Journal of Engineering and Technological Sciences

Research Paper

Feature Extraction Evaluation of Various Machine Learning Methods for Finger Movement Classification using Double Myo Armband

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Abstract

The deployment of electromyography (EMG) signals can be used in decoding finger movements for exoskeleton robotics, prosthetic hands, and powered wheelchairs and thus has attracted the attention of many researchers. However, decoding any movement is a challenging task. The success of using EMG signals depends on the appropriate choice of feature extraction and classification model, especially in the feature extraction process. Therefore, this study conducted an eight-feature extraction evaluation on various machine learning methods, i.e., Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Decision Tree (DT), Naïve Bayes (NB), and Quadratic Discriminant Analysis (QDA). Datasets from four intact subjects were used to classify twelve finger movements. Through five cross-validations, the result showed that almost all feature extractions combined with SVM outperformed the other combinations of features and classifiers. Mean absolute value (MAV) as a feature and SVM as a classifier were the best combination, with an accuracy of 94.01%.

Keywords: *classification; electromyography; feature extraction; finger movement; machine learning.*

Introduction

Machine learning has been applied in various fields, ranging from education [1], health [2], agriculture [3], and so on. One of its applications is the development of human-machine interfaces (HMI). The interest in developing HMI is gaining momentum [4]. One of the biggest barriers to the widespread acceptance of hand prostheses by amputees is their restricted usefulness. Prosthetic hand utility is greatly constrained by their lack of dexterity. Thus, research into electromyographic (EMG) signal-based robotic hand control techniques has been carried out [5]. This signal's acquisition can be conducted invasively or noninvasively [6,7]. When a desired muscular contraction occurs, the central nervous system sends EMG signals, which indicate the electrical activity of the muscles. Both invasive and non-invasive electrodes can be used to obtain myoelectric signals; the latter are frequently employed in rehabilitation. Surface electrodes (sEMG) on both forearm muscles, for instance, can be used to partially record the intention to flex and extend the fingers [8]. EMG signals have been used extensively for many purposes, including exoskeleton robotics for stroke patients [9–11], prosthetics for lower limb and hand amputees [12,13], and powered wheelchairs for physically impaired walking people [14]. Many studies focused on using EMG signals for hand movements [15,16]. Nonetheless, in real-life applications, any movement of the hand requires finger movements.

ISSN: 2337-5779

DOI: 10.5614/j.eng.technol.sci.2023.55.5.8

Studies focusing on finger movement classification based on EMG signals explored several methods. Classification of finger movements was conducted by using Artificial Neural Network (ANN), Support Vector Machine (SVM), and k-Nearest Neighbor (k-NN) in [17]. Another study used ANN to decode different finger motions [18]. The above works only investigated limited finger movements, while in real life, a higher degree of freedom (DoF) of the fingers is necessary to perform tasks flexibly.

A large part of the relevant literature investigated feature evaluation for EMG signals. The goal of the study by Toledo-Pérez [19] was to give a summary of the numerous studies that have been done on the categorization of electromyography (EMG) signals using Support Vector Machines (SVM). The accuracy attained, the quantity of signals or channels used, how the feature vectors were produced by the authors, and the kind of kernel employed were included in the study. The bands utilized to filter the signals, the suggested signal quantity, the most popular sampling frequencies, and certain characteristics that can produce the characteristic vectors are all listed. Another study evaluated the use of features in the EMG signals [20]. The research used a CNN algorithm for classification and wavelet transformation for feature extraction. Feature extraction investigation has been done too by Samuel [21], who investigated several feature extraction methods, i.e., mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and slope sign changes (SSC). In the present, these studies were compared with our newly proposed time-domain features using different performance metrics. In addition, we used the auto-regressive coefficients (AR), root mean square (RMS), and Willison Amplitude (WAMP).

Accordingly, the present study focused on evaluating eight different feature extraction methods for twelve finger movements with sixteen channels from a double Myo armband using SVM. SVM was chosen because it showed the best results in the classification task [19], and it has been widely used for the EMG signal classification [19]. In addition, three temporal moment features (TM3, TM4, TM5) were investigated. Additionally, the experiment not only employed SVM as classifier but also four other models, i.e., k-Nearest Neighbor (k-NN), Decision Tree (DT), Naïve Bayes (NB), and Quadratic Discriminant Analysis (QDA) as comparative models. Hence, we were able to achieve the purposes of getting the right features for SVM, the right temporal moment feature, and the other combination of features and models to be applied.

Method

Proposed Model System

The proposed model system presented in this paper can be seen in Figure 1. The dataset from NinaPro DB5 in Exercise 1 (E1) was first used with feature selection and the sliding window technique. Feature selection was done to take valuable information from the data and remove unwanted information. As a result, there remained two kinds of signals, i.e., EMG signals and target signals, or labeled data. A windowing process was then conducted to the length of signals with an overlap of 75%. After this stage, the EMG signals were ready to be extracted using eight evaluated features. The resulting data of the feature extraction process were then fed to five different classification models to get the accuracy rates of the output for the twelve finger movements. The accuracy of each model was validated using a k-Fold with five cross-validations. This means that the data was randomly divided into 20% testing data and 80% training data.

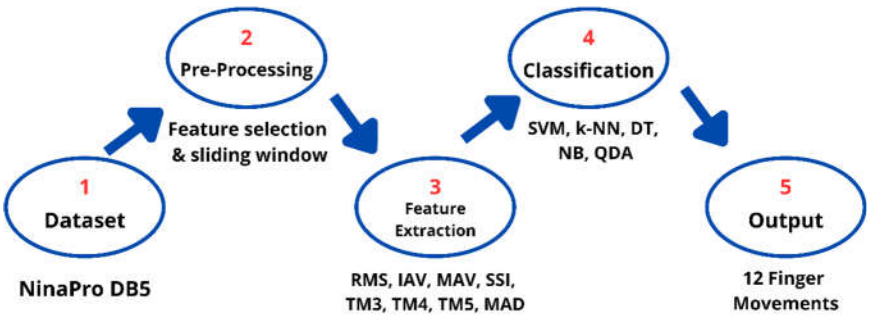

Figure 1 Model system.

DOI: 10.5614/j.eng.technol.sci.2023.55.5.5

Dataset

The dataset was acquired from publicly available data in the NinaPro Database, which consists of nine databases, from DB1 to DB9. This study only used DB5. In DB5, ten healthy subjects were tested to collect data, with three exercises representing three kinds of paradigms. The present study only used four subjects: two males (S1, S2) and two females (S4, S5), and only Exercise 1 (E1) was chosen, as it represents twelve individual finger movements, which were used as labeled data in the classification models. These movements, as shown in Table 1, included index flexion, index extension, middle flexion, middle extension, ring flexion, ring extension, little finger flexion, little finger extension, thumb flexion, thumb extension, thumb adduction, and thumb abduction, collected from a double Myo armband placed on the forearm of the subjects, as described in [22]. Each Myo armband has eight channels, so in total there were sixteen channels. The data collection protocol can be seen in Figure 2.

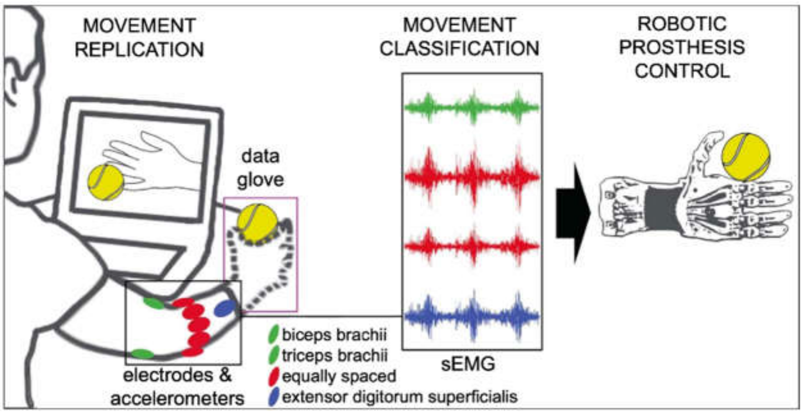

Figure 2 Data collection protocol [23].

Table 1 Twelve finger movements.

Name	Finger	Name	Finger
Index flexion		Little finger flexion	
Index extension		Little finger extension	
Middle flexion		Thumb adduction	
Middle extension		Thumb abduction	
Ring flexion		Thumb flexion	
Ring extension		Thumb extension	

Pre-processing and Windowing

To guarantee that the signal used was an EMG signal, the EMG signal was filtered with a bandpass filter at a frequency of around 10 to 400 Hz prior to any additional processing. In addition to the bandpass filter, a notch filter with a cut-off frequency of 50Hz was employed to mitigate the impact of interference signals originating from electrical networks. Following the filtering step, there was a 200-ms windowing process with a 75% overlap.

Feature Extraction

Eight feature extractions were evaluated in this work. In detail, the following were the feature extractions used.

Root Mean Square (RMS)

The first feature is the root mean square (RMS). RMS is the square root of the average square error [19], which is mathematically expressed as follows:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

Integrated Absolute Value (IAV)

The integrated absolute value is when N is equal to how many sEMG data points there are in the time frames, and x_i denotes the amplitude that corresponds to the i-th sEMG data point [24], as expressed in Eq. (2):

$$IAV = \sum_{i=1}^{N} |x_i| \tag{2}$$

Mean Absolute Value (MAV)

This feature is the average absolute value in the EMG signals [25], as shown in Eq. (3):

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{3}$$

Simple Square Integral (SSI)

The summation of square values yields the value of SSI in EMG signals. The mathematical expression can be seen in Eq. (4) [26]:

$$SSI = \sum_{i=1}^{N} {x_i}^2 \tag{4}$$

Temporal Moment 3, 4, 5 (TM3, TM4, TM5)

The temporal moment feature is a statistical analysis method that was proposed by Saradis in 1982 [19]. The mathematical equations for TM3, TM4, and TM5 can be seen in Eqs. (5), (6), and (7), respectively:

$$TM3 = \left|\frac{1}{N}\sum_{i=1}^{N} Xi^3\right| \tag{5}$$

DOI: 10.5614/j.eng.technol.sci.2023.55.5.5

$$TM4 = \left|\frac{1}{N}\sum_{i=1}^{N} Xi^4\right| \tag{6}$$

$$TM5 = \left|\frac{1}{N}\sum_{i=1}^{N} Xi^5\right| \tag{7}$$

Mean Absolute Deviation (MAD)

Mean absolute deviation calculates the values that are possible to discriminate from their average. *N* is the number of values observed, x_i is the individual value, and x̄ is the mean value observed. In detail, it can be seen in Eq. (8):

$$MAD = \frac{1}{N}\sum_{i=1}^{N} |x_i - \bar{x}| \tag{8}$$

Classification Models

This proposed study used five classification models, which were used to evaluate all feature extractions. In detail, the following were the classifier models used.

Support Vector Machine (SVM)

SVM is a popular machine learning tool that works by separating a dataset into different classes. It works using a hyperplane to discriminate data into two or more classes [19], as shown in Figure 3. Since the invention of Support Vector Machines, this method has been widely used for image, hypertext, and text categorization and segregation issues. These algorithms are highly sophisticated and can be used for things as diverse as both protein sorting in biological laboratories and handwriting recognition. Thus, they are utilized in a variety of different fields, including self-driving automobiles, chatbots, face recognition, etc. [27]. The way the hyperplane separates the data into classes is based on the maximum margin or space between dataset classes, taking advantage of each class's support-vector. In the SVM model used this study, the kernel function was set to be the radial basis function (RBF) and the value of gamma (C) was set to 100.

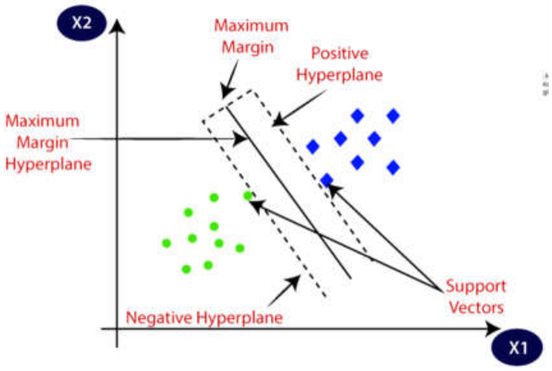

Figure 3 An example of an SVM decision boundary [27].

k-Nearest Neighbor (k-NN)

A k-NN model works by measuring the value of the distance from a dataset. Alternatively, this model classifies data based on the majority vote of its k-Neighbors [28]. The 'k' in k-NN is the number of neighbors of a new data point. In this algorithm, the process of determining the value of k is the main one. The accuracy of the k value selection will affect the accuracy, a process that is called parameter tuning. A very low k value may lead to noisy results, whereas a very high value may lead to confusion at times, depending on the data set [27]. This study used k = 3. The calculation of the k value can be done with this formula:

$$K = \sqrt{n} \tag{9}$$

where n is the total number of data points.

After that, the distance in units of Euclidean geometry between the old and new data points in the data set is determined. We have to determine the category to which the majority of the nearest neighbors belong (let us say the value at k = 5) after computing the Euclidean distance values from all points to the new data point. Then, after careful calculation, we must assign that category to the data point that is designated for classification. As can be seen in Figure 4, it may be deduced that the point belongs to class A because it has three of that category's nearest neighbors [27].

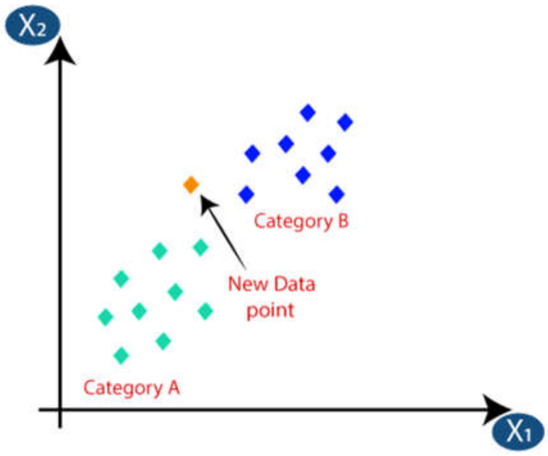

Figure 4 New data points based on k-NN neighbours [27].

Decision Tree (DT)

Decision Tree (DT) algorithms, which are supervised learning algorithms, are typically employed to solve classification problems, though they can also be used to solve regression problems [27]. In the Decision Tree method several terms are used, which can be seen in Figure 5.

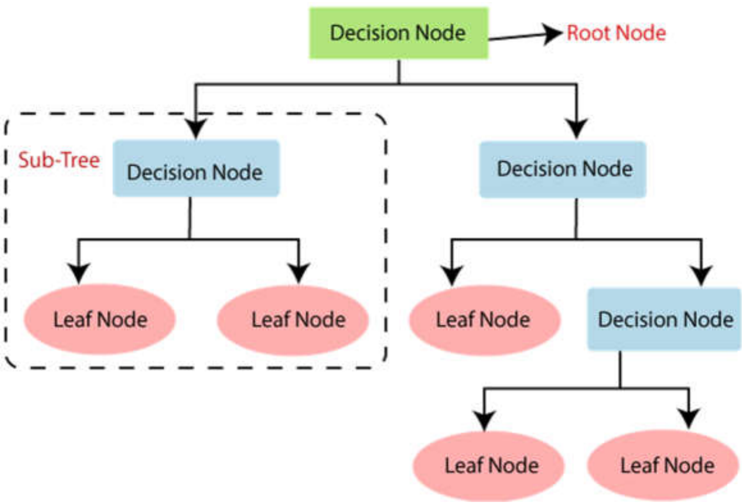

Figure 5 Decision tree architecture [27].

DOI: 10.5614/j.eng.technol.sci.2023.55.5.5

1. **Root Node**: The decision tree's first node, where the process of further dividing the entire data set into multiple homogenous potential sets begins.
2. **Leaf Node**: The last result node, at which the tree cannot be further divided.
3. **Splitting**: This is the process of further subdividing the main node into sub nodes in accordance with the given limitations.
4. **Sub Tree**: Creating sub trees or branches out of the resulting hierarchy.
5. **Pruning**: To achieve the best outcome, superfluous branches from the decision tree must be removed. This reduces the tree's size without compromising its accuracy. Cost complexity pruning and error reduction pruning are the two types of pruning used.
6. **Child and Parent Nodes**: The base node, which is also known as the parent node, is the only node that is not referred to as a child node.

Naïve Bayes (NB)

Naïve Bayes classification is a classification-based algorithm used for feature classification. This algorithm is based on Bayes' theorem. This classification is commonly used in the medical field to support decision making [29]. This value is obtained using the probability data found and the total data.

Quadratic Discriminant Analysis (QDA)

The statistical technique known as quadratic discriminant analysis (QDA) is frequently used to categorize observations from various multivariate normal populations [30]. Using a p-dimensional feature vector and discriminant analysis, individuals can be classified into one of k (≥ 2) populations. The feature vector's underlying distribution is typically thought to be multivariate normal. The Minimum Mahalanobis Distance (MMD) classification rule is another name for this rule. Quadratic Discriminant Analysis (QDA) is employed when the equality of the dispersion matrices of the underlying populations cannot be maintained. Despite being designed for data with a normal distribution, QDA can also be used for data without a normal distribution, because it is a relatively reliable algorithm in this situation [30].

Results and Discussion

This study evaluated eight different feature extractions on a support vector machine (SVM) to be used as classifier, using four subjects. For further investigation, four comparative classifiers were also tested and evaluated to know the effects of other models on the accuracy level. All feature extractions and models were employed to classify twelve finger movements, i.e., index flexion, index extension, middle flexion, middle extension, ring flexion, ring extension, little finger flexion, little finger extension, thumb flexion, thumb extension, thumb adduction, and thumb abduction.

EMG signals from the NinaPro DB 5 dataset in Exercise 1 (E1) were used to classify these twelve finger motions. Feature selection was first applied, since the data comprised not only EMG signals and re-stimulus as labeled data, but also other data, such as a glove, acc, repetition, circumference, and others. Therefore, these unwanted data were removed. Then, the remaining EMG signals and labeled data were investigated to get the best accuracy for finger movement classification.

Experimental Results Using SVM

Figure 6 shows the classification results using SVM. From all eight different feature extractions tested and evaluation using Support Vector Machine (SVM), MAV showed the highest accuracy (94.01%), followed by the other features (IAV, RMS, MAD, SSI, TM4, TM3, and TM5), respectively. The temporal moment (TM) features yielded lower results compared to the other features, with an accuracy of 77.79%, 81.33%, and 84.74% for TM5, TM3, and TM 4, respectively.

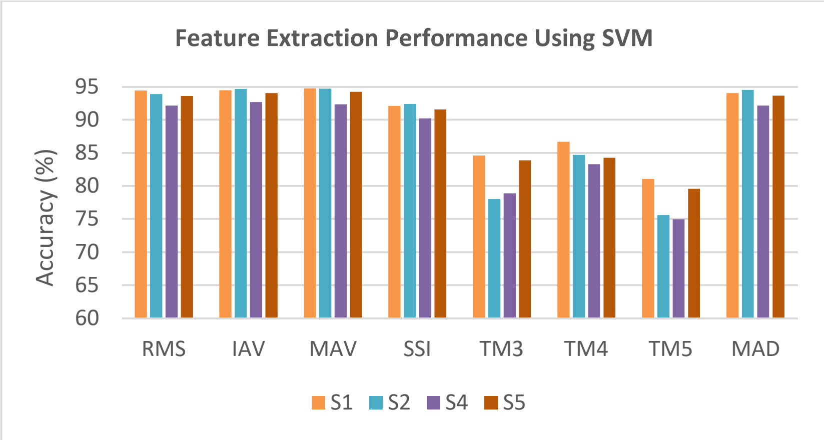

Figure 6 Feature extraction performance using SVM.

Experimental Results Using kNN

In the second evaluation, the performance of feature extraction was tested with k-Nearest Neighbor (k-NN). Figure 7 indicates how these eight features performed in terms of accuracy for the four subjects. With this method, RMS showed the best accuracy (91.65%), followed by MAD (90.72%), MAV (90.54%), IAV (90.46%), SSI (88.03%), TM4 (83.12%), TM5 (75.62%), and TM3 (75.90%). All feature extractions got a score of over 80%, except for the temporal moment features.

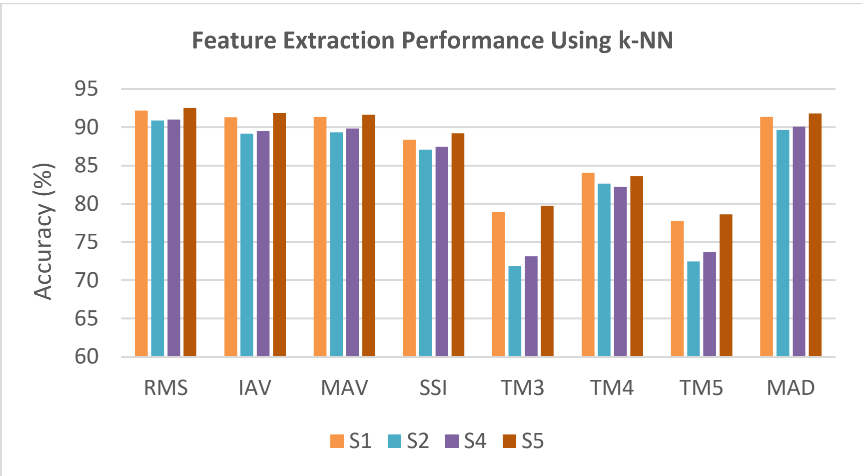

Figure 7 Feature extraction performance using k-NN.

Experimental Result Using DT

The third experiment, as shown in Figure 8, provided the result for the features evaluated in the Decision Tree (DT) classifier model. The highest accuracy rate went to TM4 (86.35%). The lowest accuracy rate was achieved by TM3 (77.74%). RMS, MAV, IAV, SSI, and MAD yielded an accuracy rate of above 85%, while TM5 resulted in an accuracy rate of only 80.44%. Although the temporal moment feature TM4 showed the highest percentage, the nontemporal moment features (RMS, MAV, IAV, SSI, and MAD) still had good results.

DOI: 10.5614/j.eng.technol.sci.2023.55.5.5

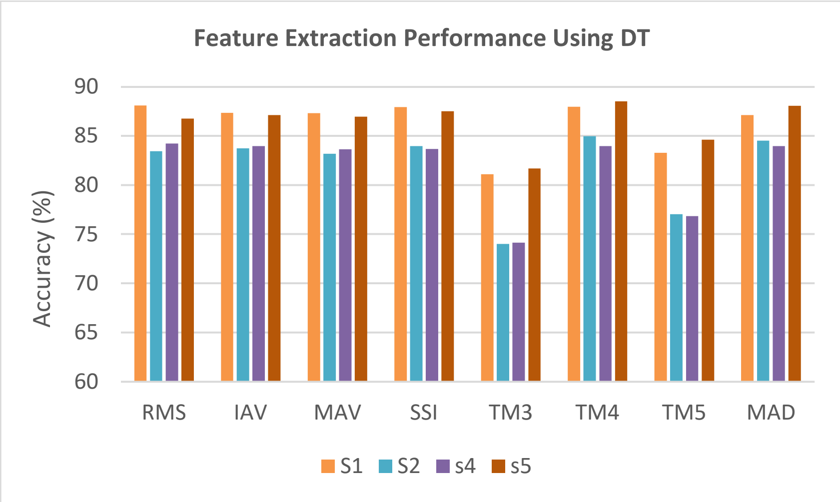

Figure 8 Feature extraction performance using DT.

Experimental Result Using NB

The fourth experiment used a Naive Bayes (NB) model, which resulted in the performance that can be seen in Figure 9. RMS outperformed the other features with an accuracy rate of 80.92%. All temporal moment features had lower results (65.08% for TM3, 60.81% for TM4, and 31.53% for TM5). Meanwhile, the remaining scores were 80.55% for SSI, 80.23% for MAD, 80.13% for IAV, and 79.98% for MAV. This model highlighted that RMS is the best feature to be applied, while temporal moment features are less recommended to use.

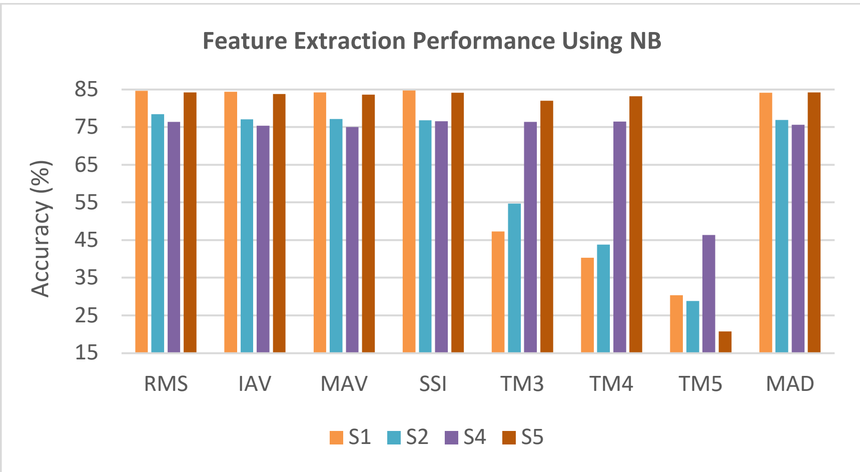

Figure 9 Feature extraction performance using NB.

Experimental Result Using QDA

The last experiment applied Quadratic Discriminant Analysis (QDA). Figure 7 illustrates the eight-feature performance of the QDA model. MAD showed the most promising result, with an accuracy rate of 92.20%. It was followed by MAV, IAV, and RMS, resulting in an accuracy rate of 92.07%, 92.06%, and 91.89%, respectively. SSI, TM3, TM4, and TM5 yielded lower rates. In this model, all temporal moment features (TM3, TM4, and TM5) yielded lower results than with the other models.

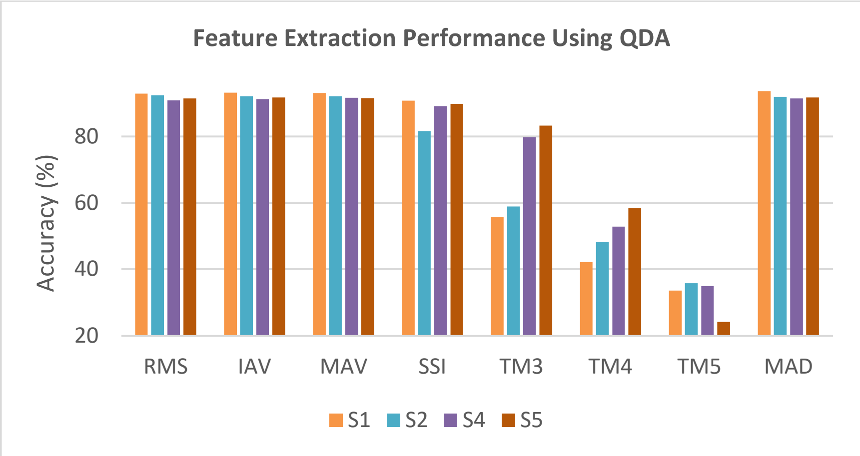

Figure 10 Feature extraction performance using QDA.

Discussion

We observed the performance outcomes of each classifier, as well as the factors that impact them. It is interesting to analyze the relative performance of the different classifiers. To evaluate the efficacy of Support Vector Machines (SVM) and other machine learning algorithms, we present a brief overview of their performance in Figure 11.

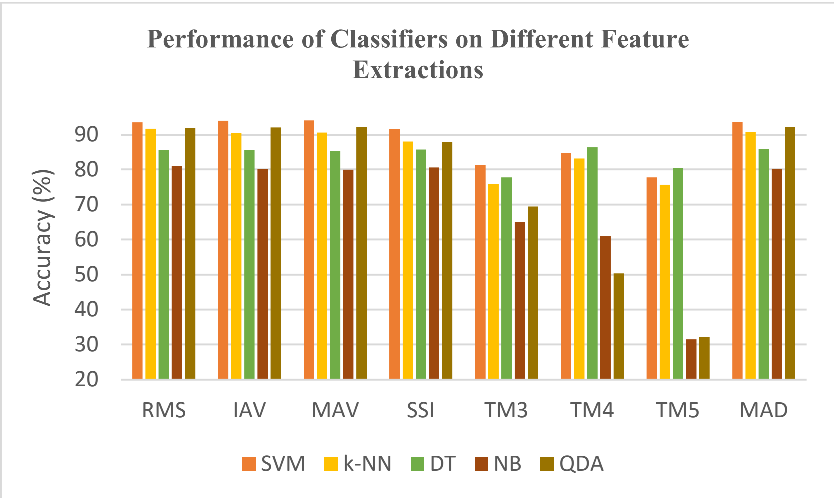

Figure 11 Classifier performance on different feature extractions

It is evident that SVM demonstrated the highest level of accuracy across most extraction features, except for TM4 and TM5. The findings of this work align with the results of prior studies that recommended the use of Support Vector Machines (SVM) as an effective and resilient machine learning technique for analyzing myoelectric signals [19]. The subsequent superior classifiers were kNN and QDA, exhibiting comparable performance. The problem with QDA lies in its extremely low accuracy for all TM characteristics, particularly TM5. Examining the reasons for the underperformance of QDA on TM features is an interesting endeavor. With an average of 80% or lower when using TM features, nearly all machine learning models were unable to generate satisfactory results. One possible explanation for this is that EMG signals exhibit significant variability because of several factors, such as electrode placement, muscle position changes, and other variables. The presence of variability is a challenge to conducting temporal analysis since it hinders the identification of consistent patterns. This observation may explain the tendency for SVM and most other machine learning algorithms to exhibit low accuracy when applied to TM.

DOI: 10.5614/j.eng.technol.sci.2023.55.5.5

Table 2 provides a more comprehensive assessment of the performance of each machine-learning algorithm. The numbers in bold are the best results. The maximum accuracy of 94.01% was achieved by employing SVM machine learning and MAV feature extraction. Nevertheless, MAV may not be the optimal characteristic for every classifier. The most notable attribute for all classifiers is the root mean square (RMS), which yielded an average performance of 88.71% across the five machine learning models. It may be necessary to consider this in the future. When implementing the extraction functionality, we have the option to pick between MAV or RMS.

When considering the merits and drawbacks of each approach, one notable advantage of SVM is its exceptional performance across a wide range of features. It performs well when combined with any feature. An obvious drawback is its low performance when used with the temporal moment (TM) function. As for kNN, it possesses the advantage of exhibiting commendable accuracy, but it falls short of SVM. Like SVM, the shortcoming of this method is its lack of effectiveness when used in conjunction with TM characteristics. As for QDA, its performance is comparable to that of kNN. However, while utilizing TM characteristics, the accuracy is very low. QDA is highly effective when used with time domain features such as RMS, IAV (integrated absolute value), and MAV (mean absolute value). As for DT, this classifier exhibited the maximum accuracy in matching the TM features displayed in TM4 and TM5. A limitation is its inability to rival the accuracy of SVM. As for Naïve Bayes, it did not demonstrate satisfactory performance in the analysis of EMG signals.

Table 2 Feature extraction performance towards five classifier models.

Classifier	**Feature Extraction**							
	RMS	**IAV**	**MAV**	**SSI**	**TM3**	**TM4**	**TM5**	**MAD**
SVM	**93.51**	**93.97**	**94.01**	**91.58**	**81.33**	84.74	77.79	**93.59**
k-NN	91.65	90.46	90.54	88.03	75.90	83.12	75.62	90.72
DT	85.62	85.54	85.26	85.76	77.74	**86.35**	**80.44**	85.91
NB	80.92	80.13	79.98	80.55	65.08	60.91	31.53	80.23
QDA	91.89	92.06	92.07	87.84	69.44	50.37	32.12	92.20
Avg±std	**88.71±4.73**	88.43±5.00	88.37±5.10	86.75±3.62	73.89±5.85	73.09±14.67	59.5±22.64	88.53±4.89

Based on the above discussion, it is evident that SVM with mean absolute value (MAV) yielded the most accurate predictions for the twelve hand movement patterns. However, this study exclusively utilized data from individuals who were in good health. The performance of SVM with RMS and the MAV features on amputees will be interesting to observe. It is important to mention that the analysis conducted in this research was performed offline rather than online or in real-time. To enhance practicality, it is important to carry out the experiment in real-time. Furthermore, it is imperative to execute the use of the derived technique to control prosthetic robots for individuals with limb loss.

Conclusions

This study evaluated several feature extraction methods applied to five classifier models to predict twelve user hand movement patterns based on electromyography signals. The implemented technique was utilized on four individuals who were in good health. The research findings indicate that Support Vector Machine utilizing the mean absolute value (MAV) feature achieved the highest level of performance, with an accuracy rate of 94.01%. Nevertheless, the most notable feature that functioned effectively across all machine learning models was RMS, showing an average accuracy of 88.71%. In the future, this research will further contribute to assisting amputees in controlling prosthetic robots based on their desired movement patterns.

Acknowledgments

We thank the Directorate of Research and Community Services, The Ministry of Research and Higher Education, and the Republic of Indonesia for Applied Research scheme no 272/E4.1/AK.04.PT/2021.

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Manuscript Received: 28 February 2023
Revised Manuscript Received: 30 October 2023
Accepted Manuscript: 4 December 2023