Comparative Analysis of Machine Learning Techniques for Hand Movement Prediction Using Electromyographic Signals

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Received 4 September 2023; Accepted 27 March 2024

Abstract. The analysis of electromyography (EMG) signals plays a vital role in diverse applications such as medical diagnostics and prosthetic device control. This study focuses on evaluating machine learning methods for EMG signal analysis, specifically in predicting hand movements and controlling prosthetic hands. In contrast to many existing studies that solely employ a limited set of feature extraction methods, we employ a comprehensive comparison technique that encompasses nine machine learning techniques K-Nearest Neighbor (KNN), State Vector Machine (SVM), Decision Tree, Random Forest, Linear Discriminant Analysis (LDA), XGBoost, Naïve Bayes, Gradient Boosting, and Quadratic Discriminant Analysis (QDA) and five combination of feature extraction methods (Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length, Willison Amplitude, and Skewness). The experimental results demonstrate promising accuracy levels, with the best result method being KNN achieving 96.66% accuracy, SVM achieving 95.83% accuracy, and RF achieving 92.5% accuracy. These findings contribute to advancing the understanding of effective machine learning approaches for EMG signal analysis and provide valuable insights for guiding future research in this field. The study also compares the results with previous studies and showcases the effectiveness of the proposed approach.

Keywords: Electromyography, machine learning, hand movement prediction, prosthetic hand control, feature extraction, execution time.

1. Introduction

The analysis of electromyography (EMG) signals has become a prominent area of research, finding applications in various fields, including medical diagnostics and the control of prosthetic devices [1]. However, the analysis and interpretation of EMG signals present challenges due to their non-linear and time-varying characteristics [4]. To address these challenges, machine learning methods have shown promise in improving the prediction of hand movements and enhancing prosthetic device control [2]. Machine learning approaches, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Deep Learning (DL), have been widely employed in the analysis of EMG signals [8]. These methods offer the potential to overcome the complexities associated with EMG signal analysis and provide accurate predictions of hand movements. By leveraging machine learning techniques, researchers have made significant advancements in this field, contributing to the development of effective control mechanisms for prosthetic devices [9].
EMG signals are bioelectric signals generated by muscle cells during neurological activation [3]. These signals can be captured and analyzed to determine the user’s intent, providing a potential control mechanism for prosthetic devices. Machine learning techniques, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Deep Learning (DL), have been applied to EMG signal analysis with promising results [5], [6]. However, selecting the most suitable machine learning method for a specific application remains challenging, as their performance varies based on data characteristics and task objectives [7].

Previous studies have explored different aspects of hand movement analysis using machine learning methods. Kumar et al. [1] investigated hand movements using the XGBoost method, although they did not mention the specific feature extraction technique employed. Young S et al. [2] applied the Random Forest (RF) method and utilized feature extraction techniques such as Root Mean Square (RMS), Variance (VAR), Integrated Absolute Value (IAV), Slope Sign Changes (SSI), Waveform Length (WL), and Mean Absolute Value (MAV). Mahmood et al. [3] focused on hand movements and employed the KNN and SVM methods, utilizing feature extraction techniques such as RMS, Differential Absolute Standard Deviation (DASDV), and Principal Component Analysis (PCA).

Sree et al. [4] conducted a study on hand movements using the KNN-SVM method and employed feature extraction techniques including Waveform Length (WL), Integrated EMG (IEMG), Zero Crossing (ZC), Slope Sign Changes (SSC), Autoregression (AR), and Integrated Absolute Value (IAV). Sattar et al. [14] investigated hand movements using the K-Nearest Neighbor (KNN) method and focused on the Waveform Length (WL) feature extraction technique. Nia et al. [10] explored hand movements using the Random Forest (RF) method. Hristov et al. [15] investigated hand movements with a dataset comprising 10 gestures, utilizing feature extraction techniques such as Mean Absolute Value (MAV), Median (MED), Variance (VAR), Root Mean Square (RMS), Slope Sign Changes (SSI), Zero Crossing (ZC), Waveform Length (WL), and Fast Fourier Transform Mean Frequency (FMD). They employed the XGBoost method. Fatayerji et al. [16] investigated hand movements using the Decision Tree method and employed the Dynamic Warping Phase Distortion (DWPD) feature extraction technique.

In our research, we aim to identify the most suitable machine learning (ML) approach for embedded systems. We will validate our findings by comparing them with the results from the eight referenced studies. Additionally, we aim to combine the feature extraction methods including MAV, RMS, WL, Willison Amplitude (WAMP), and Skewness (Sk), along with windowing techniques. The objective of this study is to determine the most effective machine learning method for predicting hand movements using electromyography (EMG) signals. The analysis includes 15 different hand movements, including Thumb (T), Index (I), Middle (M), Ring (R), Little (L), Thumb-Index (TI), Thumb-Middle (TM), Thumb-Ring (TR), Thumb-Little (TL), Index-Middle (IM), Middle-Ring (MR), Ring-Little (RL), Index-Middle-Ring (IMR), Middle-Ring-Little (MRL), and the hand close class (HC).

2. Method

In this chapter, we present our proposed method for the analysis of EMG signals to predict hand movements. Our approach stands out by combining sequential feature extraction methods, including MAV, RMS, WL, WAMP, and Sk. Furthermore, we conduct a comprehensive comparison of nine machine learning methods: KNN, SVM, Decision Tree (DT), Random Forest (RF), Linear Discriminant Analysis (LDA), Extreme Gradient Boosting (XGBoost), Naïve Bayes (NB), Gradient Boosting (GB), and Quadratic Discriminant Analysis (QDA). While each of these methods has shown potential in previous studies, their comparative effectiveness remains an open question.
By systematically evaluating and comparing these machine learning and feature extraction methods, our aim is to identify the most effective combination for accurately predicting hand movements based on EMG signals. Figure 1 is the block diagram illustrating the flow:

Step 1, the Hand Movement Dataset comprising 15 datasets is collected from the journal "Electromyogram (EMG) Feature Reduction Using Mutual Components Analysis for Multifunction Prosthetic Fingers Control" [11]. These datasets serve as the input for subsequent processing.

Step 2, the collected data undergoes data filtering to enhance its quality and remove any noise or artifacts. This step is based on the approach presented in the same journal article mentioned earlier.

Step 3: Feature extraction is performed by combining MAV, RMS, WL, WAMP, and Sk. The feature extraction is carried out with a crop size of 20000, window size of 4000, and interval of 1000.

Step 4: The 15 datasets are labeled in the code program, assigning appropriate labels to each data sample based on the corresponding hand movement.

Step 5: Machine learning models including KNN, SVM, DT, RF, LDA, XGBoost, NB, GB, and QDA are trained using the labeled datasets.

Step 6: The results of the machine learning models are analyzed and reported, including accuracy, precision, recall, and other relevant metrics. Additionally, the trained models are saved as files for future use and deployment in predicting hand movements based on EMG signals.

2.1 Data Acquisition

A group of eight individuals (six males and two females) between the ages of 20 and 35, without any neurological or muscular disorders, participated in the study. Prior to their involvement, all participants provided informed consent. The subjects were seated comfortably on an armchair with their arms supported and fixed in position. To capture the necessary data, eight EMG channels (DE 2.x series EMG sensors) were strategically placed around the circumference of the forearm. The Bagnoli desktop EMG system from Delsys Inc. was utilized for processing the recorded datasets, as depicted in Figure 2. Adhesive skin interfaces were securely applied to each sensor using a 2-slot adhesive method. Additionally, a dermatrode reference electrode, acting as a conductive adhesive reference electrode, was positioned on the wrist of each participant. The EMG signals collected were amplified with a Delsys Bagnoli-8 amplifier, employing a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) sampled the signals at a frequency of 4000 Hz. [11] Figure 2 illustrates the positions of the posterior electrodes.
A comprehensive dataset consisting of fifteen distinct hand movement classes was obtained through this experiment. These classes encompassed the flexion of individual fingers, namely (T), (I), (M), (R), (L), (T-I), (T-M), (T-R), (T-L), (I-M), (M-R), (R-L), Index-Middle-Ring (I-M-R), (M-R-L), and (HC), as illustrated in Figure 4. During the data collection phase, participants were instructed to execute each of these fifteen movements and maintain the posture for a duration of 5 seconds per trial. A total of six trials or repetitions were recorded for each movement. Out of the six trials, four were allocated for training purposes, while the remaining two were set aside for testing. The dataset comprises approximately 360 files in total. Illustration of the 15 hand movements considered in this study:

Figures 4 (shown below) present an example illustration of the filtered EMG signal, where only 8 channels are displayed. This selection of channels and the representation of a single movement serve as an illustrative example to demonstrate the signal processing and feature extraction techniques employed in the analysis.

2.2 Data Filtering

Data filtering process plays a crucial role in ensuring the reliability and accuracy of the collected EMG signals. To effectively preprocess the signals, a bandpass filter is applied within the frequency range of 20-450 Hz. This specific frequency range is chosen to capture the relevant physiological information associated with hand movements. Moreover, to eliminate the unwanted 50 Hz line interference that commonly contaminates EMG recordings, a notch filter is implemented. This filter is specifically designed to attenuate the power line noise at 50 Hz, thereby reducing its impact on the EMG signals. By combining the bandpass and notch filters, the filtered EMG signals exhibit improved quality, with the desired frequency components preserved while unwanted noise and artifacts are effectively suppressed. The utilization of these filtering techniques, as discussed in [12], contributes to the overall enhancement of the EMG data, enabling more accurate feature extraction and subsequent analysis for predicting hand movements.

Figures 4 (shown below) present an example illustration of the filtered EMG signal, where only 8 channels are displayed. This selection of channels and the representation of a single movement serve as an illustrative example to demonstrate the signal processing and feature extraction techniques employed in the analysis.
2.3 Feature Extraction

In the Feature Extraction chapter, the windowing technique is implemented to process the EMG signals. This technique involves dividing the signal into overlapping segments, known as windows, to capture specific temporal information. The windowing function takes three parameters: the crop size, window size, and interval. The crop size determines the length of the signal data (8xn), while the window size specifies the size of each window. The interval parameter defines the time gap between consecutive windows. By applying the windowing technique with a crop size of 20000, window size of 4000, and interval of 1000, the function generates a list of signal components that result from the windowed data. This process enables the extraction of relevant features from the EMG signals, facilitating further analysis and classification of hand movements. Figure 7 below illustrates the EMG signal after the windowing process, where the continuous signal is segmented into overlapping windows.

Each window captures a specific portion of the signal, defined by the window size. The intervals between consecutive windows are determined by the interval parameter. By sliding these windows along the signal, a series of overlapping segments is created, enabling a more detailed analysis of the EMG signal. After data windowing, the next step is to perform wavelet analysis. Wavelet analysis is a powerful technique utilized for decomposing signals in the time-frequency domain,
playing a crucial role in identifying frequency changes within the EMG signal over time [13]. By applying wavelet analysis to the windowed data in the provided code program, the EMG signal is effectively broken down into different frequency components. This analysis yields a time-frequency representation of the EMG signal, offering valuable insights into its dynamic frequency characteristics. This representation enables a comprehensive understanding of the signal's behavior in both the time and frequency domains, facilitating the extraction of meaningful features for subsequent analysis and interpretation.

Additional features are extracted from both raw data and data that has been analyzed using wavelet analysis:

1. MAV represents the average of the absolute values of the EMG signal. This feature describes the amplitude of the signal and is used to measure muscle contraction. It provides information about the signal's amplitude in the time-frequency domain.

2. RMS is a measure of the average squared value of the EMG signal. This feature reflects the energy of the signal and is used to assess muscle strength. It provides insight into the overall power of the muscle contraction. RMS Formula:

3. WL represents the cumulative changes of the EMG signal in the time domain. It is used to measure the signal's complexity and detect muscle activity. WL provides insights into the overall pattern and dynamics of the signal. WL Formula:

4. WAMP is the count of times the EMG signal crosses a predetermined threshold. It is used to measure the frequency of amplitude changes and identify the onset and offset of muscle contractions. WAMP captures the variations in muscle activity and provides information about the temporal dynamics of contractions. WAMP

5. Sk describes the extent to which the amplitude distribution of the EMG signal deviates from symmetry. It is used to measure the asymmetry in the signal and can provide insights into the balance between agonist and antagonist muscle activity. Skewness helps assess the overall muscular coordination and balance during movement. Skewness Formula:

Figure 6 is the comprehensive data visualization, incorporating the results:

![Figure 6. Extracted Feature](image)

### 2.4 Classification

In the chapter on Classification of EMG Signals, we explore the application of nine different machine learning methods to effectively classify EMG signals. These
methods include KNN, SVM, DT, RF, LDA, XGBoost, NB, GB, and QDA. Each of these methods offers unique capabilities and advantages in analyzing and classifying EMG signals.

1. One such study by Faiz (2010) investigated the application of KNN in EMG signal classification and reported promising results in terms of accuracy and robustness [18]. This method is well-suited for EMG signal classification as it considers sample similarities and assigns class labels based on the majority vote of the nearest neighbors.

2. A study by Anil et al. (2017) focused on the application of SVM for recognizing hand gestures based on EMG signals, reporting promising results in terms of accuracy and robustness [19]. SVM is a powerful supervised learning algorithm that constructs a hyperplane to separate different classes by maximizing the margin between them.

3. The DT method is employed for EMG signal analysis based on the study by Yousefi and Hamilton-Wright (2014) [20]. DT constructs a tree-like model by partitioning the feature space, allowing for the interpretation and understanding of the classification process. This makes DT a suitable choice for analyzing EMG signals. The research by Yousefi and Hamilton-Wright contributes to the utilization of DT in EMG data characterization and classification.

4. Random forest method is utilized for EMG signal classification based on Yaman and Subasi’s research [21]. RF is an ensemble learning technique that combines decision trees to enhance classification performance. The study compares ensemble methods for automated EMG signal classification and highlights the effectiveness of RF in achieving accurate results.

5. The LDA algorithm is utilized for the analysis of electromyogram (EMG) data from individuals with trans-radial amputation, as discussed in Dellacasa Bellingegni et al. [23]. The research investigates the performance of various machine learning algorithms, including LDA, in classifying EMG signals for prosthetic control.

6. The XGBoost machine learning algorithm is employed for the recognition of American Sign Language gestures using electromyogram (EMG) signals, as highlighted in Chen et al.'s research [22]. XGBoost is an optimized gradient boosting framework that excels in handling complex datasets and achieving high accuracy.

7. The Naive Bayes algorithm is employed for the intelligent perception recognition of multi-modal EMG signals, as discussed in Zhang et al [24]. The research focuses on utilizing machine learning techniques to classify EMG signals based on multiple modalities. Naive Bayes is chosen as a classification method due to its simplicity and effectiveness in handling high-dimensional data.

8. GB is an ensemble learning method that combines multiple weak prediction models to create a strong classifier. In EMG signal classification, GB builds an ensemble of decision trees where each subsequent tree is trained to correct the errors made by the previous trees.

9. QDA is chosen as a classification method due to its ability to model the covariance matrix of each class separately, allowing for better representation of non-linear decision boundaries. This makes QDA suitable for capturing complex relationships in EMG data and improving classification accuracy [25].
3. Experiment Result

3.1 Result

Table 1 presents a comprehensive comparison of nine ML methods, including KNN, SVM, DT, RF, LDA, XGBoost, NB, GB, and QDA, for classifying hand movements based on EMG signals. The evaluation measures their performance in accuracy, precision, sensitivity, F1-score, and execution time. These assessments utilize a combination of five extracted features: MAV, RMS, WL, WAMP, and Sk. The results in Table 1 offer valuable insights for identifying the most effective approach for hand movement prediction using EMG signals.

The execution time, from data collection to ML classification, is measured to assess the responsiveness and real-time control of the prosthetic hand system. Comparing the execution times of different methods aids in selecting the most efficient approach to meet real-time requirements [8].

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Accuracy ( % )</th>
<th>Precision ( % )</th>
<th>Sensitivity ( % )</th>
<th>F1-Score ( % )</th>
<th>Execution Time ( s )</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>96.66</td>
<td>97.18</td>
<td>96.66</td>
<td>96.69</td>
<td>2.59</td>
</tr>
<tr>
<td>SVM</td>
<td>95.83</td>
<td>96.59</td>
<td>95.83</td>
<td>95.69</td>
<td>3.35</td>
</tr>
<tr>
<td>DT</td>
<td>73.33</td>
<td>74.61</td>
<td>73.33</td>
<td>72.55</td>
<td>2.84</td>
</tr>
<tr>
<td>RF</td>
<td>92.5</td>
<td>93.53</td>
<td>92.5</td>
<td>92.16</td>
<td>6.13</td>
</tr>
<tr>
<td>LDA</td>
<td>89.16</td>
<td>90.11</td>
<td>89.16</td>
<td>89.08</td>
<td>2.49</td>
</tr>
<tr>
<td>XGBOOST</td>
<td>88.33</td>
<td>89.22</td>
<td>88.33</td>
<td>88.01</td>
<td>11.64</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>42.5</td>
<td>42.62</td>
<td>42.5</td>
<td>40.5</td>
<td>2.44</td>
</tr>
<tr>
<td>Gradient Boosting QDA</td>
<td>86.66</td>
<td>88.85</td>
<td>86.66</td>
<td>86.53</td>
<td>169</td>
</tr>
</tbody>
</table>

Measuring the specificity of machine learning algorithms is essential for accurate hand movement prediction in the context of prosthetic hand systems. This study, based on the research conducted by Johnson et al. [17]. Table 2 provides valuable insights into the performance of these algorithms in terms of specificity, which is crucial for reducing false positives and improving the accuracy of hand movement classification.

<table>
<thead>
<tr>
<th>Move</th>
<th>KNN</th>
<th>SVM</th>
<th>DT</th>
<th>RF</th>
<th>LDA</th>
<th>XGBoost</th>
<th>NB</th>
<th>GB</th>
<th>QDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>HC</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.75</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I-M-R</td>
<td>0.875</td>
<td>1</td>
<td>0.875</td>
<td>1</td>
<td>0.875</td>
<td>0.875</td>
<td>0.875</td>
<td>0.875</td>
<td>0.875</td>
</tr>
<tr>
<td>I</td>
<td>0.875</td>
<td>1</td>
<td>0.375</td>
<td>0.875</td>
<td>0.875</td>
<td>0.375</td>
<td>0.625</td>
<td>0.875</td>
<td></td>
</tr>
<tr>
<td>I-M</td>
<td>1</td>
<td>1</td>
<td>0.675</td>
<td>0.875</td>
<td>1</td>
<td>0.875</td>
<td>0</td>
<td>0.75</td>
<td>1</td>
</tr>
</tbody>
</table>
Among the nine machine learning (ML) methods compared in Table 1 for classifying hand movements based on EMG signals, the top three performers based on accuracy are KNN, SVM, and RF.

- The KNN algorithm achieved the highest accuracy rate of 96.66%, indicating its strong predictive capabilities. It also demonstrated high precision (97.18%), sensitivity (96.66%), and F1-score (96.69%). With an execution time of 2.59 seconds, KNN showed efficient processing speed, making it suitable for real-time applications.

- The SVM algorithm ranked second in terms of accuracy, with an accuracy rate of 95.83%. SVM also showed good precision (96.59%), sensitivity (95.83%), and F1-score (95.69%). However, its execution time was slightly longer at 3.35 seconds compared to KNN.

- The RF algorithm ranked third in terms of accuracy, achieving an accuracy rate of 92.5%. RF demonstrated descent precision (93.53%), sensitivity (92.5%), and F1-score (92.16%). However, it had a longer execution time of 6.13 seconds.

Based on the comparison in Table 2, all three methods, KNN, SVM, and RF, showed generally high specificity for classifying hand movements. KNN and RF achieved specificity scores of 1 for most movement classes, indicating their effectiveness in reducing false positives and accurately identifying specific hand movements.

### 3.2 Comparison to Another Journal

The results of our study have been compared to eight previous studies mentioned in the Chapter I Introduction. The comparison, shown in Table 3, assesses the accuracy of our results in comparison to the results of these previous studies. The table displays the accuracy scores for different hand gestures, along with the extracted features and classification methods used in each study. By comparing our results to these previous studies, we gain valuable insights into the performance and effectiveness of our approach in predicting hand movements based on EMG signals.

<table>
<thead>
<tr>
<th>Move</th>
<th>KNN</th>
<th>SVM</th>
<th>DT</th>
<th>RF</th>
<th>LDA</th>
<th>XGB</th>
<th>NB</th>
<th>GB</th>
<th>QDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>0.125</td>
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<tr>
<td>M-R-L</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>1</td>
<td>0.875</td>
<td>1</td>
<td>0.625</td>
<td>1</td>
<td>0.875</td>
</tr>
<tr>
<td>M</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>0.875</td>
<td>0.875</td>
<td>1</td>
<td>0.5</td>
<td>0.875</td>
<td>1</td>
</tr>
<tr>
<td>M-R</td>
<td>0.875</td>
<td>0.875</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>0.875</td>
<td>0.75</td>
<td>0.875</td>
<td>0.875</td>
</tr>
<tr>
<td>R-L</td>
<td>1</td>
<td>0.875</td>
<td>0.75</td>
<td>1</td>
<td>0.75</td>
<td>1</td>
<td>0.25</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>R</td>
<td>1</td>
<td>1</td>
<td>0.375</td>
<td>0.875</td>
<td>0.875</td>
<td>0.875</td>
<td>0.375</td>
<td>0.625</td>
<td>0.875</td>
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<tr>
<td>T-I</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>0.875</td>
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<td>0.75</td>
<td>0.625</td>
<td>1</td>
<td>0.875</td>
</tr>
<tr>
<td>T-L</td>
<td>0.875</td>
<td>1</td>
<td>0.675</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.5</td>
<td>0.875</td>
<td>1</td>
</tr>
<tr>
<td>T-M</td>
<td>1</td>
<td>1</td>
<td>0.75</td>
<td>1</td>
<td>1</td>
<td>0.875</td>
<td>0.375</td>
<td>0.875</td>
<td>1</td>
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<tr>
<td>T-R</td>
<td>0.875</td>
<td>1</td>
<td>0.875</td>
<td>1</td>
<td>0.75</td>
<td>0.875</td>
<td>0.5</td>
<td>1</td>
<td>0.875</td>
</tr>
<tr>
<td>T</td>
<td>1</td>
<td>0.625</td>
<td>0.75</td>
<td>0.5</td>
<td>0.625</td>
<td>0.5</td>
<td>0.25</td>
<td>0.625</td>
<td>0.375</td>
</tr>
</tbody>
</table>
Each study utilized different gesture recognition approaches, extracted features, classification methods, and reported accuracy results. Our study stands out with the highest total gesture count of 15 and achieved the highest accuracy of 96.66%. By comparing our results with these previous studies, we can assess the effectiveness of our approach in predicting hand movements based on EMG signals.

4. Conclusion
Based on the results presented the KNN, SVM, and RF algorithms emerged as the top performers in terms of accuracy for classifying hand movements based on EMG signals. These algorithms demonstrated high accuracy rates of 96.66%, 95.83%, and 92.5% respectively. The KNN algorithm exhibited the best overall performance, achieving high precision, sensitivity, and F1-score along with a relatively low execution time of 2.59 seconds. The SVM algorithm showed comparable performance to KNN, albeit with a slightly longer execution time of 3.35 seconds. The RF algorithm also delivered satisfactory results, although it had a longer execution time of 6.13 seconds. Additionally, the comparison in Table 2 highlighted the high specificity of these algorithms in accurately classifying hand movements. Furthermore, when comparing our results to previous studies (Table 3), our study demonstrated the highest total gesture count of 15 and achieved the highest accuracy rate of 96.66%. These findings validate the effectiveness of our approach in accurately predicting hand movements based on EMG signals, establishing its potential for applications in prosthetic hand systems and other related fields.

References


