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Integration of the K-Fold Cross-Validation Algorithm for the Classification of Pronator Teres EMG Signals

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Abstract

Individuals with disabilities often require mobility assistance, and conventional joystick-controlled wheelchairs are ineffective for users with upper-limb impairments. Electromyography (EMG) signals offer a promising alternative for wheelchair navigation by translating muscle activity into control commands. This study aims to classify four left-hand movements using EMG signals and an Artificial Neural Network (ANN). Root Mean Square (RMS) and Mean Frequency (MF) features were extracted and used as ANN inputs. The results show that each movement produces distinct RMS and MF patterns; however, these features alone are insufficient for optimal classification. The best ANN model, consisting of four hidden layers and 320 neurons, achieved 77.5% accuracy, 77.9% precision, and 77.5% sensitivity. These findings demonstrate the potential of ANN for EMG-based hand movement recognition, while suggesting that additional features and larger datasets may further improve classification performance.

1. Introduction

Indonesia, with a population exceeding 270 million people across more than 17,000 islands, faces significant challenges in providing accessible mobility solutions for individuals with disabilities. In 2023, approximately 28.05 million people (10.38% of the population) were reported to have a disability, with a higher proportion of women than men. To support independent mobility and daily activities, individuals with disabilities commonly rely on assistive technologies such as conventional wheelchairs, powered wheelchairs, mobility scooters, and walking aids [1]. These devices play a crucial role in enhancing accessibility, autonomy, and quality of life.

Electric wheelchairs provide an effective mobility solution for individuals with disabilities, enabling greater independence in daily activities. However, joystick-controlled wheelchairs are primarily suitable

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for users with intact hand function and are less practical for individuals with upper-limb amputations. Recent advances in robotic rehabilitation have demonstrated that Electromyography (EMG) signals can be used to detect movement intentions and serve as a reliable control mechanism in human–machine interface applications [2]. By capturing electrical activity generated during muscle contractions, EMG offers a promising alternative for controlling assistive devices, including electric wheelchairs and prosthetic hands, even when part of the limb has been amputated [3].

Independent mobility plays a crucial role in improving quality of life, reducing dependence on caregivers, and enhancing self-confidence among individuals with disabilities [4]. Among the muscles commonly investigated for EMG-based control systems, the Pronator Teres muscle has attracted considerable attention due to its accessibility and ability to generate distinguishable activation patterns for movement recognition [5]. Nevertheless, EMG signal classification remains challenging because of inter-subject variability, signal noise, and limited datasets. These challenges necessitate robust classification and validation methods to ensure reliable system performance.

Previous studies have demonstrated the feasibility of using forearm EMG signals from flexor and extensor muscles to control assistive devices through phantom limb movements, where users imagine movements of the amputated limb to generate detectable muscle activity [7], [8]. Such approaches have shown potential for intuitive wheelchair navigation and prosthetic control. To improve the reliability of EMG-based classification systems, K-fold cross-validation is widely employed as a model evaluation technique. By systematically partitioning data into training and testing subsets, this method provides a more comprehensive assessment of model performance while reducing the risk of overfitting [9].

Therefore, this study investigates the classification of forearm EMG signals associated with hand movements using an Artificial Neural Network (ANN) combined with K-fold cross-validation. The objective is to evaluate the feasibility of utilizing EMG signals as directional control commands for assistive mobility devices, contributing to the development of more accessible and adaptive technologies for individuals with upper-limb disabilities [10].

2. Literature Review

The classification of hand movements using EMG signals has been widely explored in previous studies. One study employed a Support Vector Machine (SVM) to classify seven hand movements, including tripod, power grip, precision grip, finger point, mouse grip, hand close, and hand open. Using EMG data collected from five healthy participants, the model achieved classification accuracies ranging from 85–89% for training data and 80–86% for testing data, demonstrating the feasibility of EMG-based hand movement recognition [11].

Other studies have investigated EMG-based classification involving both amputee and non-amputee participants. By placing electrodes on the flexor and extensor forearm muscles, researchers compared several feature extraction techniques, including spectral power density, wavelet packet transform, and S-transform. The results showed that the S-transform provided superior classification performance, highlighting the importance of appropriate feature extraction methods for EMG signal analysis [12].

Artificial Neural Networks (ANNs) have also been extensively applied for EMG signal classification. Previous research demonstrated that ANN models can recognize various hand movements, such as fist clenching, finger extension, wrist flexion, wrist extension, and relaxed positions, using features including Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), and other time-domain characteristics [13], [14]. However, some studies reported classification accuracies of approximately 80%, indicating that further improvements are needed to enhance recognition performance and model generalization [15].

In addition to hand movement recognition, EMG-based ANN systems have been successfully implemented in robotic arm control and human–machine interface applications. These studies demonstrated that ANN algorithms are capable of distinguishing complex forearm muscle activation patterns and translating them into control commands for assistive devices [16], [17].

Despite these promising results, challenges remain in achieving robust and reliable EMG signal classification due to signal variability, noise, and limited datasets. Furthermore, many previous studies focused primarily on classification accuracy without employing comprehensive validation techniques. Therefore, this study proposes the use of an Artificial Neural Network (ANN) combined with K-fold cross-validation to classify forearm EMG signals associated with hand movements. The integration of ANN and

K-fold validation is expected to provide a more reliable evaluation of classification performance while supporting the development of EMG-based control systems for assistive mobility devices.

3. Method

The EMG signals analyzed in this study were obtained from the inward flexion movements of the little, ring, middle, and index fingers, as illustrated in Figure 1. These movements were selected because they require relatively low muscle effort, making them suitable for individuals with limited upper-limb strength, including those with paralysis. The muscle activities associated with these finger movements primarily involve the Extensor Digitorum and Flexor Carpi Radialis muscles; therefore, MyoWare sensors were positioned directly over these muscle groups to capture EMG signals [18].

The EMG acquisition process was performed using MyoWare sensors placed on the upper and lower regions of the left forearm. Raw EMG signals were collected through multiple channels corresponding to the Extensor Digitorum and Flexor Carpi Radialis muscles. To characterize muscle activity, several feature extraction methods were applied, including Mean Absolute Value (MAV), Root Mean Frequency (RMF), Simple Square Integral (SSI), Variance (VAR), and Integrated EMG (IEMG) [19]. The extracted features were subsequently used as inputs for an Artificial Neural Network (ANN) based on the backpropagation algorithm to classify hand movements.

The classified movements were mapped to wheelchair navigation commands, including forward, right turn, reverse, and left turn. EMG signals were acquired through an Arduino Uno microcontroller and transmitted to a computer via serial communication for processing and analysis. The overall system architecture and data acquisition process are illustrated in Figure 2 [20].

EMG signal classification begins with data collection via Myoware sensors; the collected data consists of two raw signals (RAW), labelled as channels 1 (CH1) to 4 (CH4), which are placed on the upper and lower segments of the left arm, specifically on the extensor digitorum and flexor carpi radialis muscles. The role of these muscles relates to the movements performed, and their attributes are identified through feature extraction techniques such as Mean Absolute Value (MAV), Root Mean Frequency (RMF), Simple Square Integral (SSI), Variance of EMG (VAR), and Integrated EMG (IEMG). The procedure for determining these attributes involves inputting data from each channel, CH1 to CH8, into calculations for the five feature extraction techniques, resulting in a total of forty signals generated from a single finger movement [19]. These signals serve as input for the artificial neural network algorithm, specifically the backpropagation neural network, whilst the output is a classification. Wrist extension for the forward movement command, wrist extension for the right turn command, gripping for the reverse command, and wrist flexion for the left movement command. The connected EMG will interact with the Arduino UNO for raw data acquisition, which can then be stored on a PC via serial transmission. These stages are illustrated in Figure 2 [20].

Figure 1. Placement of EMG electrodes

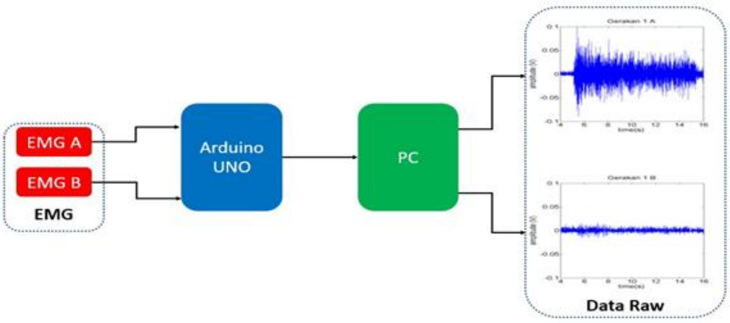

Figure 2. Schematic diagram of the data collection device

The hand movements analyzed in this study consisted of wrist extension, wrist flexion, and grasping. These movements were selected because they are directly associated with the functions of the Extensor Digitorum and Flexor Carpi Radialis muscles. The Extensor Digitorum is primarily responsible for wrist and finger extension, whereas the Flexor Carpi Radialis contributes to wrist flexion. Previous studies have shown that EMG signals generated by these muscles can still be detected in individuals with forearm amputations through residual muscle activity. This finding highlights the potential of EMG-based systems for interpreting movement intentions and controlling assistive devices in amputees. In this study, the identified hand movements were mapped to wheelchair navigation commands, providing directional control for mobility assistance, as presented in Table 1.

Table 1. Hand gestures as navigation cues

Movement Title	The Movement Performed	Direction of Wheelchair Propulsion
Movement 1	Stretching the Wrist	Currently in progress
Movement 2	Wrist Extension	Right
Movement 3	Holding	Could
Movement 4	Wrist Flexion	Left

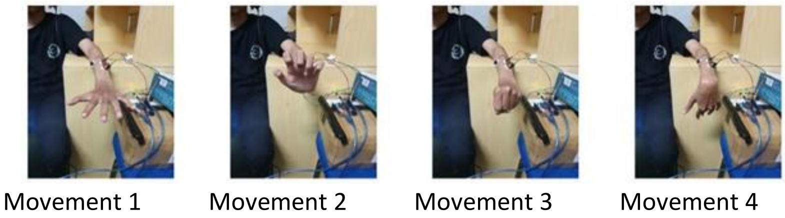

Figure 3. Hand movements

EMG electrodes were placed at two locations on the left forearm: the Extensor Digitorum and Flexor Carpi Radialis muscles. Prior to electrode placement, the skin surface was cleaned with alcohol to reduce impedance and improve signal quality. Participants were instructed to perform four predefined hand movements, with each movement repeated six times. A one-minute rest interval was provided between repetitions to minimize muscle fatigue and ensure signal consistency. This rest period is important because prolonged muscle contraction can reduce neuromuscular transmission efficiency, leading to decreased muscle performance and potentially affecting the quality of the recorded EMG signals.

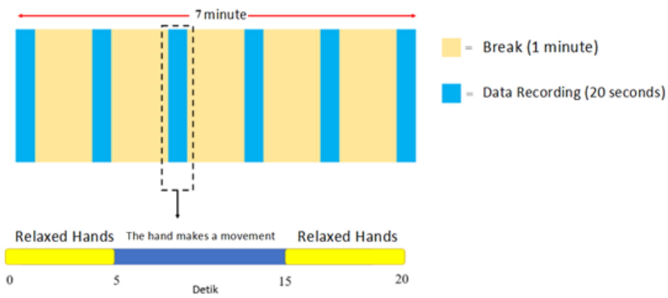

Figure 4. Data documentation for each movement

For each trial, EMG data were recorded over a 20-second period, illustrated at Figure 4. During the first 5 seconds, participants maintained a relaxed hand position, followed by the execution of a specific movement from 5 to 15 seconds, and a return to the relaxed position during the final 5 seconds. After feature extraction, including Root Mean Square (RMS) and Mean Frequency (MNF), the data were analyzed using the Wilcoxon rank-sum test in MATLAB to evaluate differences between movement classes. A significance level of $p < 0.05$ was used to determine whether a feature could effectively discriminate between movements. Features demonstrating significant differences were selected as inputs for the Artificial Neural Network (ANN). Furthermore, ANN performance was evaluated using descriptive statistics, where the mean represented the average classification performance and the standard deviation indicated the variability and consistency of the results across experiments.

4. Results and Discussion

The effect of ANN inputs on MSE and accuracy, using several ANN architecture models as shown in Table 2 and with various input data as shown in Table 3.

Table 2. ANN architectural model

Model	Number of Neurons
Model 1	200
Model 2	320
Model 3	360

Three ANN architectures were evaluated to investigate the effect of neuron number on EMG signal classification performance. As shown in Table 2, Model 1 consisted of 200 neurons, Model 2 of 320 neurons, and Model 3 of 360 neurons. These architectures were tested using the extracted EMG features to determine the optimal balance between classification accuracy and model complexity. The resulting performance metrics, including MSE, accuracy, precision, and sensitivity, are presented in Table 3 and discussed in the following section.

Table 3. Training data as input ANN

Data Name	ANN Inputs Used
Data 1	RMS A , RMS B
Data 2	MNF A , MNF B
Data 3	RMS A , RMS B, MNF A
Data 4	RMS A , RMS B , MNF B
Data 5	RMS A , MNF A , MNF B
Data 6	RMS A , RMS B , MNF A , MNF B

The first EMG channel (extensor digitorum) for movement 2 had an RMS value of 0.435, which was higher than that of the other movements, see in Figure 5. The RMS value for movement 2 also showed statistical significance ($p < 0.05$) when compared with the other movements; the RMS value of a movement can be considered higher or lower if it has a low p-value ($p < 0.05$). Movement 1 is lower than movement 2 but higher than movement 3. Meanwhile, the RMS values for movements 3 and 4 are considered to show no difference ($p > 0.05$).

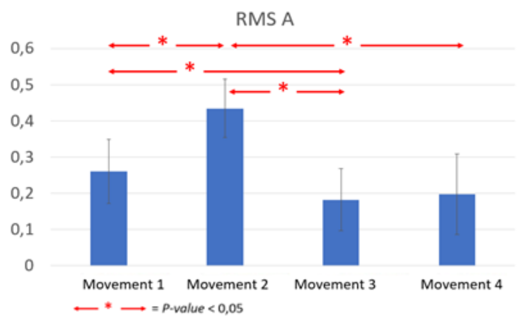

Figure 5. Graph of RMS A value

The second EMG measurement (flexor carpi radialis) showed that movement 4 had an RMS value of 0.313, which was higher than that of the other movements. Furthermore, movement 4 also had a lower significance value compared to the other movements. Movement 3 has a higher value compared to movement 1, but not compared to movement 2. Meanwhile, movement 2 has an RMS value of 0.154, which is almost the same as movement 1 at 0.133. The RMS values for the second placement can be seen in Figure 6.

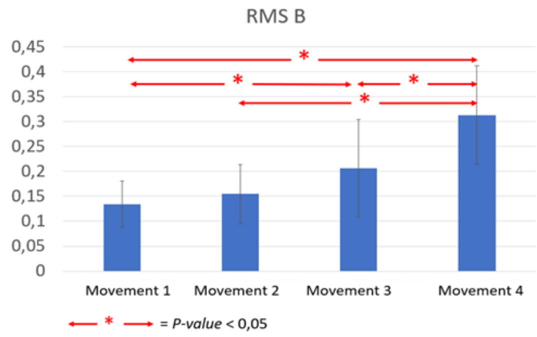

Figure 6. Graph of the RMS B value

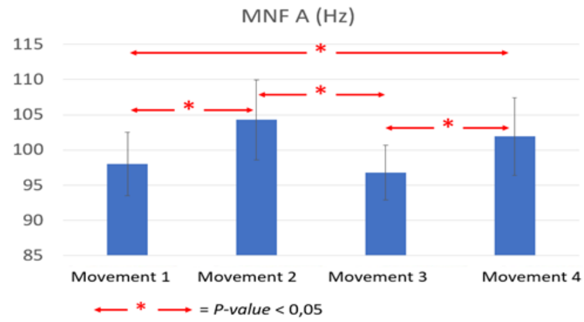

Figure 7. Graph of MNF A values

The initial EMG recording showed that movement 2 had an MNF value of 104.29 Hz and movement 4 had a value of 101.90 Hz, with both movements exhibiting higher frequencies than the others. This is illustrated in Figure 7 furthermore, movements 2 and 4 cannot yet be said to be different. This is because the significance values for movements 2 and 4 are quite high ($p > 0.05$). Movements 1 and 3 also have high significance values, so it can be said that movements 1 and 3 have identical frequencies

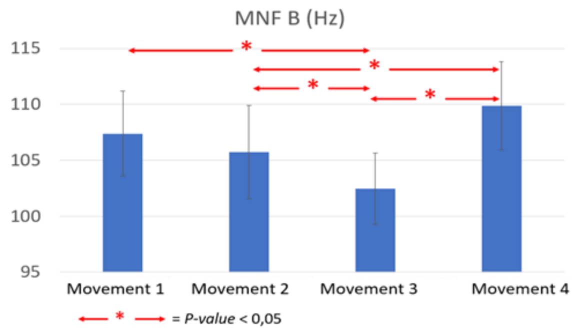

Figure 8. Graph of MNF B values

The analysis of the second EMG sensor placement revealed variations in the Mean Frequency (MNF) values among the four hand movements, see in Figure 8. Movement 4 exhibited the highest average MNF value at 109.86 Hz, followed by Movement 1 at 107.38 Hz. Although Movement 4 showed a slightly higher frequency than Movement 1, statistical analysis indicated a relatively high significance value ($p > 0.05$), suggesting that the difference between these two movements was not statistically significant. A similar observation was found between Movements 1 and 2, where the MNF values were close to each other and did not demonstrate a significant distinction. In contrast, Movement 3 produced the lowest average MNF value, 102.46 Hz, and exhibited lower significance values when compared with the other movements, indicating a greater degree of separation in frequency characteristics.

Despite these differences, the overall results indicate that the extracted features were not sufficient to clearly discriminate all movement classes. Several movements generated similar RMS and MNF values, resulting in overlapping feature distributions. Furthermore, the relatively large standard deviation observed in both parameters suggests considerable variability in muscle activation patterns across trials. This variability may be attributed to differences in contraction intensity, electrode placement, muscle fatigue, and natural physiological fluctuations during movement execution. Consequently, relying solely on RMS and MNF features may not provide adequate discriminatory power for robust movement classification.

To further investigate the effect of ANN architecture on classification performance, experiments were conducted using a fixed number of hidden layers while varying the number of neurons. The results showed a clear trend in which increasing the number of neurons led to a reduction in the Root Mean Square Error (RMSE) value. This finding suggests that a larger network capacity enables the ANN to learn more representative patterns from the EMG feature set, thereby reducing prediction error. The relationship between the number of neurons and RMSE is illustrated in Figure 9.

Linear regression analysis was performed to quantify this relationship, yielding an R^2 value of 0.8799. This result indicates that approximately 87.99% of the variation in RMSE can be explained by changes in the number of neurons, demonstrating a very strong correlation between network size and model performance. The decreasing RMSE trend confirms that increasing the number of neurons improves the ANN's ability to capture complex EMG signal characteristics. However, excessively large networks may increase computational complexity and the risk of overfitting. Therefore, selecting an optimal neuron configuration is essential to achieve a balance between classification accuracy, computational efficiency, and model generalization.

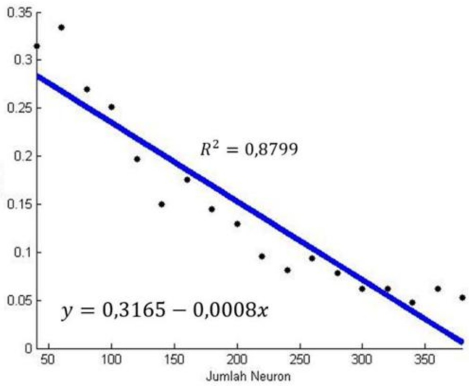

Figure 9. Relationship between RMS and the number of neurons

In addition to analyzing the relationship between RMSE and the number of neurons, this study also investigated the effect of neuron count on classification accuracy. Figure 10 presents the linear regression analysis between the number of neurons and the achieved accuracy values. The results indicate that increasing the number of neurons generally leads to a slight improvement in classification accuracy. However, the relationship is relatively weak compared to that observed for RMSE.

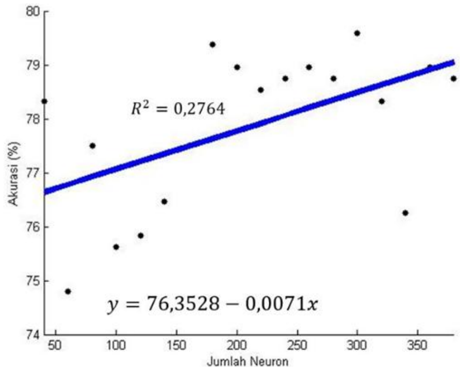

Figure 10. Relationship between accuracy and the number of neurons

This finding is supported by the coefficient of determination (R^2 = 0.2764), which indicates that only 27.64% of the variation in accuracy can be explained by changes in the number of neurons. Although a positive trend is observed, the low R^2 value suggests that the number of neurons is not the dominant factor affecting classification accuracy. Other factors, such as the quality of the extracted EMG features, signal variability, dataset size, training parameters, and network architecture, may have a greater influence on overall classification performance.

These results suggest that simply increasing the number of neurons does not guarantee a substantial improvement in accuracy. While a larger network may enhance the model's ability to learn complex patterns, the classification performance remains highly dependent on the discriminative capability of the input features and the quality of the training data. Therefore, future studies should focus not only on optimizing the ANN architecture but also on improving feature extraction techniques and expanding the dataset to achieve more robust and accurate EMG signal classification.

This study also evaluated the effect of the number of hidden layers on ANN performance. The results indicate that architectures with four hidden layers provided the most favorable balance between learning capability and classification performance. As illustrated in Figure 11, the Root Mean Square Error (RMSE) values varied across the tested models, with architectures containing three and five hidden layers exhibiting relatively higher RMSE values. This suggests that both insufficient and excessive network depth may negatively affect the model's ability to generalize EMG signal patterns.

Among the evaluated architectures, Model 1 achieved the best performance, producing the lowest RMSE value of 0.0332 along with a relatively small standard deviation, indicating stable and consistent classification results. Although Model 5, which contained the largest number of neurons, achieved a slightly higher RMSE value of 0.0399, its error remained relatively low and comparable to that of Model 1. These findings suggest that increasing the number of neurons can contribute to reducing prediction error; however, the relationship is not strictly linear, as other architectural factors also influence model performance.

The results are consistent with the analysis presented in Section 4.4, which demonstrated that a larger number of neurons tends to reduce RMSE values by improving the network's capacity to learn complex EMG signal characteristics. Nevertheless, the findings also indicate that simply increasing network complexity does not always yield proportional performance gains. Therefore, an ANN architecture with four hidden layers appears to provide an optimal configuration for EMG-based hand movement classification, offering low prediction error while maintaining model stability and computational efficiency.

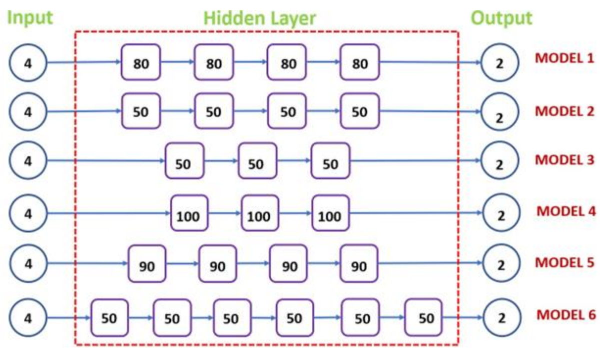

Figure 11. ANN model

To improve the reliability of model evaluation, the Artificial Neural Network (ANN) was assessed using K-fold cross-validation across several ANN architecture configurations. This validation technique ensures that all data samples are used for both training and testing, resulting in a more robust and unbiased estimation of model performance. Each architecture was evaluated based on its classification accuracy, precision, sensitivity, and Root Mean Square Error (RMSE). The trained models were subsequently tested using unseen test data to evaluate their generalization capability. Among the evaluated architectures, Model 1, consisting of four hidden layers and 320 neurons, demonstrated the best overall performance. This model achieved an accuracy of 77.5%, a precision of 77.9%, and a sensitivity of 77.5%, indicating a balanced ability to correctly classify the four hand movement classes. Across all tested architectures, classification performance generally ranged between 70% and 80%, demonstrating that ANN is capable of recognizing EMG-based hand movements with satisfactory accuracy.

The superior performance of Model 1 suggests that the selected architecture provides an effective balance between network complexity and classification capability. While increasing the number of neurons or hidden layers may improve the network's learning capacity, excessive complexity does not necessarily translate into better classification results. Based on the experimental findings, an ANN architecture with four hidden layers and 320 neurons is recommended as the most suitable configuration for classifying the four left-hand movements. These results support the feasibility of using EMG signals as directional control inputs for assistive technologies, such as intelligent wheelchairs and other human–machine interface applications.

5. Conclusion

The results demonstrate that the EMG signals recorded from the Extensor Digitorum and Flexor Carpi Radialis muscles exhibit distinct characteristics for different hand movements. In the first EMG channel, Movements 1 and 2 produced higher signal amplitudes, resulting in larger RMS values, while Movements 2 and 4 showed higher MNF values. In the second EMG channel, higher RMS values were observed in Movements 3 and 4 due to their greater signal amplitudes, whereas Movements 1 and 4 exhibited the highest MNF values. Although these findings indicate that RMS and MNF capture meaningful differences in muscle activation patterns, the overlap between feature values across movements suggests that these two features alone are insufficient for reliable discrimination of the four left-hand movements. To address this limitation, an Artificial Neural Network (ANN) was employed to classify hand movements using RMS and MNF features extracted from both muscle groups. Among the evaluated architectures, the best performance was achieved by an ANN consisting of four hidden layers and 320 neurons, which produced an RMSE of 0.0332, an accuracy of 77.5%, a precision of 77.9%, and a sensitivity of 77.5%. These results confirm the feasibility of using ANN for EMG-based hand movement classification; however, the performance remains below the desired level of 80%, indicating room for further improvement. Further analysis revealed a strong relationship between the number of neurons and model error, as evidenced by an R^2 value of 0.8799 between RMSE and neuron count. This finding suggests that increasing the number of neurons enhances the network's ability to learn EMG signal patterns and reduces prediction error. In contrast, the relationship between neuron count and classification accuracy was relatively weak ($R^2 = 0.2764$), indicating that accuracy is influenced not only by network size but also by factors such as feature quality, signal variability, and dataset characteristics.

Overall, the proposed ANN model demonstrates promising potential for recognizing forearm EMG signals as control commands for assistive technologies. Future work should focus on incorporating additional EMG features, increasing the amount and diversity of training data, and optimizing network architectures to further improve classification accuracy, robustness, and real-world applicability in EMG-based human–machine interface systems.

Credit Authorship Contribution Statement

Anjar Setiawan : Conseptualization, Methodology, Software, and Project administration. **Fauzan Dika :** Writing and Editing. **Hayadi Hamuda :** Writing, Review, and Validation.

Declaration of Competing Interest

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Data Availability

Data will be made available on request.

Use of Artificial Intelligence

The authors used artificial intelligence (AI) tools solely to assist with language improvement, grammar checking, and manuscript editing. All methodological design, algorithm development, experimental implementation, data analysis, interpretation of the results, and final manuscript preparation were performed by the authors. The authors reviewed and approved all AI-assisted outputs and take full responsibility for the content of this manuscript.

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