Machine Learning and Signal Processing Based Analysis of sEMG Signals for Daily Action Classification

AYESHA SADIQ1, SAJID GUL KHAWAJA1, MUHAMMAD USMAN AKRAM1, AIMAL KHAN1, NORAH SALEH ALGHAMDI2 AND ARSALAN SHAUKAT1

1Department of Computer and Software Engineering, College of Electrical and Mechanical Engineering, National University of Sciences and Technology, Pakistan
2Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudia Arabia

Corresponding author: Norah Saleh Alghamdi (e-mail: nosalghamdi@pnu.edu.sa).

ABSTRACT
The way of living of many individuals around the world endures as a result of mental and physical disability associated with the movement of limbs. The usage of the assistive technology and systems will enhance the quality of affected peoples. In this situation, by transforming the physical actions from movement to a computer assisted application can open the way for solution. Surface Electromyography (sEMG) introduce the non-invasive procedure through which we can convert the physical activity to signals for classification and then practice it in applications. In this paper, we suggest a machine learning based scheme for the classification of 20 physical actions. The scheme follow up the distinct features from various signatures includes time-domain, frequency-domain and inter-channel statistics of a sEMG signal. Afterward, we performed a comparative examination of k-NN and SVM classifier by considering the feature set for multiple normal and aggressive activities. Effect of different arrangements of feature set has also been reported. Eventually, the SVM classifier gives an accuracy of 100% for 10 normal actions and 1-NN for a subgroup of features achieves an accuracy of 98.91% for 10 aggressive actions respectively. Additionally, we combine both SVM and 1-NN to propose a hybrid approach to classify 20 physical actions. The hybrid classifier gives an accuracy of 98.97% respectively. These recommendations are valuable for algorithm designer to select the finest approach by keeping in mind the resources available for the execution of an algorithm.

INDEX TERMS Segmentation, Feature extraction, Feature concatenation, Surface Electromyography, Support Vector Machine, Machine learning, Physical Activity Classification

I. INTRODUCTION
Recently, the physical disabilities cause major issues in daily life. There are several factors responsible for these disabilities. They include limb impairment or gait disorder, as the age increases [1], occupational hazards or traumas like sports accidents, drastically affect the life. Another major reason of disabilities in adults, is stroke [2]. Most of the affected ones require prosthetic or partial limb support to have assistance in day to day tasks. Aside from that, neurological disorders contribute towards physical disability either directly through hindrance in daily activities or through injuries caused through accidents [3]. Epilepsy is a common neurological disease, normally caused by the activities of nerve cells in brain [4], that affects more than 50 million people worldwide [5]. Hence it is need of the hour that a system is established which classifies physical signals in order to design prosthetic limbs or to get the notification of an epileptic attack well in time, in order to prevent injuries.

In this regard, a feasible solution could be to detect the intended motion and act accordingly. Surface Electromyo-
graphy (sEMG) is known to be the most accurate non-invasive performer for analyzing activities [6]. sEMG focuses on the electrical activity recordings that are produced when muscles move. Figure 1 is displayed to portray a side by side comparison of two signals, the sEMG signals observed against aggressive activities (like elbowing) and against the normal ones (like clapping). The nature of EMG signals allow its use for analysis in several cases, i.e. the development of modern human-computer interaction and identifying the ailments of muscular system, as well as in clinical and biomedical applications too [3], [7]. These signals are then used to examine medical abnormalities [8], [9], prosthetic limbs control [10], and emotion detection [7]. Numerous approaches include wavelet transform (WT), empirical mode decomposition (EMD) and filtering etc. have been suggested over the time to inspect the sEMG signals.

![Figure 1: Raw sEMG signal for two activities (Normal and Aggressive) signifying the difference](image-url)

An innovative algorithm is proposed in this paper that will classify multiple physical activities based on the sEMG signals. In the proposed framework a window of raw sEMG signal is primarily pre-processed to improve the variability among the signals of normal and aggressive activities. The processed window is then progressed to feature extractor where among the well-known time and frequency-based features for sEMG. Afterwards, inter-channel statistics (correlation and covariance) based signatures for classes are also extracted. The feature set is then fed to Support Vector Machines and K-Nearest Neighbor classifier to process the output label of the signal. The proposed technique even with the use of simple classifier performs better than the previous techniques with complex classifiers. The remaining paper is organized in the subsequent manner: Section II discusses the development of the algorithms proposed by the researchers for the recognition of physical activities using sEMG signals. Proposed framework is given in Section ?? which is followed by dataset description, experimentation and the results which are covered by Section III. At the end, the discussion on these results and the conclusion are detailed in Sections IV and V respectively.

II. RELATED WORK

In the literature, focus of the researches has been on numerous aspects including pre-processing, hand-crafted feature engineering and classification. With regard to classification, sEMG signals have been used for various activities ranging from muscle movement to actions identification leading to abnormality detection.

Akhundov et al. evaluates the quality of sEMG signal by conducting comparison of five distinct classifiers [11]. They used both supervised and unsupervised artificial neural networks. Supervised classifiers includes ANFIS (Adaptive Neuro Fuzzy Inference System) and PNN (Probabilistic Neural Network) whereas, Convolutional Neural Network (CNN), Alex-Net and ResNet50 were used as unsupervised classifiers. In this work, discrete wavelet transform (DWT) feature extraction algorithm is applied to extract mean absolute value, variance, root mean square, power spectrum ratio for the supervised learning algorithms. For all three CNNs they take an envelope extraction of an EMG signal and then transformed it to an Image for further processing. In the end, it was concluded that unsupervised artificial neural networks achieve better classification accuracy of 98% as compared to supervised artificial neural networks. Duan et al. elaborates the gesture motion recognition, the collection of EMG data takes place for 10 different hand gestures using Myo arm band [12]. They introduced multi task learning and multi label classification concepts to increase the generalization ability for motion recognition system. On comparing both CNN and SVM, CNN performs better classification accuracy of 94.06% than SVM because of weight sharing properties of CNN, it exhibits good translation invariance. Consequently, the spectrogram images acquired by evaluating SEMG signals and used as an image to CNN.

In [13], Sezgin et al. describe that EMG signal was analyzed using bispectrum which belongs to a family of higher order spectra. The binary class EMG dataset (normal action or aggressive action) was taken from U.

For more information, see https://creativecommons.org/licenses/by/4.0/
they take an envelope extraction of an EMG signal and then transformed it to an Image for further processing. In the end, it was concluded that unsupervised artificial neural networks achieve better classification accuracy of 98% as compared to supervised artificial neural networks. Duan et al. elaborates the gesture motion recognition, the collection of EMG data takes place for 10 different hand gestures using Myo arm band [12]. They introduced multi task learning and multi label classification concepts to increase the generalization ability for motion recognition system. On comparing both CNN and SVM, CNN performs better classification accuracy of 94.06% than SVM because of weight sharing properties of CNN, it exhibits good translation invariance. Consequently, the spectrogram images acquired by evaluating SEMG signals and used as an image to CNN.

In [13], Sezgin et al. describe that EMG signal was analyzed using bispectrum which belongs to a family of higher order spectra. The binary class EMG dataset (normal action or aggressive action) was taken from UCI machine learning repository. First they analyzed EMG signals using bispectrum and afterwards QPCs (Quadratic Phase Coupling) of each EMG segment was calculated. Next, the features of the analyzed EMG signals were fed into learning machines in order to classify the EMG signals as either belonging to normal activity or aggressive activity. The performance comparison was based on ANN (Artificial neural networks), SVM (support vector machine), LR (Logistic regression), LDA (Linear discriminant analysis), and ELM (an extreme learning machine) classifiers. The training testing rate for ELM was randomly chosen as 50:50 from the extracted features of EMG. It shows that ELM is more efficient and gives higher classification accuracy of 99.75% as compared to conventional learning machines. In [14], Mishra et al. demonstrated that improved EMD (Empirical Mode Decomposition) method in which traditional EMD method followed by median filter to remove the impulse noise from IMFs (intrinsic mode functions) performs better. Amplitude modulation bandwidth, frequency modulation bandwidth, spectral moment of power spectral density and first derivative of instantaneous frequency are the features extracted from improved IMFs for the detection of ALS (Amyotrophic Lateral Sclerosis) and Normal sEMG signals. In [15], Jana et al. discussed the differentiation of aggressive activities from normal activities based on ANFIS (adaptive neuro-fuzzy inference system). In this work, discrete wavelet transform was used for the extraction of features from EMG signals. The EMG signals decomposed using DB-4 (Daubechies) wavelet up to level 5 and approximate coefficients are extracted. Approximate coefficients from the signals are taken as input to the ANFIS module to classify the physical activities. They used the training testing ratio as 70:30. The accuracy of proposed ANFIS based method using features was found to be 98% for binary class problem. Alaskar et al. presented a novel approach in which three convolutional neural networks are evaluated using the two time-frequency representations [16]. The Spectrogram and Scalograms images are produced from surface EMG signals as the input dataset of CNNs. From the analysis, it can be proven that EMG signal representation affects the performance of CNNs. Spectrogram Images are used as the input dataset to the convolutional neural network in order to differentiate between normal and aggressive activity. As a result, this algorithm achieved the accuracy of 94.61% for a binary class problem.

Moving towards action classification, several researchers have presented models for classification of multiple actions either from normal or aggressive action. Sukumar et al. perform identification of ten normal physical activities like bowing, clapping, waving, jumping, etc. of sEMG signal based on Variational Mode Decomposition (VMD) for the analysis of musculoskeletal disorder [17]. VMD decomposes the signal into several modes. These modes are used for the extraction of statistical features like coefficient of variance, zero crossing rate, standard deviation, entropy, mean and negentropy. Next, the extracted features are fed into MC-LS-SVM (multi class least square support vector machine) with RBF kernel for the discrimination of 10 normal activities and the system achieved an accuracy of 98.17% as compared to existing methods. In [18], Subasi et al. proposed an EMG pattern recognition system for the exoskeleton robot control and rehabilitation purpose. In this study, multi-scale principal component analysis is used for the de-noising of various sEMG signals. The discrete wavelet transform based statistical features includes mean absolute value, mean power, standard deviation and ratio of mean absolute value have been extracted. The extracted features are then fed into the SVM with gaussian kernel. The experimental results show that the proposed system got an accuracy of 92.27% for 10 normal classes. Sravani, et al. discussed an extreme learning machine (ELM) classifier based on FAWT (Flexible Analytic Wavelet Transform) for the classification of multi-class problem in [19]. FAWT decomposes EMG signals into eight sub bands. Following features including negentropy, mean absolute value, variance, modified mean absolute value, Tsallis entropy, simple square integral, waveform length and integrated EMG are extracted from each decomposed sub band. After that these features are fed into the ELM classifier for the identification of 10 normal activities and the proposed algorithm achieves an accuracy of 99.36%. Moreover, In [20], Demir et al. discussed another method in which spectromaps i.e. a time frequency based image is used as input to pre-trained convolutional neural networks. Deep feature extraction is implemented using VGG-16 and Alex Net whereas SVM is used for the categorization of sEMG based Physical activities. The highest accuracy of 99.04% for 10 normal activities includes bowing, handshaking, clapping, standing, seating, waving, jumping, hugging and walking etc. is achieved by the deep feature concatenation of fully connected layers of both Alex Net and VGG-16.

Furthermore, an improved classification framework for the multi-class problem is proposed in [21]. The EMG dataset has been taken from machine learning repository. The dataset is comprised of 20 physical activities i.e. 10 normal actions
and 10 aggressive actions. The ten normal actions include bowing, hand shaking, hugging, clapping, etc. The ten aggressive actions include elbowing, hammering, Headering, slapping, etc. The classification framework includes probabilistic neural network and subspace KNN. The features are extracted from different signal signatures includes time domain, inter channel correlation, modified spectral moment based features, and local binary patterns. Afterwards sequential forward feature selection algorithm is used to reduce the dimensions. The classification is performed using multiple classifiers like subspace KNN, probabilistic neural network, cubic SVM, gaussian SVM, functional KNN, Bagged trees and LDA with the selected subset of features. But, subspace KNN gives highest accuracy of 93.91% for 20 physical actions. In the current paper, as described in the following sections, we address the above mentioned multi-class classification problem.

In the previous literature, the researchers mostly address the binary class problem of physical activities using both traditional machine learning and deep learning. They also address the multi-class normal actions but didn’t focus on multi class aggressive activities. There is only research paper that directs the problem of 20 physical activities. In our paper, we address the classification of Multi class problem of 20 physical actions as well as 10 aggressive activities and 10 normal activities based on multi-channel EMG data. Following are the contributions made in the article.

- We propose an improved feature set consisting of selected feature subsets from different feature signatures including time domain (TD) statistics, the inter-channel correlation and co-variance, the spectral moment ratios and products and the spectral band powers based statistics.
- We have combined the SVM and 1-NN models to design a hierarchical classifier to improve the classification performance.
- We perform the classification of multiple aggressive activities based on 1-NN model with selected subset of features and results in an accuracy of 98.91%.
- Finally, we also demonstrate that by combining SVM and 1-NN models results in an accuracy of greater than 98.97% for 20 physical actions.

In our paper, we consider the problem of multi-class classification of physical activities which is based on 8-channel of sEMG data. The proposed approach is split into pre-processing of raw sEMG signals, feature extraction and classification into 20 categories. The system level flow diagram representing the proposed framework is presented in Figure 2.

A. PRE-PROCESSING AND SEGMENTATION

The first step in our proposed methodology is to pre-process the multi-channel sEMG signals. Let us consider the length of each signal \((s_{ch})\) to be of \(D\) duration sampled at sampling rate \(f_s\) having \(c\) channels. In this step, each record of sEMG is segmented into smaller chunks, \(\varphi_i\), using rectangular window \((wind(l))\) of length \(W\), where \(W < \text{length of the signal using equation 1.}\)

\[
\varphi = s_{ch}(l) * wind(l)
\]

whereas,

\[
wind(l) = \begin{cases}
1 & 0 \leq l \leq W - 1 \\
0 & \text{otherwise}
\end{cases}
\]

The rectangular window is moved over the whole signal in sliding manner with an overlap of 25% as shown in Fig. 3. The length \(W\) of the window is managed by the sampling frequency through which the desired signal is acquired. Note that after segmentation now each sEMG signal is converted to \(N_e\) trials of length \(W\) having \(ch\)-channels.

After that, feature extraction is made on each of the sub-window \((s)\) from every sEMG pattern.

B. FEATURE VECTOR GENERATION

In order to generate a valid feature vector our proposed methodology makes use of diverse features from both time and frequency domain. It contains signatures from Time Domain, Frequency Domain and Inter-Channel Correlation and Covariance. In the subsections we elaborate on these features.

1) Similarity Index and Covariance

This subset of features is based on channel wise analysis among the corresponding segment of two channels \((ch_\alpha)\) and \((ch_\beta)\) of a sEMG signal \(\varphi\), where \(\alpha \neq \beta\). The channel wise pairing for calculation of these features is shown in Figure 4.

Initially, maximum correlation between 2 channel is computed based on work done in [21] using equation 2.

\[
correlation(ch_\alpha, ch_\beta) = \max(\text{Corr}(\varphi_{i,\alpha}(l), \varphi_{i,\beta}(l)))
\]

(2)

Additionally, we propose the use of an additional feature which is the maximum covariance between 2 channels using equation 3.

\[
covariance(ch_\alpha, ch_\beta) = \max(\text{Cov}(\varphi_{i,\alpha}(l), \varphi_{i,\beta}(l)))
\]

(3)

Equations 2 and 3 represents the maximum correlation and covariance respectively between the segments of two channels \(ch_\alpha\) and \(ch_\beta\) of a sEMG signal. As we have 8 channels so we can get a feature vector \(f_{ICS}\) of \(7 \times 8\) values after performing the maximum cross correlation and covariance between corresponding channels of the signal.

2) Power Spectral Density

The spectral features were previously proposed for the identification of a sEMG pattern in [22]. In the proposed technique, power spectral estimate is calculated using Burg’s transform.
3) Log Moments of Fourier Spectra

The logarithms of moments and their ratios from the frequency domain are computed for the sEMG segments based on [21]. The total 17 log moment ratios have been calculated for each channel. Hence we get a feature vector, $f_{LMF}$, of length $17 \times 8$ for a segment of EMG activity.

4) Time Domain Statistics

One of the most frequently used signatures is time domain analysis of sEMG signal. This modality shows how a signal changes its parameters or shape with respect to time.

Amplitude: The maximum amplitude of the signal can be expressed as in equation 4:

$$f_{t1} = \max(|\varphi_{i}(l)|^2)$$

(4)

Root Mean Square: The RMS represents the square root of the average power of the EMG signal for a given period of time as shown in equation 5.

$$f_{t2} = \sqrt{\frac{1}{W} \sum_{l=1}^{W} |\varphi_{i}(l)|^2}$$

(5)

Here, ‘s’ represents the segment of a sEMG signal and ‘W’ is the length of the segment.

Variance: Variance is used to measure the power of a signal as expressed in equation 6.

$$f_{t3} = \frac{1}{W - 1} \sum_{l=1}^{W} |\varphi_{i}(l)|^2$$

(6)

Waveform length: WL is a cumulative variation of the EMG that can indicate the degree of variation about the EMG signal [23]. It can be calculated using equation 7.

$$f_{t4} = \sum_{l=1}^{W-1} |\varphi_{i}(l + 1) - \varphi_{i}(l)|$$

(7)

Mean Absolute Value: It is described as the average of the summation of the absolute value of signal [23] and can be calculated using equation 8.

$$f_{t5} = \frac{1}{W} \sum_{l=1}^{W} |\varphi_{i}(l)|$$

(8)

Simple Square Integral: This is defined as the summation of square values of a sEMG signal amplitude [23], and it can be computed using equation 9.
between two adjacent samples that exceeds a defined threshold.

**Zero Crossing:** ZC counts the times that the signal changes sign [23]. The two given contiguous sEMG amplitude samples \( \varphi_i(l) \) and \( \varphi_i(l + 1) \) the ZC can be calculated using equation 10.

\[
f_{t7} = \sum f(s)
\]

where \( f(s) \) is set as 1 or 0 for consecutive samples of a segment.

\[
f(s) = \begin{cases} 
1 & \text{sgn}(\varphi_i(k)) \neq \text{sgn}(\varphi_i(k - 1)) \\
0 & \text{otherwise}
\end{cases}
\]

where \( k \in 1, 2, \cdots, W - 1 \)

**Slope Sign Change:** SSC counts the times the slope of the signal changes signs [23]. Given three contiguous EMG amplitude samples \( \varphi_i(l - 1), \varphi_i(l), \) and \( \varphi_i(l + 1) \), the number of slope sign changes is calculated using equation 11:

\[
f_{ts} = \sum f(s)
\]

where \( f(s) \) is set as 1 or 0 for three consecutive samples of a segment.

\[
f(s) = \begin{cases} 
1 & \text{sgn}(\varphi_i(k)) \neq \text{sgn}(\varphi_i(k - 1)) \\
0 & \text{otherwise}
\end{cases}
\]

**Willison Amplitude:** It represents the total counts that are responsible for the variation in the sEMG signal amplitude between two adjacent samples that exceeds a defined threshold [23]. It is calculated using equation 12.

\[
f_{t9} = \sum_{l=1}^{W-1} f(\mid\varphi_i(l + 1) - \varphi_i(l)\mid)
\]

where \( f(s) \) is calculated as:

\[
f(s) = \begin{cases} 
1 & s > \text{threshold} \\
0 & \text{otherwise}
\end{cases}
\]

**Integrated EMG:** This is usually used as a pre-activation index for muscle movement. It is the integration of the rectified sEMG signal [23]. It can be simplified as the summation of the absolute values of the sEMG amplitude as shown in equation 13.

\[
f_{t10} = \sum_{l=1}^{W} \mid\varphi_i(l)\mid
\]

\[
W
\]

**Log detector:** It is a feature that is good at estimating the exerted force [23], and it can be defined using equation 14.

\[
f_{t11} = e^{\frac{1}{W} \sum_{l=1}^{W} \log(\mid\varphi_i(l)\mid)}
\]

**Myopulse percentage rate:** MYOP is defined as the mean of Myopulse output in which the absolute value of EMG signal exceeds the pre-defined threshold value [23] and can be calculated as equation 15.

\[
f_{t12} = \frac{1}{W} \sum_{l=1}^{W} f(\varphi_i(l))
\]

Where, ‘s’ is the wavelet coefficient of respective channel, and ‘W’ is the window length of coefficient.

**Difference absolute standard deviation value:** DASDV is another frequently used EMG feature [23], and it can be expressed as

\[
f_{t13} = \sqrt{\frac{\sum_{l=1}^{W-1} (\varphi_i(l + 1) - \varphi_i(l))^2}{W - 1}}
\]

**Enhanced Mean Absolute value:** It is a feature that is good at estimating the exerted force [23], and it can be defined as the following function whereas, the parameter \( p \) is used to identify the influence of sample within the signal

\[
f_{t14} = \frac{1}{W} \sum_{l=1}^{W} |\varphi_i(l)|^p
\]

where \( p \) is set using the following

\[
p = \begin{cases} 
0.75 & \text{0.2W} \leq l \leq 0.8W \\
0.5 & \text{otherwise}
\end{cases}
\]

**Enhanced Wavelength:** In EMAV and EWL, a greater number of \( p \) is utilized for 20% to 80% of regions. This is because by strengthening the information content at the middle region, more valuable information can be obtained. In this way, the quality of features can be improved. Furthermore, it is seen that EMAV and EWL are the extension of MAV and WL with simple modification, and thus no much additional computational time is required in the evaluation as provided in [23].

\[
f_{t15} = \sum_{l=2}^{W} \mid\varphi_i(l) - \varphi_i(l - 1)\mid^p
\]

where \( p \) is set using the following

\[
p = \begin{cases} 
0.75 & \text{0.2W} \leq l \leq 0.8W \\
0 & \text{otherwise}
\end{cases}
\]

**Modified Mean Absolute Value:** Modified mean absolute value (MMAV) is an extension of MAV feature by assigning the weight window function as in [23]. Mathematically, MMAV can be computed as

\[
f_{t16} = \frac{1}{W} \sum_{l=1}^{W} (w_l |\varphi_i(l)|)
\]

where \( w_l \) is set using the following
\[
    w_l = \begin{cases} 
    0.75 & 0.2W \leq l \leq 0.75W \\
    0.5 & \text{otherwise}
    \end{cases}
\]

**Modified Mean Absolute Value 2:** This is another extension of mean absolute value feature by keeping the continuous weight window function as in [23], it can be expressed using equation 19 but with modified value of \( w_l \). The modified value of \( w_l \) is set using

\[
    w_l = \begin{cases} 
    \frac{1}{W} & 0.25W \leq l \leq 0.75W \\
    \frac{l - W}{W} & \text{otherwise}
    \end{cases}
\]

**Maximum Fractal Length:** This is a recent technique that is used for measuring low-level muscle activation. When the smallest scale is set to one, the definition of this feature corresponds to a modified version of WL by considering the RMS and logarithm functions which can be calculated using equation 20 similar to [24].

\[
    f_{18} = \log \left( \frac{W - 1}{W} \sum_{l=1}^{W-1} (\varphi_{i}(l+1) - \varphi_{i}(l))^2 \right)
\]  

(20)

**Average Amplitude Change:** Average amplitude change (AAC) is nearly equivalent to WL feature, except that wavelength is averaged as shown in [25]. It can be formulated using equation 21.

\[
    f_{19} = \frac{1}{W} \sum_{l=1}^{W-1} |\varphi_{i}(l+1) - \varphi_{i}(l)|
\]  

(21)

**Kurtosis:** Kurtosis is a time domain based feature. Kurtosis is known as a statistical method that is used to describe the distribution and identifies the tendency of peak data. Kurtosis level data is determining by comparing the peak of the curve inclination data as given in [26].

**Skewness:** Skewness is one of the EMG signal features that is included in the time domain function. Skewness is defined as the inclination distribution data. The data is said to have a normal distribution when the the average value, the median value and data mode are on a single line in the curve. If these values are not located on one line in the curve then skewness or heeling occurs as discussed in [26].

After calculating the above mentioned time domain features for each channel, all features are grouped to form a feature vector \( f_t \). As the number of channels are eight, so \( 21 \times 8 \) will gives us the feature vector of length 168.

**C. CLASSIFIER**

The extracted feature vector mentioned in section II-B is then fed into a classifier to predict the activity class out of 20 possible activities. In this work, we implemented the various classification techniques with focus toward using a simple classifier such as Support Vector Machine and K-Nearest Neighbor. The aggressive and Normal activities is classified by KNN and SVM. After that, we hybridized both SVM and KNN for the better classification results. This hybrid approach performs better classification accuracy for multi-classes. The performance of classifiers is evaluated using classification accuracy, sensitivity, specificity, precision, \( F_1 \)-score, and kappa coefficient.

1) **Support Vector Machine**

A support vector machine (SVM) is a supervised machine learning algorithm which is used for both classification and regression problems. SVM is a fast and dependable classification algorithm that performs very well with a limited amount of data to analyze. In this algorithm, each data value is plotted as a point in an N-dimensional space whereas N indicates the number of features/dimensions. For the classification of data, SVM finds the hyper-plane that does not only separates the two classes but also maximizes the margin (i.e. the distance between the margin and the closest data point of each class). In this work, to classify the normal actions the SVM model performs better classification as compared to k-NN model discussed in experimentation section III-B. The performance of the classifier is analyzed using 5-fold cross validation, the ‘Quadratic’ kernel function, and ‘One vs. all’ multi-class method.

2) **k-Nearest Neighbor**

k-Nearest Neighbor is one of the most basic and easy-to-implement supervised machine learning algorithm used for both classification and regression problems. It is widely used to recognize patterns, intrusion detection, and data mining. According to this classifier, the value of data point is determined by the data points around it or based on the majority voting principle. The mechanism of k-NN is to find the distances (i.e., Euclidean, Manhattan, Minkowski, hamming etc.) between a new data point and all the neighbor examples in the training data, selecting the specified number neighbor examples (k) closest to the new data point. Afterwards it votes for the most frequent label in classification problems. In our proposed methodology, k-NN is used for the classification of aggressive actions with a subset of features and perform better classification as compared to SVM model discussed in experimentation section. The performance of the classification model is analyzed by setting the value of \( k = 1 \) whereas the distance metric is set as Manhattan distance which is also known as city block distance. It is the sum of absolute differences between points across all the dimensions. Equation 22 is the generalized formula for calculation of distance for an n-dimensional space.

\[
    dist = \frac{1}{W} \sum_{l=1}^{W-1} |s_{ch}(l+1) - s_{ch}(l)|
\]  

(22)

3) **Hybrid approach (1-NN and SVM)**

In Hierarchical classification model, the classification models are grouped together in the form of hierarchy in order to
solve the problem of multi-class classification. Considering the given EMG data the classification is well separable and discriminant for two class problem. This can be visualized from Figure 5 shows the effect of mean EMG signals of all ten aggressive and all ten normal activities.

![Mean Normal v/s Aggressive classes](image)

**FIGURE 5.** Mean of Normal v/s Aggressive classes

On considering this, we started the classification form binary and leading towards the multi-class problem (10 normal classes, 10 aggressive classes and 20 physical action classes etc.)

Finally, we combine both SVM and 1-NN classification model in hierarchical manner to classify the 20 different physical actions as shown in Figure 6. First of all, we trained three different models using SVM and 1-NN classifiers. The Binary class model is trained using 1-NN which is based on 440 features, as it classifies the data into either normal or aggressive class. Another SVM based model uses the features from all signatures (i.e. 440 number of features) in order to classify the 10 normal actions. The 1-NN based model uses the subset of features (i.e. 272 features from inter channel correlation and covariance, Log moment of Fourier spectra and spectral band power domains) for the classification of 10 aggressive activities.

![Hybrid classifier for multi-class classification](image)

**FIGURE 6.** Hybrid classifier for multi-class classification

### III. EXPERIMENTATION AND RESULTS

#### A. DATASET

The dataset of physical activities that is used for the analysis of our proposed methodology is taken from UCI Machine Learning Laboratory database [27]. The dataset contains sEMG data of 4 subjects, 3 males and 1 female of age range between 25 and 30. Each subject performed a total of 20 actions which are divided into 10 normal (i.e. Bowing (1), Clapping (2), Hugging (3), Handshaking (4), Jumping (5), Running (6), Seating (7), Standing (8), Walking (9), Waving (10)) and 10 aggressive actions (i.e. Elbowing (11), Frontkicking (12), Hammering (13), Headering (14), Kneeling (15), Pulling (16), Punching (17), Pushing (18), Sidetapping (19), Slapping (20)). sEMG signals collected from these subjects has 8 channels, 4 each for the upper limb and lower limbs, where each channel corresponds to time series data from each electrode which consists of approximately 10000 samples.

#### B. EXPERIMENTATION

The dataset of physical activity as stated above contains approximately 10000 samples per action per subject. Firstly, these samples are divided into multiple overlapping segments where the interval of each segment is set to 1000 with an overlap of 25%. Thus each activity can be subdivided to get a healthy sample space, having 600-900 segments which depends on signal length. Secondly, the sample space is further used to extract a feature vector against each segment using different signatures which have been discussed in section ??.

The experimental setup for validation consists of measuring this parameter for a 20-class problem. SVM and k-NN have been applied to classify using complete set of features and their subset. The complete feature set has been sub-divided into subsets containing individual feature type.
(time, frequency etc.) and its possible combinations to get the best classification rate. The details of these subsets are available in Table 1.

**TABLE 1. Feature subset details used for different experimentation**

| Name       | Feature Set                              |
|------------|------------------------------------------|
| All_CW     | All features (Channel wise)              |
| All_MW     | All features (TDS Mean wise)             |
| Subset-1   | ICS+LMF (Channel wise)                   |
| Subset-2   | ICS+LMF+PSD                              |
| Subset-3   | ICS+PSD                                  |
| Subset-4   | LMF+PSD                                  |
| Subset-5   | TDS+ICS                                  |
| Subset-6   | TDS+ICS+LMF                              |
| Subset-7   | TDS+ICS+LMF (TDS Mean Wise)             |
| Subset-8   | TDS+ICS(TDS Mean Wise)                  |
| Subset-9   | TDS+ICSPS+D                              |
| Subset-10  | TDS+ICSPD(TDS Mean Wise)                |
| Subset-11  | TDS+LMF                                  |
| Subset-12  | TDS+LMF(TDS Mean Wise)                  |
| Subset-13  | TDS+LMF+PSD                              |
| Subset-14  | TDS+LMF+PSD (TDS Mean Wise)             |
| Subset-15  | TDS+PSD                                  |
| Subset-16  | TDS+PSD (TDS Mean Wise)                 |

In view of measuring the performance of our proposed algorithm, different parameters including accuracy, sensitivity, specificity, f-measure, precision, misclassification rate and Kappa coefficient have been calculated. The 5-fold cross validation for SVM and k-NN is used for classification of our data into 20 and 10 class each.

Initially, the complete feature vector of length 440 is passed to the classifiers to classify data into 20 and 10 class respectively for normal and aggressive actions. Table 2 represents that the subset contains features from Inter Channel Statistics, Log moments of Fourier spectra and power spectral density have better classification accuracy for 10 aggressive classes.

**TABLE 2. Comparison of 1-NN based classification using various subset of features**

|       | 10 Normal (%) | 10 Aggressive (%) | 20 Class (%) |
|-------|---------------|-------------------|--------------|
| All_CW| 97.722        | 89.409            | 98.971       |
| Subset-1| 97.515        | 85.743            | 90.759       |
| Subset-2| 98.136        | 98.91             | 91.991       |
| Subset-3| 97.929        | 85.132            | 91.478       |
| Subset-4| 97.722        | 86.558            | 91.478       |
| Subset-5| 96.273        | 86.761            | 90.965       |
| Subset-6| 97.722        | 88.798            | 91.273       |
| Subset-7| 97.308        | 86.558            | 92.094       |
| Subset-8| 85.921        | 80.04             | 79.979       |
| Subset-9| 96.687        | 86.965            | 91.375       |
| Subset-10| 92.132        | 85.539            | 88.09        |
| Subset-11| 96.894        | 85.336            | 89.835       |
| Subset-12| 97.101        | 87.169            | 89.322       |
| Subset-13| 97.722        | 86.965            | 87.782       |
| Subset-14| 96.687        | 87.78             | 89.014       |
| Subset-15| 95.445        | 83.095            | 89.219       |
| Subset-16| 90.062        | 78.615            | 83.059       |

It is clear from Table 3 that SVM model performs better using all features to classify 10 normal actions as compared to k-NN model. So, from this observation we can combine both SVM and KNN models to classify 20 physical actions.

Moreover, a thorough analysis of SVM for classification of physical actions using complete and subset of features is taken but subset of features didn’t give good classification accuracy.

**TABLE 3. SVM based classification using various subset of features**

|       | 10 Normal (%) | 10 Aggressive (%) | 20 classes (%) |
|-------|---------------|-------------------|---------------|
| All_CW| 100           | 86.761            | 91.067        |
| All_MW| 98.757        | 84.725            | 92.299        |
| Subset-1| 98.343        | 79.633            | 89.63         |
| Subset-2| 98.964        | 84.317            | 91.478        |
| Subset-3| 96.066        | 83.299            | 87.577        |
| Subset-4| 98.136        | 75.967            | 87.371        |
| Subset-5| 98.343        | 81.466            | 91.273        |
| Subset-6| 99.378        | 85.743            | 91.683        |
| Subset-7| 97.308        | 82.892            | 89.527        |
| Subset-8| 91.304        | 67.006            | 77.31         |
| Subset-9| 98.343        | 86.15             | 91.17         |
| Subset-10| 96.066        | 82.077            | 88.193        |
| Subset-11| 98.55         | 82.484            | 89.014        |
| Subset-12| 98.136        | 76.171            | 85.318        |
| Subset-13| 98.343        | 84.114            | 90.759        |
| Subset-14| 98.55         | 79.226            | 88.706        |
| Subset-15| 98.136        | 82.688            | 89.014        |
| Subset-16| 96.066        | 74.338            | 84.702        |

**IV. DISCUSSION**

Non-invasive signal acquisition sensors such as sEMG can play an important role in uplifting the life style of people suffering from various neurological and physical disabilities/diseases. Correct classification of physical activities is the main step in providing a feasible solution to such patients. In this write-up, we have proposed a framework which can assist in designing an assistive technology by providing classification of physical actions.

In our methodology, use of pre-processing significantly affects the classification accuracy, both for comprehensive feature set and an optimal subset. The results clearly indicate that SVM and 1-NN using the feature combinations of $f_{ICS}$ and Frequency Domain Analysis provide better classification accuracy in comparison to complete feature set and other classifiers. The respective classification accuracies for 1-NN and SVM are 98.91% and 100%.

**A. BINARY CLASSIFICATION**

The confusion matrix is obtained by performing 80:20 split on 974 observations of binary class (Normal and Aggressive) using 1-NN classifier on considering features from all signatures. The resultant model has been trained on 780 samples whereas has it has been tested on 194 samples. The model gives us the testing accuracy of 100% which is reflected in Table 4.
### TABLE 4. Confusion matrix for binary classification using proposed technique

| Output Class | 98  | 0   |
|--------------|-----|-----|
| Target Class | 0   | 96  |

#### B. NORMAL ACTIVITIES CLASSIFICATION

The confusion matrix is obtained by performing 80:20 split on 483 observations of 10 normal physical activities using SVM classifier on considering features from all signatures. The resultant model has been trained on 393 samples whereas it has been tested on 90 samples. Hence, the model gives us the testing accuracy of 100% as shown in Figure 7.

#### C. AGGRESSIVE ACTIVITIES CLASSIFICATION

The confusion matrix is obtained by performing 80:20 split on 491 observations of 10 Aggressive actions using 1-NN classifier on considering the subset of features from the signatures include Intercal channel statistics, Log moment of Fourier spectra and Power spectral density. In this classification, Time domain features are not considered. The resultant model has been trained on 399 samples whereas it has been tested on 92 samples. Hence, the model gives us the accuracy of 98.91% as shown in Figure 8.

#### D. ALL ACTIVITIES (HYBRID CLASSIFIER)

The confusion matrix is obtained by testing 194 observations of 2 class using 1-NN classifier on considering the features from all different signatures. As a result, optimized k-NN classify the samples into either normal class or aggressive class. The samples classified as Normal are fed into the optimized SVM classifier (trained using all features) whereas the samples classified as aggressive are fed into the optimized KNN classifier which are trained on the subset of features from the signatures include $f_{ICS}$, $f_{LMF}$ and $f_{PSD}$. Hence the 20 class classification is performed by training two different classifiers in hierarchy. The model gives us the average testing accuracy of 98.97% as shown in Figure 9.

The comparison between performance measure, such as sensitivity, specificity and precision, f-measure, misclassification rate and kappa constant is shown in Table 5 from both binary classes and multi-classes. Specificity and sensitivity indicates the true negative rate and true positive rate of our classifier against proposed feature set. Precision determines the true positive rate that genuinely belong to that class.

#### TABLE 5. Comparison of performance parameters

|                   | Binary | 10 Normal | 10 Aggressive | 20 class |
|-------------------|--------|-----------|---------------|----------|
| Accuracy          | 1      | 0.9891    | 0.9897        | 0.9897   |
| Sensitivity       | 1      | 0.9889    | 0.8505        | 0.9913   |
| Specificity       | 1      | 0.9988    | 0.9831        | 0.9995   |
| Precision         | 1      | 0.99     | 0.8564        | 0.9896   |
| FPR               | 0      | 0.0012    | 0.0169        | 5.41E-04 |
| F1-score          | 1      | 0.9889    | 0.8466        | 0.9899   |
| Kappa             | 1      | 0.9383    | 0.1546        | 0.8915   |

The performance comparison of our proposed method with the latest research work is shown in Table 6. The obtained features from different signal signatures for each segment gives a good response to the classification of 20 physical actions of sEMG. It provides robustness to the variation between classes. This result shows that the hybridization
of SVM and KNN models provides better performance for automatic identification of surface EMG signals.

| Author                        | Accuracy (%) | No. of Classes |
|-------------------------------|--------------|----------------|
| Turla paty et al, 2019 [21]   | 93.91%       | 20-classes     |
| **Proposed methodology**     | **98.97%**   | **20-classes** |
| Sukumar et al, 2018 [17]      | 98.17%       | 10-classes normal |
| Demir et al, 2019 [20]        | 99.04%       | 10-classes normal |
| Sravani et al, 2020 [19]      | 99.36%       | 10-classes normal |
| **Proposed methodology**     | **100%**     | **10-classes** |
| A. Swetapadma et al. [15]     | 98%          | 2-classes       |
| H. Alaskar et al. [16]        | 94.61%       | 2-classes       |
| A.Kumar et al. [7]            | 99.03%       | 2-classes       |
| **Proposed methodology**     | **100%**     | **2-classes**   |

V. CONCLUSION
In this study, we have proposed a multi-class classification framework based on SVM and KNN to categorize the physical actions using the features derived from eight channels of the surface EMG data. A set of 440 features were extracted from various signatures including the statistical features of time domain, the inter channel cross correlation and covariance, logarithm of moments of Fourier spectra and the mean band power of power spectral density estimates based on the Burg’s algorithm. The results show that the SVM performs better for the classification of ten normal classes whereas KNN improves the accuracy for the ten aggressive classes. In the case of 20 class classification, adopting hybrid approach by combining SVM with KNN models improves the accuracy especially if the dataset is limited. The classification results of proposed method show better performance in terms of accuracy as compared to other existing methods.

REFERENCES
[1] Henning Stolze, Stephanie Klebe, Christoph Baeccker, Christiane Zechlin, Lars Friege, Sabine Pohle, and Gunther Deuschl. Prevalence of gait disorders in hospitalized neurological patients. Movement disorders: official journal of the Movement Disorder Society, 20(1):89–94, 2005.
[2] Tommaso Prietoni, Vincent Crocher, Agnes Roby-Brami, and Nathanael Jarrasse. Upper-limb robotic exoskeletons for neurorehabilitation: a review on control strategies. IEEE reviews in biomedical engineering, 9:4–14, 2016.
[3] Mariska Van Den Broek, Ettoore Beghi, and RESIt-1 Group. Accidents in patients with epilepsy: types, circumstances, and complications: a European cohort study. Epilepsia, 45(6):667–672, 2004.
[4] Robert S Fisher, Carlos Accevedo, Alexis Arzimanoglou, Alicia Bogacz, J Helen Cross, Christian E Elger, Jerome Engel Jr, Lars Forssen, Jacqueline A French, Mike Glynn, et al. Ilae official report: a practical clinical definition of epilepsy. Epilepsia, 55(4):475–482, 2014.
[5] Epilepsy. https://www.who.int/news-room/factsheets/detail/epilepsy. Accessed: 2021-08-12.
[6] Charles Long and Mary Eleanor Brown. Electromyographic kinesiology of the hand: muscles moving the long finger. JBJS, 46(8):1683–1706, 1964.
[7] Mahmoud Tavakoli, Carlo Benussi, and Joao Luis Lourenco. Single channel surface emg control of advanced prosthetic hands: A simple, low cost and efficient approach. Expert Systems with Applications, 79:322–332, 2017.
[8] Varun Bajaj and Anil Kumar. Features based on intrinsic mode functions for classification of emg signals. International Journal of Biomedical Engineering and Technology, 18(2):156–167, 2015.
[9] Rajat Emmanuel Singh, Kamran Iqbal, Gannon White, and Jennifer K Holtz. A review of emg techniques for detection of gait disorders. Artificial Intelligence-Applications in Medicine and Biology, 2019.
[10] Daniela Girardi, Filippo Lanubile, and Nicole Novielli. Emotion detection using noninvasive low cost sensors. In 2017 Seventh international conference on affective computing and intelligent interaction (ACII), pages 125–130. IEEE, 2017.
[11] Riad Akhundov, David J Saxby, Suzie Edwards, Suzanne Snodgrass, Phil Clausen, and Laura E Diamond. Development of a deep neural network for automated electromyographic pattern classification. Journal of Experimental Biology, 222(5):jeb198101, 2019.
[12] Na Duan, Li-Zheng Liu, Xian-Jia Yu, Qingsing Li, and Shih-Ching Yeh. Classification of multichannel surface-electromyography signals based on convolutional neural networks. Journal of Industrial Information Integration, 15:201–206, 2019.
[13] Nemcettin Sezgin. Analysis of emg signals in aggressive and normal activities by using higher-order spectra. The Scientific World Journal, 2012, 2012.
[14] Vipin K Mishra, Varun Bajaj, Anil Kumar, Dheeraj Sharma, and Gk Singh. An efficient method for analysis of emg signals using improved empirical mode decomposition. AEU-International Journal of Electronics and Communications, 72:200–209, 2017.
[15] Gopal Chandra Jana, Aleena Swetapadma, and Prasant Pattnaik. An intelligent method for classification of normal and aggressive actions from electromyography signals. In 2017 1st International Conference on Electronics, Materials Engineering and Nano-Technology (IEMENTech), pages 1–5. IEEE, 2017.
[16] Haya Alaskar. Deep learning of emg time–frequency representations for identifying normal and aggressive actions. IJCSNS Int. J. Comput. Sci. Netw. Secur. 18:12, 2018.
[17] Nageni Sukumar, Sachin Taran, and Varun Bajaj. Physical actions classification of surface emg signals using vmd. In 2018 International Conference on Communication and Signal Processing (ICCPP), pages 0705–0709. IEEE, 2018.
[18] Ermin Podrug and Abdulhamit Subasi. Surface emg pattern recognition by using dwt feature extraction and svm classifier. In The 1st conference of medical and biological engineering in Bosnia and Herzegovina (CM-BEBIH 2015), pages 13–15, 2015.
[19] C Sravani, V Bajaj, S Taran, and A Sengur. Flexible analytic wavelet transform based features for physical action identification using emg signals. Irbm, 41(1):18–22, 2020.
[20] Fatih Demir, Varun Bajaj, Melih C Ince, Sachin Taran, and Abdullahkadir Şengir. Surface emg signals and deep transfer learning-based physical action classification. Neural Computing and Applications, 31(12):8455–8462, 2019.
[21] Anish C Turlapaty and Balakrishna Gokaraju. Feature analysis for classification of physical actions using surface emg data. IEEE Sensors Journal, 19(4):12196–12204, 2019.
[22] N. Khushaba, Maen Takruri, Jaime Valls Miro, and Sarath Kodagoda. Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features. Neural Networks, 55:42–58, 2014.
[23] Jingwei Too, Abdul Rahim Abdullah, and M Mohd Saad. Classification of hand movements based on discrete wavelet transform and enhanced feature extraction. Int. J. Adv. Comput. Sci. Appl, 10(6):83–89, 2019.
[24] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. Fractal analysis features for weak and single-channel upper-limb emg signals. Expert Systems with Applications, 39(12):11156–11163, 2012.
[25] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. Feature analysis for classification of surface emg signals using vmd. In 2018 International Conference on Communication and Signal Processing (ICCPP), pages 0705–0709. IEEE, 2018.
[26] P Kuegler, C Jaremenko, J Schalachelzki, et al. Automatic recognition of Parkinson disease using surface electromyography during standardized gait test. IEEE, No. 4208, pages 5781–5784, 2013.