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Electric wheelchair navigation based on hand gestures prediction using the k-Nearest Neighbor method

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Abstract

The advancement of technology in the medical field has led to innovations in assistive devices, including wheelchairs, to enhance the mobility and independence of individuals with disabilities. This study investigates the use of electromyography (EMG) signals from hand muscles to control a wheelchair using the k-Nearest Neighbor (kNN) classification method. kNN is a classification algorithm that identifies objects based on the proximity of similar objects in the feature space. The wheelchair control process begins with the development of a kNN model trained on EMG signal data collected from five respondents over 30 seconds. The data was processed using feature extraction techniques, namely mean absolute value (MAV) and root mean square (RMS), to identify motion characteristics corresponding to five types of movement: forward, backward, right, left, and stop. The extracted features were classified using the kNN algorithm implemented on a Raspberry Pi 3. The classification results were then used to control the wheelchair through an Arduino UNO microcontroller connected to a BTS7960 motor driver. The study achieved an average accuracy of 96 % with the MAV feature and k = 3. Furthermore, combining MAV and RMS features significantly improved classification accuracy. The highest accuracy was obtained using the combination of MAV and RMS features with k = 3, demonstrating the effectiveness of feature selection and parameter tuning in enhancing the system's performance.

Keywords: assistive technology; electromyography signal; feature extraction; k-Nearest Neighbor classification; wheelchair control system.

I. Introduction

People with physical disabilities often encounter substantial mobility barriers, including limited accessibility, high transportation costs, and complex travel planning [1][2]. These issues affect both motorized and non-motorized travel, ultimately limiting access to essential services and reducing quality of life [2]. Autonomous vehicles (AVs) have been proposed as a long-term solution, with studies reporting generally positive attitudes toward AVs among people with disabilities [3]. Nonetheless,

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concerns remain regarding their accessibility, safety, and reliability [3]. For older adults with chronic mobility impairments, daily activities pose persistent challenges, often requiring adaptive strategies such as assistive tools, caregiver support, or modified routines [4]. Addressing these challenges calls for increased awareness among policymakers and targeted actions to improve transportation accessibility [2].

In the short term, electric-powered wheelchairs (EPWs) have emerged as a promising mobility solution. Recent advancements include pedal-operated speed controls [5], seating safety mechanisms using position sensors [6], and head gesture-based controls employing gyroscopes for users with tetraplegia [7]. electromyography (EMG)-based control systems have also been developed, leveraging muscle contractions—particularly from the neck and facial regions—for wireless control in users with quadriplegia [8]. These innovations aim to increase autonomy and improve the quality of life for individuals with diverse mobility limitations.

Recent research has focused on utilizing EMG signals to enable intuitive wheelchair control through the detection of muscle contractions from the face, neck, and forearms [9]. EMG-based wheelchairs can interpret subtle muscle twitches to perform directional movements [10]. Wireless systems have gained traction due to their flexibility and user comfort [11], and integration with electroencephalography (EEG) has been explored to enhance control accuracy [12]. These systems typically process EMG signals through stages of data acquisition, feature extraction, and classification to execute commands such as moving forward, turning, or stopping [13][14][15].

These systems typically involve data acquisition, signal processing, feature extraction, and classification to generate control commands [15]. In this context, the effectiveness of EMG-controlled wheelchairs largely depends on the extraction of relevant features from EMG signals. Commonly used time-domain features include mean absolute value (MAV), root mean square (RMS), variance (VAR), and zero crossing (ZC), which provide meaningful indicators of muscle contraction intensity and variability [16][17][18]. MAV and RMS are essential for capturing amplitude characteristics of the signal, while VAR offers insights into contraction variability, and ZC indicates the frequency content of muscle activity [19][20][21][22]. Incorporating these features can improve classification robustness and responsiveness, particularly in real-time assistive applications such as wheelchairs and prosthetic control [23].

Studies have also explored various machine learning algorithms to classify EMG signals, achieving accuracies up to 95.42 % using decision trees and random forests [24]. A hand gesture-based control method for electric-powered wheelchairs (EPW) has been proposed to assist users with finger impairments. Among the tested recognition methods, linear regression (LR) and regularized linear regression (RLR) achieved accuracies of 94.85 % and 95.88 %, respectively, though they required user-specific training. To address this, user-independent models like multi-class support vector machines (MC-SVM) and decision trees (DT) were employed, reaching 99.05 % and 97.77 % accuracy, respectively [25].

Although various classification algorithms such as decision trees, random forests, support vector machines (SVM), and linear regression have achieved high accuracy in EMG signal recognition tasks, the k-Nearest Neighbor (kNN) method remains an attractive alternative due to its simplicity, ease of implementation, and robustness when working with small or noisy datasets. Time-domain EMG features such as MAV, VAR, ZC, and RMS are also widely used because they are computationally efficient and effective for capturing key characteristics of muscle activity. However, most existing studies have focused primarily on general gesture recognition or controlled laboratory scenarios, and there is still limited research on the practical performance of these methods for real-time wheelchair control, especially when relying on hand muscle signals. Challenges such as individual signal variability, susceptibility to noise, and the demand for consistent feature extraction in real-world conditions remain open issues. Therefore, this study aims to address these gaps by implementing the kNN method in combination with MAV, VAR, ZC, and RMS features to classify hand muscle contractions for electric wheelchair control. This approach is expected to improve classification accuracy, enhance real - time performance, and contribute to the development of practical, reliable, and user-friendly EMG - based wheelchair control systems for individuals with motor impairments.

II. Materials and Methods

The study employed an experimental approach, as illustrated in Figure 1. Muscle signal (EMG) data were collected using a Myoarmband attached to the respondent's arm. Respondents were instructed to perform five specific movements corresponding to wheelchair control commands: relaxing for moving forward, clenching the fist for stopping, bending the arm backward for turning left, bending the arm sideways for turning right, and performing a shooting gesture for moving backward. The collected EMG data

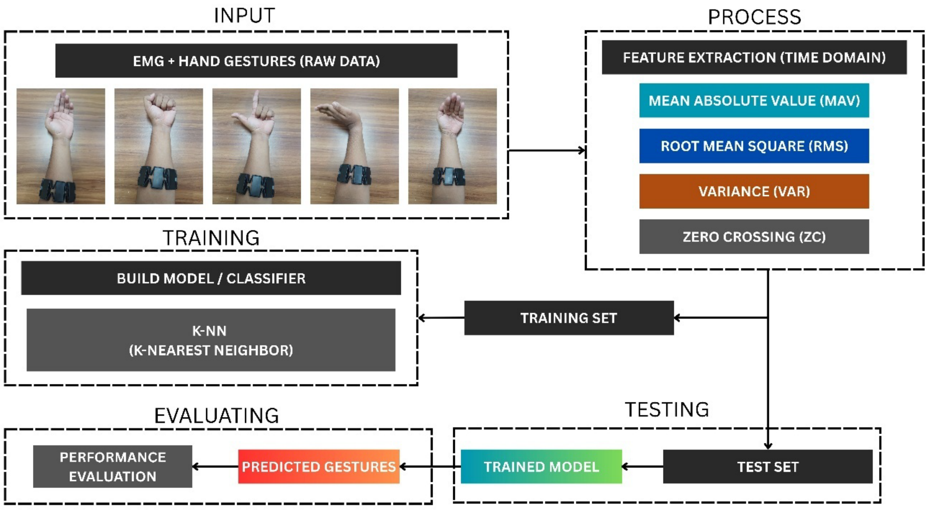

Figure 1. Block diagram of hand gesture classification process for electric wheelchair control using EMG signal and kNN method.

were recorded and processed using feature extraction techniques, including MAV [26], VAR [27], ZC [28], and RMS [29] to identify the unique characteristics of each movement.

MAV and RMS both represent the amplitude of the signal, with MAV representing the average muscle contraction force, and RMS representing the power component of the signal more sensitively. These two characteristics serve as the basis for distinguishing movement intensity, such as distinguishing between strong and weak movements. VAR completes the analysis by measuring the variability of muscle contraction, helping to distinguish between stable (grip holding) and dynamic (turning or changing direction) movements.

These extracted features were then analyzed using the k-Nearest Neighbor (kNN) method to classify the test data, and the classification results were subsequently used to control the wheelchair.

A. Data collection

The data collection phase was conducted with five respondents, each guided through the procedure during the session. The respondents' characteristics are tabulated in Table 1.

First, the EMG sensor was attached to the forearm just below the elbow, with the LED indicator on the Myo Armband aligned to the back of the hand to ensure consistent positioning for targeting the desired muscle groups. The use of eight equally spaced surface EMG electrodes circumferentially around the forearm follows the configuration employed by widely adopted devices such as the Myo Armband, aligning with standard practices in multi-channel surface electromyography (sEMG) gesture recognition [30][31]. This arrangement ensures comprehensive coverage of both flexor and extensor muscle groups, supporting uniform and reliable signal acquisition as illustrated in Figure 2 [32].

In the next step, respondents were instructed to perform each movement for 30 seconds. The movements were in accordance with certain commands, including: a gesture of relaxing the hand to move forward, a gesture of clenching the hand to stop, a gesture of shooting the hand to move backward, a gesture of bending the arm backward to turn left, and a gesture of bending the arm sideways to turn right. The instructional movements are illustrated in Figure 3.

Table 1.
Respondent characteristics.

No.	Age	Weight (kg)	Height (cm)	BMI
1.	22	65	163	24.5
2.	22	75	187	21.4
3.	22	78	169	27.3
4.	22	48	150	21.3
5.	22	70	169	24.5

**BMI = Body mass index*

B. Muscle signal data

At this stage, the muscle signal data, for each movement, were analyzed to identify the characteristics of the hand movements. The EMG signal is characterized by a frequency range of 20 Hz to 500 Hz and generates an amplitude when muscle contraction occurs [33][34]. An example of the muscle signal readings for the thumb and index finger open movement is shown in Figure 4.

This paper utilized surface EMG (sEMG). sEMG is a non-invasive technique for recording electrical activity from superficial skeletal muscle during contractions [35]. The signal characteristics depend on muscle fiber membrane potentials and neural activation from motor neurons [36]. Each data

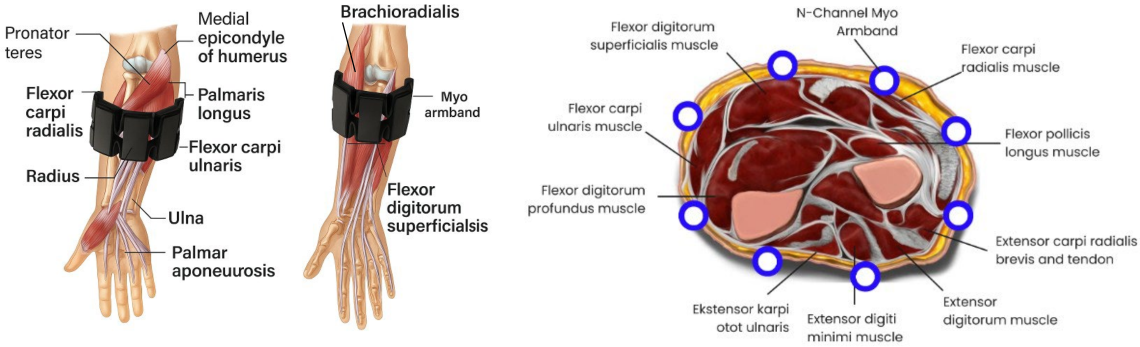

Figure 2. Placement of the EMG sensor [32].

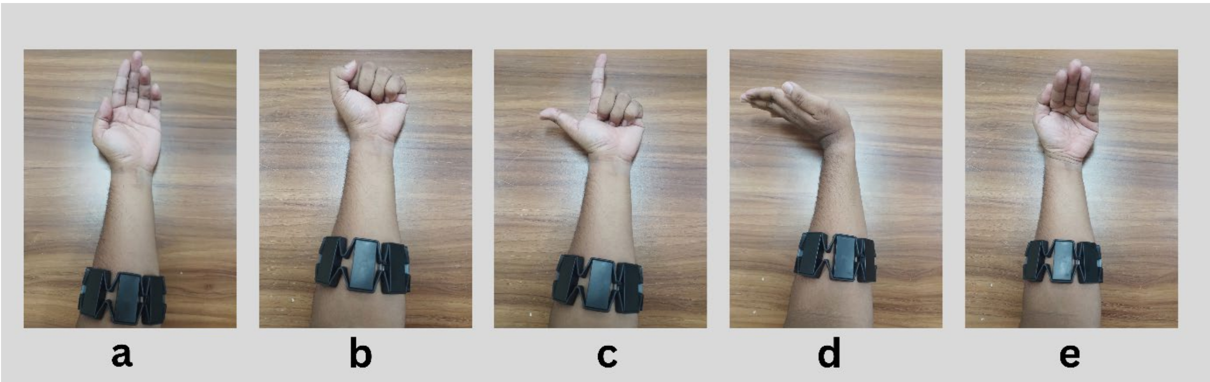

Figure 3. (a) Relaxed movement; (b) palmar grasping with thumb straight; (c) finger gun gesture; (d) sideways wrist extension; and (e) backward wrist flexion.

Table 2.
Respondent characteristics.

No.	Movement class	C1	C2	C3	C4	C5	C6	C7	C8
1	Relax								
2	palmar grasping with thumb straight								
3	sideways wrist extension								
4	finger gun gesture								
5	backward wrist flexion								

collection has 8 signal readings that show differences in muscle activity. Figure 4 shows channel 3 (green), channel 2 (red), and channel 1 (blue) experiencing muscle activity that causes contraction, while on other channels, there is no muscle contraction. Table 2 shows the 8-channel muscle activity characteristics in five different movements.

C. Feature extraction

In analyzing muscle signals using EMG, a method is needed to facilitate data processing, namely, feature extraction. Feature extraction is performed after the data normalization process (threshold) to change the EMG data to positive values. Negative signals in EMG data are removed through the threshold process, so only positive data is obtained. This process is carried out for signal amplitude processing because the calculation uses positive values. The amount of data obtained in each movement is approximately 3000 data points on each channel. The data is processed with extraction features including MAV, VAR, and RMS, after which the data is used as training or testing input.

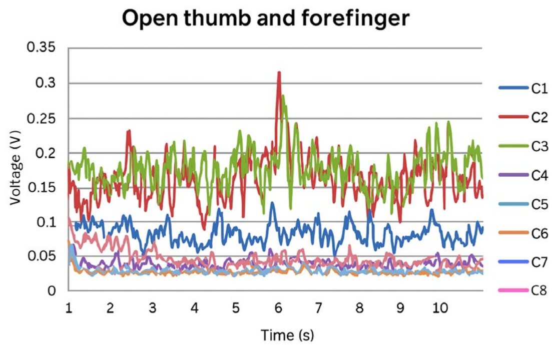

Figure 4. Muscle signals when performing open thumb and index finger movements.

1) Mean absolute value (MAV)

The MAV is a simple and widely used method for calculating the average amplitude of the EMG signal within a moving window [37]. In this study, MAV is computed by shifting the window every 100 data points. The MAV is calculated using equation (1).

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \quad (1)$$

where N is the total number of signal samples in each window and x_n is the value of the n^{th} sample. The absolute value operator ensures that only the magnitude of each sample is included.

2) Variance (VAR)

The VAR is used to measure how much the EMG signal values deviate from the mean within a window [38]. A higher variance indicates greater fluctuation in the signal. Equation (2) shows the VAR feature formula as follows:

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu)^2 \quad (2)$$

where N is the number of samples, x_n is the n^{th} sample value, and μ is the average value of all samples in the window.

3) Root mean square (RMS)

The RMS method is another common feature that represents the square root of the mean of the squared EMG signal values [39]. It provides an estimate of the signal's power. Equation (3) is the formula for RMS;

$$RMS = V_{RMS}\sqrt{\frac{1}{N}\sum_{n=1}^{N}x_n^2} \quad (3)$$

where N denotes the total number of samples, and x_n is the n^{th} signal sample.

4) Zero crossing (ZC)

The ZC counts how often the EMG signal changes its sign by crossing the zero line [40]. This feature can help detect frequency information in the signal. To reduce noise effects, a minimum threshold is applied so that only significant crossings are counted. The ZC is calculated using equation (4):

$$ZC = \sum_{i=1}^{N-1}[f(x_i.x_{i+1})| \cap |x_i - x_{i+1}| \geq 10] \quad (4)$$

$$f(x) = f(x) = \begin{cases} 1, & if\_x < 0 \\ 0, & otherwise \end{cases}$$

where x_i and x_{i+1} are two consecutive signal samples, and N is the total number of samples. The function $f(x_i, x_{i+1})$ equals 1 if the product $x_i.x_{i+1}$ is negative—meaning a zero crossing occurs—and the absolute difference $x_i - x_{i+1}$ is greater than or equal to the threshold; otherwise, it equals 0.

D. kNN algorithm design

Classification of wheelchair control using finger gestures is done using the kNN method. The k-Nearest Neighbor (kNN) method is a classification technique that categorizes new objects based on their proximity to training data samples [41]. In this research, the kNN method is used for the classification of hand movements in wheelchairs. This method uses Euclidean distance to determine the class of a data object [42].

The system produces five output classes (labels), each of which is explicitly linked to a specific hand gesture detected from EMG signals, and corresponds to a distinct movement command for the wheelchair, as described below:

- Class 0: Relaxed hand gesture → Move forward
- Class 1: Fist (clenched hand) gesture → Stop
- Class 2: Finger gun (shooting) gesture → Move backward
- Class 3: Arm bent backward gesture → Turn left
- Class 4: Arm bent sideways gesture → Turn right

Each class represents a unique EMG signal pattern associated with a specific gesture. These gestures were performed by the user and recorded using the Myo Armband on the left forearm. The EMG signals were processed on a Raspberry Pi 3 using the Python programming language. The kNN classification was tested using different values of k, specifically k = 3, 5, 9, and 11, to determine the most suitable parameter setting for accurate real-time gesture recognition. The Euclidean distance equation is shown in equation (5):

$$d = \sqrt{(a_1^2 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_n - b_n)^2}$$
$$= \sqrt{\sum_{i+1}^{n}(a_i - b_1)^2} \quad (5)$$

After training and testing the data from several respondents using various values of k, the next step involves sending the classification output to the Arduino microcontroller. To ensure compatibility with serial communication protocols, each of the five kNN classification results (0 to 4) is converted into its corresponding ASCII value, as follows:

- Class 0 (Move forward): ASCII 51 ('3')
- Class 1 (Stop): ASCII 50 ('2')
- Class 2 (Move backward): ASCII 49 ('1')
- Class 3 (Turn left): ASCII 48 ('0')
- Class 4 (Turn right): ASCII 52 ('4')

These ASCII values are transmitted via serial communication from the Raspberry Pi to the Arduino. On the Arduino side, each received character is mapped to a specific control command for the wheelchair motors. This mapping ensures that the recognized hand gesture is correctly translated into the intended movement in real time.

E. Motor control circuit of a wheelchair

The system design is composed of low-level control and high-level control. High-level control consists of a Raspberry Pi as muscle signal processing and a Myo armband as a sensor. Data that has been trained on a Raspberry Pi using the kNN method will be programmed in the Arduino UNO microcontroller. Components at the low-level control consist of an Arduino UNO, 2 BTS7960 motor drivers, LM7805 regulator, and a power supply in the form of a 24 V battery. The electronic system of the wheelchair can be seen in Figure 5.

F. Evaluation

Prior to real-time evaluation, an offline evaluation was conducted to determine the best combination of feature extraction method and k value in the k-Nearest Neighbor (kNN) algorithm. This evaluation uses accuracy metrics to assess the performance of hand gesture classification based on EMG signals. From the results, the configuration that gave the highest accuracy was selected as the basis for implementing the control system in the live test phase.

The test track used to evaluate the performance of the wheelchair control system based on EMG sensors is illustrated in Figure 6. This evaluation focused on measuring the system's accuracy, responsiveness to movement commands, and user comfort during

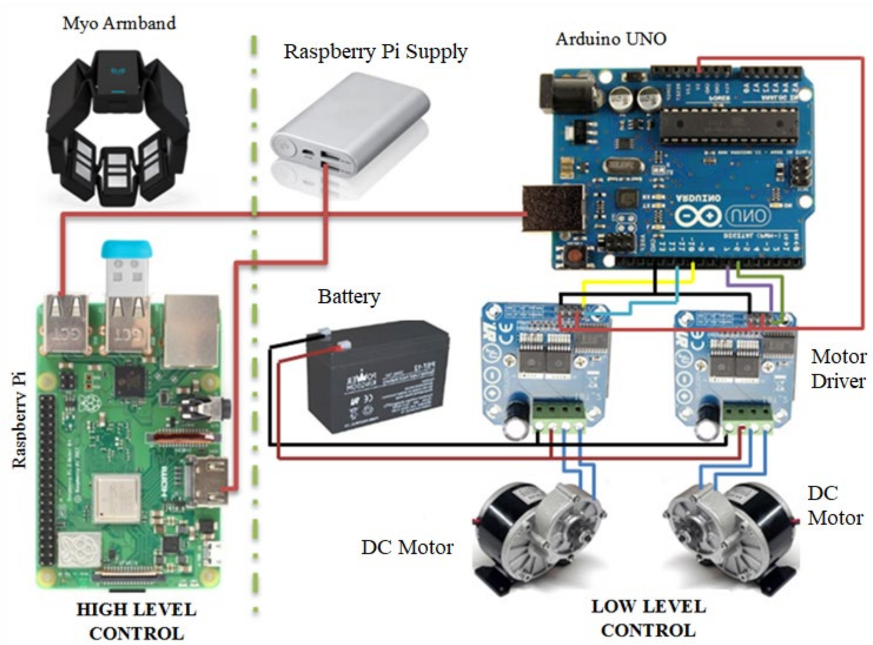

Figure 5. Wheelchair electronic system.

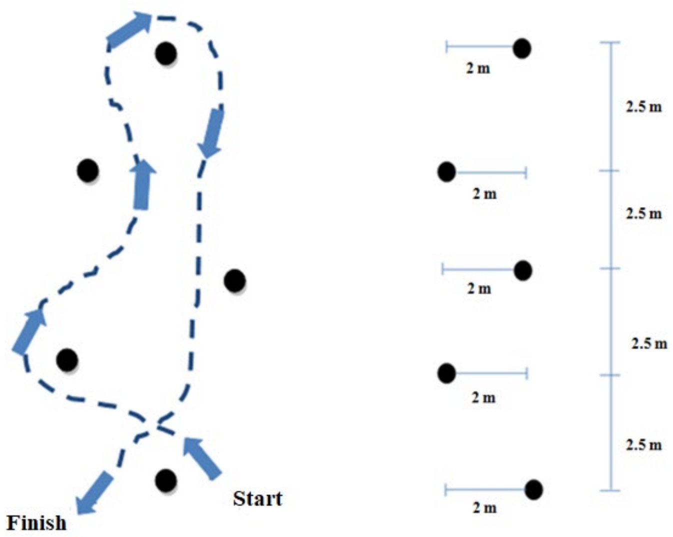

Figure 6. Test drive evaluation track.

operation. The user was required to navigate the wheelchair along a predefined path marked by black circles, which served as obstacles or directional markers. The path, shown with dashed lines and arrows, begins at the "Start" point and ends at the "Finish" point. On the right side of the figure, the spatial configuration of the obstacles is shown, with a horizontal spacing of 2 meters and a vertical spacing of 2.5 meters. These dimensions were selected to provide a consistent testing environment and enable an objective assessment of the system's navigation performance under conditions that mimic real-world scenarios.

To evaluate the performance of the system at this stage, several indicators were recorded, namely: average travel time (in seconds), number of movement errors, and total number of movement commands performed during navigation. In addition, the number of repetitions of track training before testing was also recorded to record the level of user familiarity with the system. This evaluation aims to assess how well the system recognizes gestures in real conditions and how efficient and accurate the system is in translating user commands into wheelchair movements.

III. Results and Discussions

In the kNN classification stage, the data were categorized into five classes: forward, backward, right turn, left turn, and stop. A sample size of 1,500 data points was collected from each respondent over a 30 second recording period. The features used in the classification included RMS, MAV, VAR, ZC, as well as combinations of two or three features. To evaluate the effect of the parameter k on classification accuracy, various values of k were tested, including $k = 3, 5, 9$, and 11. Additionally, a test drive evaluation was conducted to measure the response time of movements to instructions and the duration required to operate the wheelchair along a predefined track.

A. Feature extraction training data results

The respondent data collected during the acquisition phase were subsequently trained using variations in k-values for each feature. This process involved testing four different k-values ($k = 3, 5, 9, 11$) across four individual features (RMS, MAV, VAR, ZC) as well as their combinations. The goal was to evaluate the influence of k-value variations on the classification performance for each feature. After the training process, the resulting models were used for testing to assess their accuracy and reliability. Figure 7 presents the testing results for each feature under varying k-values, providing insights into the impact of feature selection and parameter tuning on system performance.

Based on the graph, it can be observed that training data using a single feature type achieved optimal accuracy with $k = 3$. The average accuracy across the five respondents was 96 % when using $k = 3$ and 94 % with $k = 9$, both employing the MAV feature extraction method. Additionally, other feature types, such as RMS and ZC, achieved similar accuracy levels of 95 % with $k = 3$. In contrast, the VAR feature extraction method yielded the lowest accuracy, with only 83 % at $k = 3$. These results highlight the influence of feature selection and k-value on the system's classification performance.

Figure 7. Graph of the effect of K value on accuracy

B. Testing the influence of feature combinations

Feature extraction using combined features involves merging two or more types of feature extraction methods. The classification results using all combined features were compared with those obtained using combinations of two and three features. The purpose of this test was to analyze the impact of feature combinations on classification performance using the kNN method, focusing on Subject 5. Four different types of features were evaluated to determine which combinations improved classification accuracy and which combinations reduced it. The first test utilized combinations of two features, the second test involved three feature combinations, and the final test used all features combined. The results of the tests are summarized in Table 3.

The investigation of feature combinations' influence on EMG signal classification revealed significant patterns in classification accuracy across different feature sets and k-values. The analysis was conducted using combinations of mean absolute value (MAV), root mean square (RMS), variance (VAR), and zero crossing (ZC) features through systematic testing of dual, triple, and quadruple feature combinations.

In dual feature analysis, the MAV-RMS combination demonstrated superior performance with 100.0 % classification accuracy consistently across all k-values (k = 3, 5, 9, and 11), indicating a strong complementary relationship between these features. However, combinations involving the VAR feature showed noticeable performance degradation, with MAV-VAR and RMS-VAR combinations maintaining 93.9 % accuracy at k = 3 and k = 5, before declining to 86.3 % at k = 11. Combinations with the ZC feature maintained robust performance at 100.0 % for lower k-values before slightly decreasing to 96.9 % at higher k-values.

The triple feature combinations revealed that MAV–RMS-VAR showed the poorest performance, with accuracy declining from 93.9 % to 86.3 % as k-values increased. Other triple combinations incorporating ZC demonstrated more stable performance, maintaining 100.0 % accuracy at lower k-values with only a modest decline to 96.9 % at higher k-values. This suggests that the ZC feature helps mitigate the negative impact of VAR in combined features.

The integration of all four features maintained perfect accuracy (100.0 %) at k = 3 and k = 5, with a slight decrease to 96.9 % at higher k-values. The VAR feature consistently emerged as a critical factor influencing classification stability, with its inclusion typically resulting in accuracy degradation of up to 6.1 %. Conversely, the MAV-RMS combination proved most robust, while the ZC feature demonstrated a stabilizing effect when combined with other features.

These findings emphasize the importance of strategic feature selection in EMG signal classification systems. The results indicate that while increasing the number of features doesn't necessarily improve classification performance, specific combinations can significantly enhance accuracy and stability. The consistent performance patterns observed provide valuable insights for developing more robust EMG classification systems, particularly where classification accuracy and stability are crucial factors.

Table 3.
Accuracy results of merging two feature types.

Trial	Feature				Accuracy (%)			
					k = 3	k = 5	k = 9	k = 11
Combining two feature types								
1	MAV	RMS			100.0	100.0	100.0	100.0
2	MAV	VAR			93.9	93.9	92.4	86.3
3	MAV	ZC			100.0	100.0	96.9	96.9
4	RMS	VAR			93.9	93.9	92.4	86.3
5	RMS	ZC			100.0	100.0	96.9	96.9
6	VAR	ZC			100.0	100.0	96.9	96.9
Combining three feature types								
1	MAV	RMS	ZC		100.0	100.0	96.9	96.9
2	MAV	VAR	RMS		93.9	93.9	92.4	86.3
3	MAV	ZC	VAR		100.0	100.0	96.9	96.9
4	RMS	VAR	ZC		100.0	100.0	96.9	96.9
Combining four feature types								
1	MAV	RMS	ZC	VAR	100.0	100.0	96.9	96.9

To provide a comprehensive understanding of the advancements in EMG-based wheelchair control systems, a comparative analysis of this study with prior research is presented in Table 4. This comparison highlights the relative strengths and limitations of various methods, offering a clearer context for evaluating the performance and practicality of the proposed approach.

The comparison in Table 4 highlights the exceptional performance of the proposed kNN-based approach in EMG signal classification for wheelchair control. This study achieves the highest accuracy of 100% using a combination of MAV and RMS features, showcasing the effectiveness of carefully selected feature combinations and the kNN algorithm in delivering reliable results.

Prior studies, such as [25], demonstrate strong performance with MC-SVM, achieving 99.05 % accuracy. However, the slightly lower accuracy compared to this study reflects the advantages of the feature extraction and classification techniques applied here. Similarly, [24] reports a maximum accuracy of 95.42 % using Decision Tree and Random Forest models, emphasizing the competitive edge of the kNN method in providing both simplicity and high accuracy.

On the other hand, [15] achieves a maximum accuracy of 81.5 % using QDA, which is notably lower than the results achieved by kNN. This highlights the importance of selecting robust classification methods and effective feature sets for EMG signal analysis. In summary, the findings demonstrate that the proposed kNN-based approach, when paired with optimal feature combinations, outperforms alternative methods in terms of accuracy and reliability. This positions the method as a leading solution for EMG-based wheelchair control systems.

C. Drive testing test

The system performance was evaluated in a controlled indoor environment by involving three subjects, who were part of the five subjects used in the previous stage. The selection of these three subjects was based on considerations of consistency in performing gestures, as well as time efficiency and supervision during real-time testing. Thus, the testing remained methodologically consistent as it used the same subjects, and the main focus was on evaluating the performance of the system directly, rather than generalizing to new users.

The test track, as illustrated in Figure 8, was designed with specific dimensions of 10 m in length and 2 m in width, featuring ceramic tile flooring. To optimize the wheelchair's performance on this surface, the control parameters were carefully calibrated: forward and backward movements utilized a PWM value of 80 (30 % duty cycle), while turning movements (left and right) employed a PWM value of 100 (40 % duty cycle). These parameters were specifically tuned to ensure precise control and smooth operation on the ceramic surface.

The evaluation protocol involved three subjects with varying physical characteristics, as shown in Table 5, each required to complete a sequence of nine distinct movements from the initial position to the return point. Prior to the actual testing, subjects underwent different numbers of training sessions to familiarize themselves with the gesture control system. This varying exposure to training provided an opportunity to assess the relationship between practice and performance.

The results, as presented in Table 5, provide an early overview of how user characteristics and training exposure may influence performance in the EMG-

Table 4.
Comparative analysis of EMG-based wheelchair control systems using various classification methods and features.

Study	Method used	Performance
[15]	Quadratic discriminant analysis, LDA, SVM, decision tree	Maximum accuracy of 81.5 % (QDA)
[24]	Decision tree, random forest	Up to 95.42 % accuracy
[25]	Linear regression (LR), RLR, MC - SVM, Decision tree	Accuracy: LR 94.85 %, RLR 95.88 %, MC - SVM 99.05 %, DT 97.77 %
This study	k-Nearest Neighbor (kNN)	96 % accuracy (MAV), 100 % (MAV + RMS combination)

Table 5.
Test drive results.

No	Subject	BMI	Track training	Average travel time	Number of errors	Total movement
1	Subject 1	24.5	3X	75 s	2	9
2	Subject 2	21.4	2X	79 s	3	9
3	Subject 3	27.3	4X	70 s	1	9

Figure 8. Wheelchair test drive track.

based control system. Subject 3, with the highest BMI (27.3), achieved the most efficient performance—completing the task in 70 seconds with only one prediction error. Notably, this subject also underwent the highest number of training sessions (4x), which likely contributed to their improved familiarity with the system and better overall control accuracy.

In contrast, Subject 2, who had the lowest BMI (21.4) and the least amount of training (2x), recorded the longest completion time (79 seconds) and the highest number of errors (3). Subject 1, with a moderate BMI (24.5) and intermediate training exposure (3x), showed moderate performance results. These patterns suggest that training frequency may have a more direct impact on system performance than BMI alone.

Although Subject 3 had a higher BMI, which in theory might attenuate surface EMG signals due to increased subcutaneous fat, the system's performance remained robust. This may indicate that the EMG-based control system is relatively resilient to moderate variations in user anthropometrics.

Overall, the findings emphasize the important role of training in improving user control efficiency. While early observations hint that BMI may not critically impair performance, especially when sufficient training is provided, further studies with larger sample sizes are needed to explore these effects in greater depth. The system's apparent stability across varying user profiles in this small-scale trial supports its potential applicability, while also highlighting the need for structured user familiarization protocols during deployment.

IV. Conclusion

The conclusion that can be drawn based on the research that has been done is the classification of hand movements in controlling a wheelchair using the k-Nearest Neighbor method. The best average accuracy is obtained using the MAV extraction feature, which is 96% using the $k = 3$ value. The combination of extraction features can also affect the level of accuracy. Based on the training data, one of the respondents obtained a stable accuracy of 100% for the combined MAV feature with RMS, even though the value of k varies. Whereas in testing a combination of three features, the lowest accuracy value is obtained, namely the combination of MAV, VAR, and RMS features, with the highest accuracy of 93.90% with a value of $k = 3$ and an accuracy of 86.30% with a value of $k = 11$. Apart from the features used, the k value in the test also affects the accuracy rate. The duration of travel time required for wheelchair control on a predetermined trajectory is 70 s with a distance of 10 m and 1 error.

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Declarations

Author contribution

Khairul Anam: Conceptualization, Methodology, Supervision, Writing – Review and Editing. **Safri Nahela**: Formal Analysis, Data Curation, Writing – Original Draft. **Muchamad Arif Hana Sasono**: Writing – Original Draft, Visualization, Software, Validation. **Naufal Ainur Rizal**: Resources, Data Curation, Formal Analysis, Writing – Review and Editing. **Aviq Nurdiansyah Putra**: Software, Validation, Writing – Review and Editing, Data Curation. **Bambang Wahono**: Supervision, Methodology, Writing – Review and Editing. **Yanuandri Putrasari**: Conceptualization, Supervision, Methodology, Validation. **Muhammad Khristamto Aditya Wardana**: Supervision, Formal Analysis, Resources, Visualization. **Taufik Ibnu Salim**: Methodology, Writing – Original Draft, Writing – Review and Editing.

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Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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