–scale methods. The wavelet transform can be used as yet another way to describe the properties of a waveform that changes over time, but in this case the waveform is divided not into sections of time, but segments of scale [11].

Wavelets are an excellent tool for biomedical signal analysis. Wavelets are utilized for the study of signals that are non-stationary and is time varying in characteristics. The EMG signal carries transient signals linked to muscle movement. EMG signals have typically multiple temporary components (MUAP), which are very impressive to separate and classify according to their physiological importance. A wavelet based decomposition is a vital tool for analyzing EMG signal; The EMG signal is decomposed in various levels (resolution) of the wavelet [5]. The noisy elements of the wavelet decomposition are pruned, and the signal is rebuilt from the remaining. The rebuild de-noised signals exhibit muscle action. The wavelet transform (WT) is a useful analytical tool for the study of non-stationary and fast transient signals. One of the principal characteristics of WT is that it can be applied for a discrete time filter bank. The Fourier transforms of the wavelets are mentioned to as WT filters. The WT serves a very suitable technique for the analysis of EMG signals. Guglielminotti and Merletti [12] theorized that if the wavelet is chosen so as to match the shape of the MUAP, the resulting WT produces the best possible energy localization in the time-scale plane. Based on the study, Laterza and Olmo [8] concluded that the WT is especially useful for MUAP discovery in the presence of additive white noise. In this circumstance, the noise participations are disseminated over the whole-time scale plane, independently of the wavelet applied.

Vi. Proposed Algorithm

The procedure of an extraction of the EMG features from wavelet coefficients and reconstructed EMG signals. Wavelet transform and feature extraction methods Wavelet transform method is divided into two types: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). DWT was selected in this study because of the concentration in real-time engineering applications [1-2]. DWT is a technique that iteratively transforms an interested signal into multi-resolution subsets of coefficients. Like the conventional time-frequency analysis, the

DWT transforms the EMG signal with a suitable wavelet basis function (WF). Therefore, the WF plays a key role in the multi-resolution analysis.

In this study, we investigated the usefulness of the multi-resolution analysis through studying of the EMG features with different scales and local variations and also the elimination of the undesired frequency components. In addition, the selection of an optimal WF is proposed.

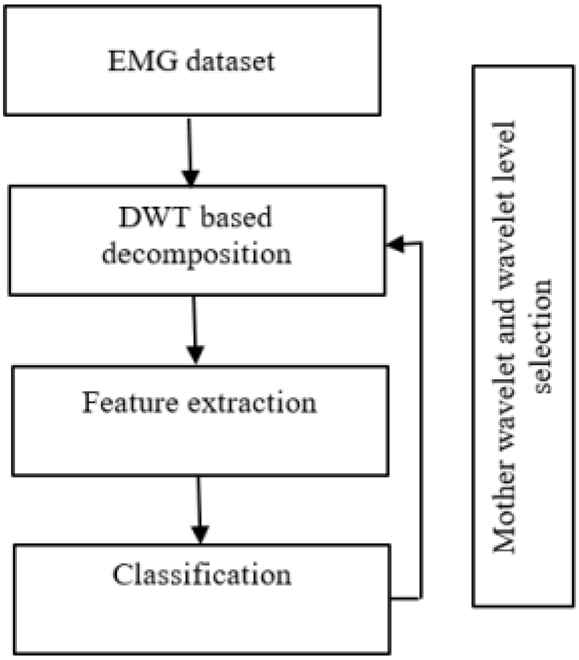

Fig 2. Block diagram for the wavelet-based automated classification system.

Proposed Machine learning algorithm

1. Support Vector Machines (SVM)

Support Vector Machines (SVM) is a popular machine learning algorithm used for classification and regression tasks. Linear SVM is a specific type of SVM that works well for linearly separable data. In the context of electromyographic (EMG) signal classification, Linear SVM can be used to classify different muscle activities based on EMG signals.

Approach EMG signal classification using Linear SVM:

Steps-

a. Data Collection: Collect EMG signal data from sensors placed on fingers.

b. Signal Filtering: Preprocess the raw EMG signals by applying filters (e.g., bandpass filters) to remove noise and artifacts.

c. Feature Extraction: Extract relevant features from the preprocessed signals. Common features for EMG signals include mean absolute value, waveform length, zero crossing rate, and others.

2. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a simple and widely used machine learning algorithm for both classification and regression tasks. It is a type of instance-based learning, where the model makes predictions based on the majority class (for classification) or the average (for regression) of the k-nearest data points in the feature space.

Steps-

- **Training Phase:**

For each data point in the training set, the algorithm stores the features and their corresponding class labels (for classification) or target values (for regression).

No explicit training process occurs in KNN. The model effectively memorizes the entire training dataset.

- **Prediction Phase:**

Given a new, unseen data point, the algorithm calculates its distance (usually Euclidean distance) to all data points in the training set.

It identifies the k-nearest neighbors of the new data point based on the calculated distances.

- **Classification (for KNN Classification):**

For classification, the algorithm assigns the class label that is most frequent among the k-nearest neighbors to the new data point.

- **Regression (for KNN Regression):**

For regression, the algorithm assigns the average of the target values of the k-nearest neighbors to the new data point.

The choice of the parameter "k" (the number of neighbors) is a critical factor in KNN. A small value of k makes the model sensitive to noise and outliers, while a large value of k may lead to a loss of important patterns. Therefore, the value of k should be chosen carefully based on the characteristics of the data.

3. Decision tree

A **decision tree** is a decision support hierarchical model that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements.

Decision trees are commonly used in operations research, specifically in decision analysis,[1] to help identify a strategy most likely to reach a goal, but are also a popular tool in machine learning.

The accuracy of the decision tree can change based on the depth of the decision tree. In many cases, the tree's leaves are pure nodes.[9] When a node is pure, it means that all the data in that node belongs to a single class.[10] It is important to note that a deeper tree is not always better when optimizing the decision tree. A deeper tree can influence the runtime in a negative way. If a certain classification algorithm is being used, then a deeper tree could mean the runtime of this classification algorithm is significantly slower. There is also the possibility that the actual algorithm building the decision tree will get significantly slower as the tree gets deeper. If the tree-building algorithm being used splits pure nodes, then a decrease in the overall accuracy of the tree classifier could be experienced. Occasionally, going deeper in the tree can cause an accuracy decrease in general, so it is very important to test modifying the depth of the decision tree and selecting the depth that produces the best results. To summarize, observe the points below, we will define the number as the depth of the tree.

Possible advantages of increasing the number:

- Accuracy of the decision-tree classification model increases.

Possible disadvantages of increasing

- Runtime issues
- Decrease in accuracy in general
- Pure node splits while going deeper can cause issues.

4. Boosted tree

In machine learning, **boosting** is an ensemble meta-algorithm for primarily reducing bias, and also variance[1] in supervised learning, and a family of machine learning algorithms that convert weak learners to strong ones.[2] Boosting is based on the question posed by Kearns and Valiant (1988, 1989):[3][4] "Can a set of weak learners create a single strong learner?" A weak learner is defined to be a classifier that is only slightly correlated with the true classification (it can label examples better than random guessing). In contrast, a strong learner is a classifier that is arbitrarily well-correlated with the true classification.

Vii. Results And Discussion

The purpose of this work is to study the EMG signals acquired from the finger movements by applying DWT in order to determine the suitable mother wavelet and level of decomposition, which yield the best classification performances. The EMG signals are decomposed into maximum level decomposing using different mother wavelets. The Surface EMG (SEMG) signals was denoised using discrete wavelet transform (DWT) and a threshold method. The DWT and threshold based denoising was implemented using MATLAB.

Table 1. Finger movement's features.

Class	Mean	Median	SD
1	$-1.985\text{x}10^{-07}$	0.0009766	0.0337
1	$-1.527\text{x}10^{-07}$	0.001221	0.04983
1	$1.833\text{x}10^{-07}$	0.001221	0.0711
1	$-1.375\text{x}10^{-07}$	0.007325	0.03057
1	$3.207\text{x}10^{-07}$	0.001221	0.01745
1	$-6.108\text{x}10^{-08}$	0.0009766	0.0244
2	$6.115\text{x}10^{-08}$	0.0009766	0.04443
2	$2.359\text{x}10^{-07}$	0.001221	0.06839
2	$-5.242\text{x}10^{-08}$	0.0007325	0.09294
2	$4.368\text{x}10^{-08}$	0.0007324	0.03987
2	$1.048\text{x}10^{-07}$	0.001221	0.01697
2	$6.115\text{x}10^{-08}$	0.0007325	0.02645
3	$-9.209\text{x}10^{-08}$	0.0009766	0.02535
3	$-1.679\text{x}10^{-08}$	0.001221	0.07129
3	$-5.86\text{x}10^{-08}$	0.0009766	0.687
3	$-1.172\text{x}10^{-07}$	0.0007325	0.0298
3	$-6.697\text{x}10^{-08}$	0.001221	0.03474
3	0	0.0009766	0.06114
4	0	0.0009766	0.01028
4	0	0.001221	0.01128
4	0	0.001465	0.01443

4	0	0.0007325	0.02445
4	0	0.001221	0.01287
4	0	0.0009766	0.01036
5	0	0.0009766	0.02531
5	0	0.001465	0.0826
5	0	0.001221	0.06669
5	0	0.0007325	0.03362
5	0	0.001221	0.01712
5	0	0.0009766	0.06986

Table 2. Classification Evaluation.

METHOD	CLASS CLASSIFICATION											
	1-INDEX FINGER with 2-LITTLE FINGER			1-INDEX FINGER with 3-MIDDLE FINGER			1-INDEX FINGER with 4-RING FINGER			1-INDEX FINGER with 5-THUMB FINGER		
	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp
LINEAR SVM	50.00	50.00	50.00	58.3	59.95	57.11	66.7	75.07	62.51	33.3	33.4	33.4
KNN	50.00	50.00	50.00	50.0	50.00	50.00	58.3	59.95	57.11	75.0	80.04	71.40
DECISION TREE	58.3	59.95	57.11	41.7	42.88	40.04	75.0	80.04	71.40	58.3	59.95	57.11
BOOSTED TREE	41.7	42.88	40.04	50.00	50.00	50.00	66.7	75.07	62.51	**91.7**	**100**	**85.76**
	2-LITTLE FINGER with 1-INDEX FINGER			2-LITTLE FINGER with 3-MIDDLE FINGER			2-LITTLE FINGER with 4-RING FINGER			2-LITTLE FINGER with 5-THUMB FINGER		
	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp
LINEAR SVM	41.7	42.88	40.04	75.0	80.04	71.40	**100**	**100**	**100**	58.3	59.95	57.11
KNN	50.0	50.0	50.0	58.3	59.95	57.11	**91.7**	**100**	**85.76**	58.3	59.95	57.11

DECISION TREE	58.3	59.95	57.11	50.0	50.0	50.0	58.3	59.95	57.11	58.3	59.95	59.95
BOOSTED TREE	50.0	50.0	50.0	75.0	80.04	71.40	58.3	59.95	57.11	**83.3**	**74.9**	**100**
	3-MIDDLE FINGER with 1-INDEX FINGER			3-MIDDLE FINGER with 2-LITTLE FINGER			3-MIDDLE FINGER with 4-RING FINGER			3-MIDDLE FINGER with 5- THUMB FINGER		
	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp
LINEAR SVM	41.7	42.88	40.04	75.0	80.04	71.40	**91.7**	**100**	**85.76**	**91.7**	**100**	**85.76**
KNN	41.7	42.88	40.04	58.3	59.95	57.11	**83.3**	**74.9**	**100**	66.7	75.07	62.51
DECISION TREE	33.3	33.4	33.4	58.3	59.95	57.11	58.3	59.95	57.11	66.7	75.07	62.51
BOOSTED TREE	41.7	42.88	40.04	58.3	59.95	57.11	41.7	42.88	40.04	75.0	80.04	71.40
	4-RING FINGER with 1-INDEX FINGER			4-RING FINGER with 2-LITTLE FINGER			4-RING FINGER with 3-MIDDLE FINGER			4- RING FINGER with 5-THUMB FINGER		
	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp
LINEAR SVM	58.3	59.95	57.11	**91.7**	**100**	**85.76**	**91.7**	**100**	**85.76**	75.0	80.04	71.40
KNN	66.7	75.07	62.51	**91.7**	**100**	**85.76**	**83.3**	**100**	**74.96**	75.0	80.04	71.40
DECISION TREE	50.0	50	50	50.0	50	50	58.3	59.95	57.11	58.3	59.95	57.11
BOOSTED TREE	75.0	80.04	71.40	66.7	75.07	62.51	41.7	42.88	40.04	75.0	80.04	71.40
	5-THUMB FINGER with 1-INDEX FINGER			FINGER5-THUMB FINGER with 2-LITTLE			5-THUMB FINGER with 3- MIDDLE FINGER			5-THUMB FINGER with 4- RING FINGER		
	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp	A	Sn	Sp
LINEAR SVM	50.0	50	50	41.7	42.88	40.04	**91.7**	**100**	**85.76**	66.7	75.07	62.51

KNN	75.0	80.04	71.40	58.3	59.95	57.11	66.7	75.07	62.51	66.7	75.07	62.51
DECISION TREE	50.0	50	50	58.3	59.95	57.11	66.7	75.07	62.51	66.7	75.07	62.51
BOOSTED TREE	**91.7**	**100**	**85.76**	75.0	80.04	71.40	66.7	75.07	62.51	75.0	80.04	71.40

Where,

A = Accuracy in %

Sn = Sensitivity in %   Sp = Specificity in %

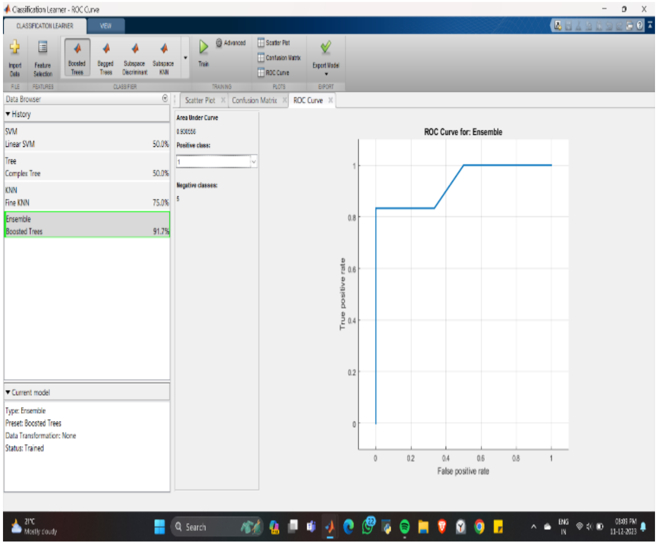

Fig 3. Index Finger and thumb Finger Boosted Tree Classification ROC curve.

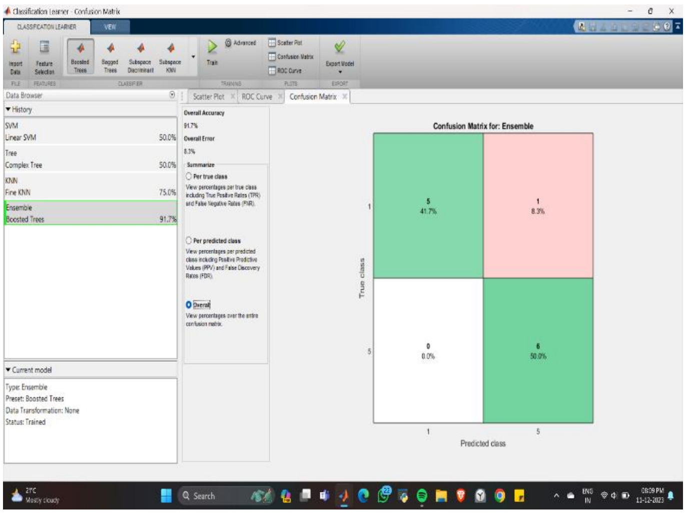

Fig 4. Index Finger and thumb Finger Boosted Tree Classification confusion matrix.

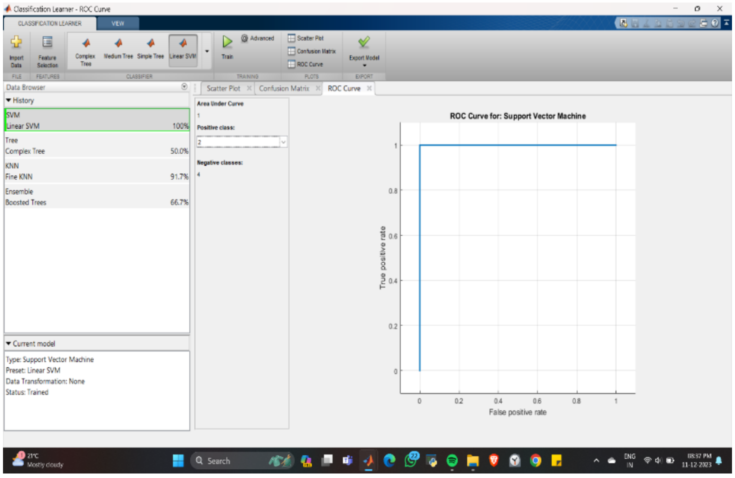

Fig 5. Little Finger and 4th Ring Finger linear SVM Classification ROC Curve.

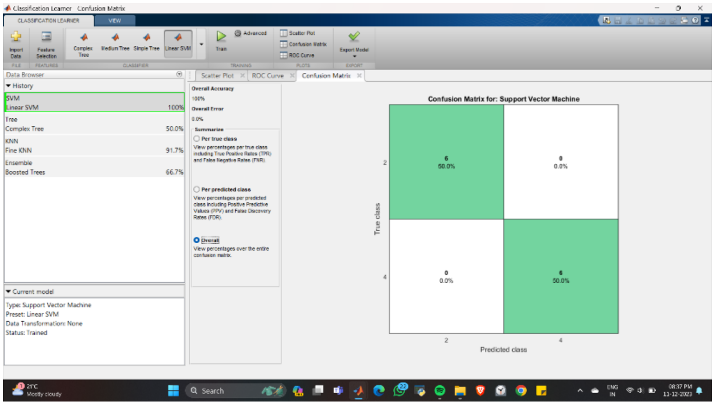

Fig 6. Little Finger and 4th Ring Finger linear SVM Classification confusion matrix.

Table 3. Comparison between previous and proposed method Accuracy.

S.N.	Previous Method Accuracy	Proposed Method Accuracy
	90% [21]	91.7%

VIII. Conclusion

The purpose of this study was to devise a new method for decomposing and classifying surface EMG signals using spectral coding approach in finger movements order to extract useful information. The proposed method is based on spectral domain signal denoising, which highlights the lowest distortion and allows the system to retrieve the smallest signal feasible. The resulting technology can greatly enhance signal retrieval accuracy. Spectral energy peaks as feature sets when applied to multiclass machine learning models performed better with accuracy and other parameters.

Support Vector Machine enhanced performance and it can help with the accurate classification. The subjects with exhibited significant different muscle activity at than those with the control group. The theme of the study also highlighted the importance of having a comprehensive understanding of the complex finger movements.

In this work, EMG signals are denoised and decomposed using various wavelet and energy localization in time scale plane is computed. It is found that this energy localization for different EMG signals is not similar. This energy localization of EMG signal can be used classify the EMG signal generated from different gesture and functionalities. For future direction, classification of the EMG signal will be done using the energy localization pattern.

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