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Optimizing usability of electric wheelchairs with voice user experience for acceleration wheel rotation design by the kinematics method

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ABSTRACT

Individuals with quadriplegia experience total paralysis of all four limbs due to spinal cord injuries, leaving them unable to operate conventional electric wheelchairs that rely on joystick control. Existing alternative interfaces, such as head motion and eye-gaze sensors, are often cost-prohibitive and fail to deliver the maneuverability and accuracy required for daily use. Voice recognition emerges as a practical solution because speech ability is typically retained in quadriplegia, offering a hands-free, intuitive control method. This study proposes an electric wheelchair system integrating voice user experience (VUX), machine learning (ML), and kinematics-based wheel rotation control to address these challenges. Voice commands are processed using natural language processing (NLP) for word recognition and support vector machines (SVM) for amplitude classification to dynamically adjust speed and direction. Forward and inverse kinematics optimize wheel rotation angles, ensuring smooth and precise navigation even in constrained spaces. Experimental results demonstrate 92.82% word recognition accuracy and 94.48% accuracy in frequency and amplitude detection. Functional testing recorded average speeds of 0.343 m/s (no load) and 0.305 m/s (with 60 kg load). Usability testing with 15 quadriplegic users reported 93%.

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1. INTRODUCTION

Quadriplegia is a medical condition that results in paralysis of all four limbs due to spinal cord injury caused by a sudden and forceful impact, such as in accidents [1]. This condition leads to neurological dysfunction, affecting both motor and sensory nerve functions, ultimately causing paralysis in all four limbs [2]. Paralysis in all four limbs makes individuals with quadriplegia highly dependent on wheelchairs and assistants, even for simple mobility tasks [3]. Although individuals with quadriplegia experience paralysis in their limbs, their ability to speak remains intact. Therefore, there is a need for innovation in electric wheelchairs that accept voice commands [4]. Conventional electric wheelchairs, typically operated using a joystick, cannot be used by individuals with quadriplegia because they are unable to move their hands. Several innovations in electric wheelchair control systems for individuals with quadriplegia have been developed to improve interaction with users [5], including the use of head motion sensors and eye-gaze sensors. However, these innovations are still expensive and have not achieved the desired level of accuracy for maneuvering [6], [7]. A voice control system is the most feasible option for individuals with quadriplegia, providing flexibility in direction and range of maneuvers as desired. [8], as it offers maneuvering accuracy that meets user expectations and is affordable. However, various studies related to voice recognition-based control systems are still limited to word recognition [9]. These systems can only move the wheelchair statically according to specific commands, such as “forward,” “backward,” “right,” “left,” and “stop.” Therefore, this innovation has not yet provided the necessary acceleration for maneuvering.

While advancements in robotics and automated control systems can be adopted in the development of electric wheelchairs to enhance human-machine interaction more naturally and efficiently, one of the key aspects of this development is the ability to control the wheel's direction accurately and responsively through the integration of voice commands. Using voice recognition as an input method to control the direction and speed of wheel rotation offers convenience and comfort to users without the need for direct physical interaction [10]. However, the main challenge in implementing such a system is optimizing the wheel's rotational angle to ensure smooth, accurate, and efficient movement following the given voice command [11]. The application of voice recognition for voice command recognition uses machine learning (ML) methods to classify and predict voice data, whether it is word data or amplitude data. Word data, processed using natural language processing (NLP) algorithms, is recognized as commands to adjust the wheel's direction, while sound amplitude data, processed using support vector machine (SVM) algorithms, is recognized as commands to control the voltage regulator's strength [12], [13]. The inverse kinematics algorithm functions to determine the required wheel rotation angle based on the target's position and orientation. The combination of the voice recognition-based control system and inverse kinematics algorithms provides the optimal rotation angle to reach a desired position [3], [10].

Voice commands are highly susceptible to recognition errors due to variations in intonation and a low signal-to-noise ratio [14]. Challenges arise when noise or additional sounds interfere with the intended command. In low signal-to-noise ratios, external noise can disrupt the program's ability to accurately interpret verbal commands [15]. To address this issue, NLP algorithms are employed to enhance word recognition, and ML algorithms, specifically SVM, are used for amplitude classification [16], [17]. For the wheel rotation system design, kinematic methods are used to control the wheel's rotation, while ML algorithms are applied for classifying and predicting commands [18]. Additionally, the kinematic model is implemented to control the left and right wheel rotations, ensuring that the minimum rotation angle is achieved, thus optimizing system efficiency [19]. Dynamic wheel rotation is controlled using both forward kinematics and inverse kinematics methods. Forward kinematics is used to calculate the wheel's rotation angles, while inverse kinematics is applied to determine the wheelchair's range of motion [20]. The integration of voice recognition, machine learning, and inverse kinematics is expected to result in significant and accurate movement acceleration, ultimately improving user comfort and enhancing the overall system's usability.

The research on the prototype of an electric wheelchair control system with a voice-user experience (VUX)-based control system, complemented by a wheel rotation system using kinematic methods, is expected to make a significant contribution to assistive technology for individuals with disabilities, particularly those suffering from quadriplegia. The VUX-based voice recognition system serves as the foundation for developing an intelligent system based on artificial intelligence (AI) [21]. By integrating voice recognition algorithms, ML, and NLP to recognize voice commands based on VUX [22]. Along with kinematic methods such as forward kinematics and inverse kinematics, the maneuverability of the electric wheelchair is optimized. The ML and NLP algorithms used to recognize voice commands are focused on improving speech recognition accuracy under real-world conditions, including addressing user voice variability and noise disturbances [23].

The main contributions and novelties of this research in the development of the electric wheelchair control system are as follows:

- This research optimizes the usability of the electric wheelchair with a voice recognition control system, optimized with ML and kinematic methods.
- This system provides a practical solution in the form of more intuitive voice control, enhancing comfort, safety, and accessibility for individuals with quadriplegia.
- The main novelty of this research lies in the combination of voice recognition technology, ML, and kinematics to control wheel movement dynamically and responsively.

2. METHOD

2.1. Research methods

The design of the electric wheelchair prototype with a wheel rotation acceleration control system based on VUX in this research combines ML methods and forward-inverse kinematics methods. To achieve optimal usability, the development of the control system is carried out in three stages. The first stage is the voice recognition process, which aims to convert voice commands into word data and amplitude data in digital form. The second stage is the classification and prediction of word and sound data using ML methods with NLP algorithms. Word data is recognized and processed into the control system for wheel direction and amplitude data is recognized and processed into the control system for current strength that adjusts the wheel's rotational angle. The third stage involves forwarding the classification and prediction results from the ML process of word and amplitude data to the control system for wheel direction and speed [24], which is controlled using forward-inverse kinematics, as shown in Figure 1.

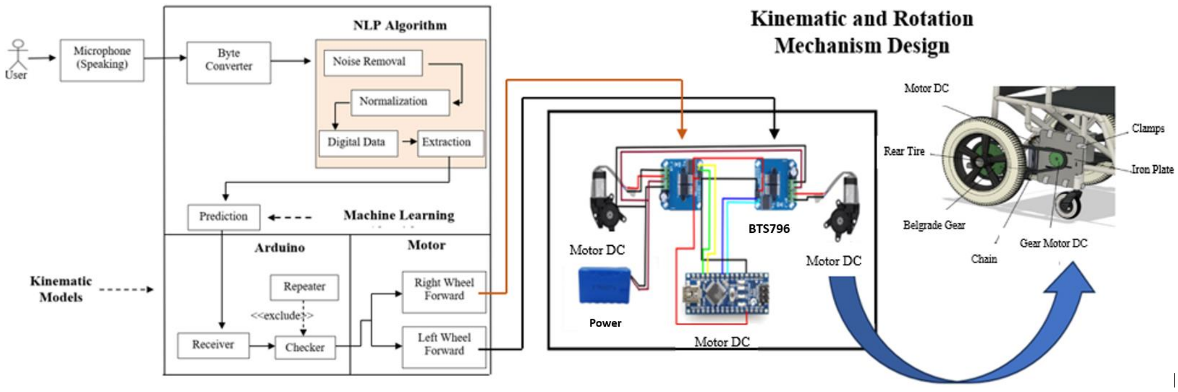

Figure 1. Framework of voice recognition-based control system

2.2. Voice recognition and machine learning methods

The classification of command data in the voice-based control system involves a complex process as it combines voice recognition methods with machine learning techniques [25]. The voice input received by the converter is converted into digital data, whether it is word data or amplitude data. Next, feature extraction is performed on both the word and amplitude data to separate the interfering noise, ensuring that only the primary data is processed further [26]. Once the data is isolated, a classification process using machine learning methods and NLP algorithms is applied to identify the class of the data, followed by a training process on the dataset. This allows the voice recognition system to accurately recognize each voice command, as shown in Figure 2.

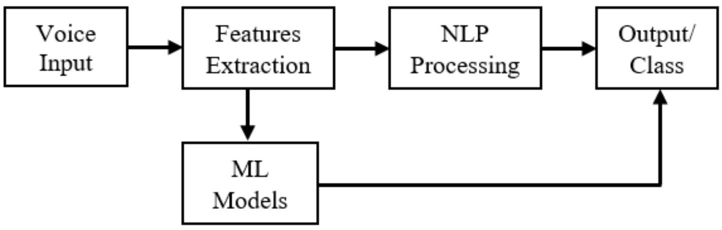

Figure 2. Voice recognition and machine learning methods

2.3. Feature extraction

After preprocessing, the next step is feature extraction from the speech signal. Feature extraction is a crucial step in the speech recognition process to build a meaningful and compact set of representations, making it easier for machine learning models to process [27]. This step captures the most important characteristics of the speech signal while minimizing irrelevant information, leading to accurate speech pattern recognition even in noisy environments or with varying speech rates [28], [29]. To achieve this, the digital signal is divided into smaller frames, each representing a short segment of the speech signal, which helps in accurately identifying the words and commands spoken [30], [31]. These features are mathematical representations that capture important characteristics of the sound, such as frequency and amplitude, using techniques such as mel frequency cepstral coefficients (MFCC) [32], [33].

2.4. Machine learning models of voice recognition

Voice recognition is a critical component in modern assistive technology, particularly in control systems for managing electric wheelchairs. Converting audio data into useful features using MFCC is an important step in the voice recognition system [33]. MFCC captures the timbral features of sound by applying the Fourier transform to the signal and mapping it to the Mel scale (a perceptual scale of pitches) [34]. The amplitude features form a nonlinear function, which is then extracted into digital power. This digital data, in the form of fuzzy data, is then trained using a machine learning model [35]. The methodology for applying machine learning models in voice recognition involves several key steps, starting from the preprocessing of voice data to training models that can accurately interpret voice commands [36], as shown in Figure 3.

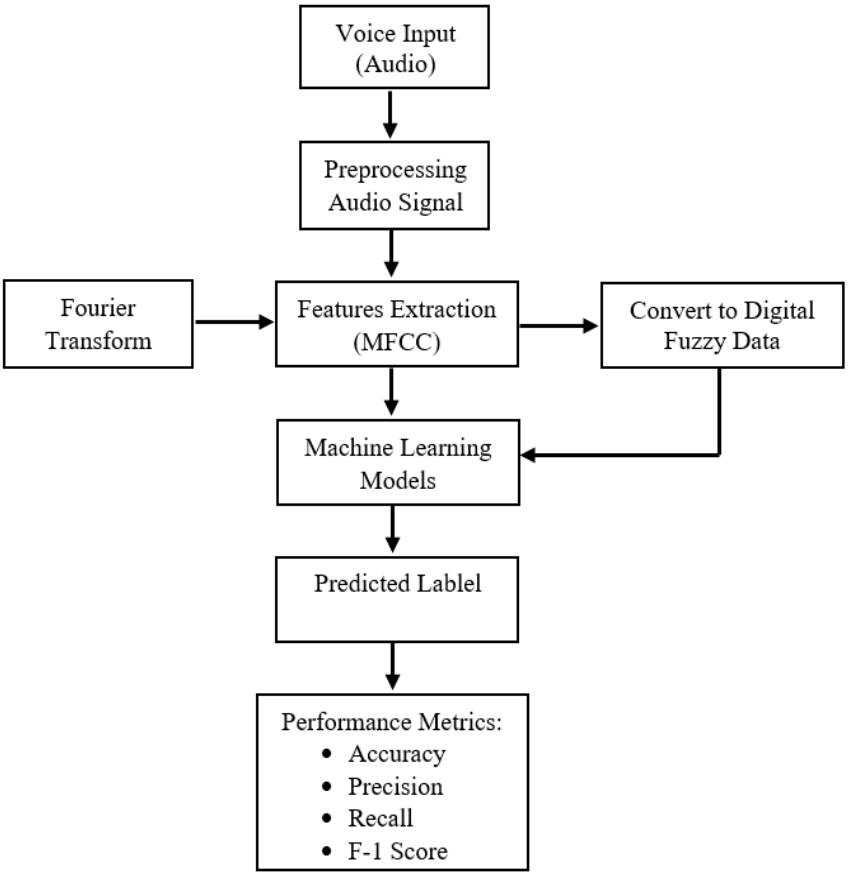

Figure 3. Machine learning framework of voice-signal recognition

2.4.1. Training the model of machine learning

The processed data, including the extracted features, is used to train the machine learning model for classifying the voice commands. In this research, the classification of voice commands based on the extracted features is performed using the SVM algorithm [37]. SVM works by finding the optimal hyperplane that separates different classes (such as different commands) in the feature space. To ensure the accuracy and robustness of the voice recognition model, several performance metrics are employed, including accuracy to measure the overall percentage of correct predictions made by the model, precision, and recall to evaluate how many of the predicted positive labels are correct [38]. The balance of the machine learning model's performance is measured by the F1-score, which is the harmonic mean of precision and recall.

2.4.2. Labeling and classification of data

After the voice features are extracted, a dataset is formed consisting of feature label pairs (input-output) to improve the user experience and evaluate usability [39]. This dataset is then used to train a machine learning model. Each entry in the dataset typically consists of a feature vector that represents the characteristics of the audio signal, which is labeled based on the spoken word or command, such as "forward," "backward," "right," "left," and "stop" [31], [40]. Subsequently, voice command classification is performed using a machine learning model, specifically employing the SVM algorithm to distinguish between different voice command classes [37], [41]. SVM was selected due to its superior performance with small to medium-sized datasets and its robustness in high-dimensional feature spaces such as MFCC vectors. The model is then trained using the labeled dataset. Once the model has been trained, the next step is validation and testing using previously unseen data [42]. This step aims to assess how well the model can convert amplitude data into digital input suitable for classification in identifying electric currents at varying rotation angles [43]. The assessment uses performance metrics such as accuracy, precision, recall, and F1-score, which are standard measures for evaluating the effectiveness of machine learning models in classification problems [44]–[46].

2.5. Natural language processing of voice recognition

2.5.1. Removal of noise

In the voice recognition process, noise removal plays a crucial role in ensuring the system's accuracy and efficiency. Noise refers to unwanted signals or disturbances present in the recording environment, such as background conversations, electrical noise, or microphone imperfections. These noises can significantly degrade the quality of the sound signals and hinder the accuracy of the recognition model. The primary objective of noise removal is to extract relevant sound information while minimizing or eliminating the impact of unwanted sounds, making it a vital preprocessing step in the sound recognition system [47], [48]. The noise removal technique used in this study is Wiener filtering, which adjusts the speech signal based on the estimated signal-to-noise ratio (SNR). This filter reduces the noise component in the signal by applying varying amounts of filtering based on the noise level in specific frequency bands [49], [50]. For instance, in signals with high SNR, the Wiener filter allows more speech signals to pass, while in noisier parts, it attenuates the noise more aggressively. This dynamic adaptation improves the speech signal quality, making it clearer for the recognition algorithm [51].

2.5.2. Normalization of signal data

Normalization in speech recognition is an important preprocessing step that helps ensure consistent input to a speech recognition system. The main purpose of normalization is to adjust the recorded speech signal so that variations in factors such as loudness, microphone sensitivity, or recording environment do not negatively impact the performance of the recognition system. Variability in these factors can lead to inconsistent speech recognition accuracy, especially when the system encounters voices recorded under different conditions [52], [53].

In this study, normalization is carried out by adjusting the volume of the speech signal to match a predetermined range between -1 and 1 in order to eliminate possible variations in signal amplitude, so that mathematically the average value of the signal scale is zero with a standard deviation of one, as (1):

$$x_{norm}(t) = \frac{x(t) - \mu}{\sigma} \quad (1)$$

where $x(t)$ is the raw signal, μ is the average signal, and σ is its standard deviation [30], [54]. Meanwhile, to reduce the volume of the loudest sound signal and increase the uniformity of the sound volume in this study, dynamic range compression was carried out so that the data signal was more stable with the following calculation:

$$x_{comp}(t) = \log(x(t) + 1) \quad (2)$$

This technique helps improve the overall robustness and consistency of the speech signal for more accurate recognition [30].

2.5.3. Signals-to-digital data

The next stage is to transform the speech signal into digital data so that the speech signal can be processed by the algorithm. In this study, a continuous analog speech signal was converted into a discrete digital signal to form digital data from the command speech signal given to move the wheelchair, such as the commands "forward," "backward," "right," "left," and "stop." Each analog data point is converted into digital data in the form of a 3×3 matrix as shown in Figure 4.

Voice	Analog Data	Digital Data		
"Forward"		0	1	1
		0	0	1
		1	1	1
"Backward"		0	1	1
		0	1	1
		1	1	0
"Right"		1	0	0
		0	0	1
		1	1	0
"Left"		0	1	1
		1	1	0
		0	1	0
"Stop"		0	1	1
		1	1	1
		1	0	0

Figure 4. Conversion of analog to digital data

2.6. Kinematics control model of rotation

Kinematically design the rotation [9] of the right and left wheels to change the angle of rotation of the DC motor, which is regulated using the V3 module on the Arduino, which is coded using the C++ programming language according to the angle and speed needed when the V3 module receives commands from machine learning. Specifically, the novelty in the wheel rotation adjustment system is that to move straight, the right and left wheels rotate at the same speed, to turn with an effective area, the wheel rotation will be opposite between right and left where one wheel (BC) moves around the center of rotation (C) and the other wheel rotates in the opposite direction as presented in Figure 5. The triangle (KBC) is constant when the wheel gear angles (β_1, β_2) change, where:

$$\beta_2 + \alpha = 75° \quad (3)$$

Consider triangle (OBA), the following equations can be obtained:

$$BA = \sqrt{OB^2 + OA^2 - 2\,OB.OA.\cos(\beta_1 + \beta_2)} \quad (4)$$

$$\frac{BA}{\sin(\beta_1+\beta_2)} = \frac{OA}{\sin\alpha} \quad (5)$$

From (3) to (5), one can find the expression (6):

$$\sin(75 - \beta_2)\sqrt{\frac{D_2^2}{4} + \frac{D_1^2}{4} + \frac{D_1 D_2}{2}\cos(\beta_1 + \beta_2)} = \frac{D_1}{2}\sin(\beta_1 + \beta_2) \quad (6)$$

The calculation of the rotation angle in the forward-inverse kinematics model to achieve the desired range of motion is illustrated in Figure 6.

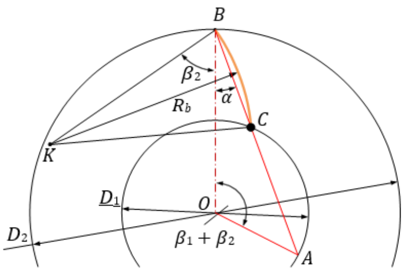

Figure 5. Geometric parameters of wheel rotation

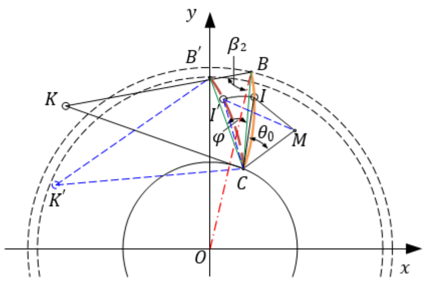

Figure 6. Calculation diagram of the design wheel's rotation (x_β, y_β)

To determine the coordinates of the points $B'(x'_\beta, y'_\beta)$ and $K'(x'_K, y'_K)$ when (BC) rotates around the center $C(x, y)$, first apply translation $T(-x_r, -y_r)$ to move the center back to the origin. Second, apply rotation R(φ) to rotate (BC) around the origin by an angle φ. Finally, apply the translation $T(x_r, y_r)$ to move the center of rotation from the origin to the original position. The rotation matrix equation is represented by multiplication and translation, as the matrix sum representation. With homogeneous coordinates, the coordinates of the point (x, y) can be represented in the form $(x/h, y/h, h)$. For convenience, h=1 is chosen, the geometric transformation matrix is given as:

$$R(x_r, x_r, \varphi) = T(x_r, y_r).R(\varphi).T(-x_r, -y_r) = \begin{bmatrix} 1 & 0 & x_r \\ 0 & 1 & y_r \\ 0 & 0 & 1 \end{bmatrix}. \begin{bmatrix} cos\varphi & -sin\varphi & 0 \\ sin\varphi & cos\varphi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \begin{bmatrix} 1 & 0 & x_r \\ 0 & 1 & y_r \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix} \quad (7)$$

The coordinates of the starting points $B(x_B, y_B)$, $I(x_I, y_I)$, $K(x_K, y_K)$, and fixed-point $M(x_M, y_M)$ were determined using AutoCAD. The coordinates of the point after rotation at an angle are determined as follows as point $B(x_B, y_B)$ as:

$$B = \begin{bmatrix} x_B \\ y_B \\ 1 \end{bmatrix} = \text{R}(x_r, y_r, \varphi) \begin{bmatrix} x_B \\ y_B \\ 1 \end{bmatrix} \quad (8)$$

$$B' = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix}. \begin{bmatrix} x_B \\ y_B \\ 1 \end{bmatrix} \quad (9)$$

The coordinates of point $K(x_K, y_K)$ are:

$$K = \begin{bmatrix} x_k \\ y_K \\ 1 \end{bmatrix} = R(x_r, y_r, \varphi) \begin{bmatrix} x_K \\ y_K \\ 1 \end{bmatrix} \quad (10)$$

$$K' = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r(sin\varphi \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_K \\ y_K \\ 1 \end{bmatrix} \quad (11)$$

The coordinates of point $I(x_i, y_i)$ are defined as:

$$I = \begin{bmatrix} x_I \\ y_I \\ 1 \end{bmatrix} = R(x_r, y_r, \varphi) \begin{bmatrix} x_I \\ y_I \\ 1 \end{bmatrix} \quad (12)$$

$$I' = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix}. \begin{bmatrix} x_I \\ y_I \\ 1 \end{bmatrix} \quad (13)$$

From (9), (11), and (13) the following vector is generated:

$$\underset{BK}{\rightarrow} = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} x_{K} - x_B \\ y_K - y_B \\ 0 \end{bmatrix} \quad (14)$$

$$\underset{BO}{\rightarrow} = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} -x_B \\ -y_B \\ -1 \end{bmatrix} \quad (15)$$

$$\underset{MI}{\rightarrow} = \begin{bmatrix} cos\varphi & -sin\varphi & x_r(1-cos\varphi)+y_r sin\varphi \\ sin\varphi & cos\varphi & y_r(1-cos\varphi)-x_r sin\varphi \\ 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} x_I \\ y_I \\ 1 \end{bmatrix} - \begin{bmatrix} x_M \\ y_M \\ 1 \end{bmatrix} \quad (16)$$

The $\overrightarrow{MI}$ vector in (16) defines the length of $\overrightarrow{MI}$ when the plane (BC) rotates at an angle φ. The angle $\beta 1$ can be when the plane (BC) is rotated at an angle φ.

$$cos\ \beta_1 = \frac{\overrightarrow{BK}\overrightarrow{BO}}{|\overrightarrow{BK}||\overrightarrow{BO}|} \quad (17)$$

2.7. Usability testing of voice recognition-based electric wheelchair

Usability testing for a voice recognition-based electric wheelchair control system provides valuable insights into system performance and user satisfaction [55]. By focusing on real-world usability, including accuracy, response time, and overall comfort, this testing methodology ensures the system meets the needs of people with disabilities, especially those with quadriplegia, thereby improving their mobility and independence. Testing was conducted with 15 users limited to the commands "forward," "right," "left," "backward," and "stop." The overall system acceptance evaluation of the voice recognition-based wheelchair regarding VUX includes "ease of navigation," "instrument aesthetics," "system responsiveness," "ease of use," and "overall satisfaction" [56].

3. RESULTS AND DISCUSSION

3.1. Evaluation and performance of voice recognition

Voice recognition was implemented using machine learning algorithms coded in Python. The system was trained to identify basic command words such as "forward," "right," and "left" to enable dynamic processing of user input. The training process included an early stopping mechanism within 50 epochs to prevent overfitting. Each command was trained through 100 iterations, resulting in a word recognition accuracy of 91%. In addition to word classification, the model also processed voice pitch features, specifically frequency and amplitude, to control motor speed. These features were trained through 30 iterations per frequency level and achieved an accuracy of 89 percent. The classified voice and pitch data were then converted into motor control commands and transmitted to the Arduino V3 module to regulate the rotation of the DC motors, enabling directional movement of the electric wheelchair.

The performance of the voice recognition model in recognizing voices based on the type of words spoken by the user, with a total of 255-word repetitions for each word, has a fairly high accuracy, as shown in Table 1. Meanwhile, speech recognition based on the frequency and amplitude of the user's voice also demonstrated high accuracy, as shown in Table 2. Each voice was tested 51 times per frequency level. Beyond simple word classification, these acoustic features were further utilized to dynamically regulate the motor's rotational speed through a proportional mapping to pulse width modulation (PWM) signals. The system interprets higher voice amplitudes as indicators of stronger user intent, thus increasing the current sent to the motor controller and widening the wheel rotation angle. Conversely, lower-intensity voice commands result in reduced motor current and slower rotation. This approach enables scalable and intuitive control: the louder and firmer the voice, the faster the wheelchair responds. The integration of pitch-based modulation contributes significantly to the system's responsiveness and user-centered mobility adaptation.

Table 1. Voice recognition classification results based on word-commands

Voice command	Precision	Recall	F1-score	Accuracy (%)
Forward	0.94	0.92	0.93	92.2
Backward	0.91	0.89	0.90	91.6
Right	0.96	0.94	0.95	94.3
Left	0.93	0.91	0.92	91.4
Stop	0.97	0.94	0.93	94.6
Average	0.94	0.92	0.93	92.82

Table 2. Results of voice recognition classification based on frequency-command

Frequency (Hz)	Precision	Recall	F1-Score	Accuracy (%)
Very low	0.91	0.89	0.90	92.3
Low	0.92	0.90	0.91	93.1
Medium	0.94	0.92	0.93	94.5
High	0.96	0.94	0.94	95.8
Very high	0.96	0.96	0.95	96.7
Average	0.938	0.922	0.926	94.48

The results of the classification of speech recognition based on words and frequencies from the machine learning algorithm are used as commands that the V3 module passes to adjust the rotation angle of the DC motor gears, right and left, to adjust the wheel rotation. The right and left DC motor gear rotations against the given command are synchronized using the Kinematics method.

3.2. Classification kinematics performance testing

Performance testing is carried out to ensure that the wheelchair prototype and the system can work properly as a whole. Command testing from this application aims to determine the suitability of commands with the resulting DC motor movement, as shown in Table 3. Table 3 shows the results of the application command testing that has been carried out. The test results show that all direction commands for movement, whether forward, backward, right, left, or stop, can be sent and received by the DC motor rotation simulator device, as shown in Figure 7. All movements produced also follow the instructions without any obstacles, such as swapped directions or one of the directions not working, as shown in Table 4.

Table 3. Module V3 application command testing

No	Commands performed	Command response
1	Forward	True
2	Backward	True
3	Right	True
4	Left	True
5	Stop	True

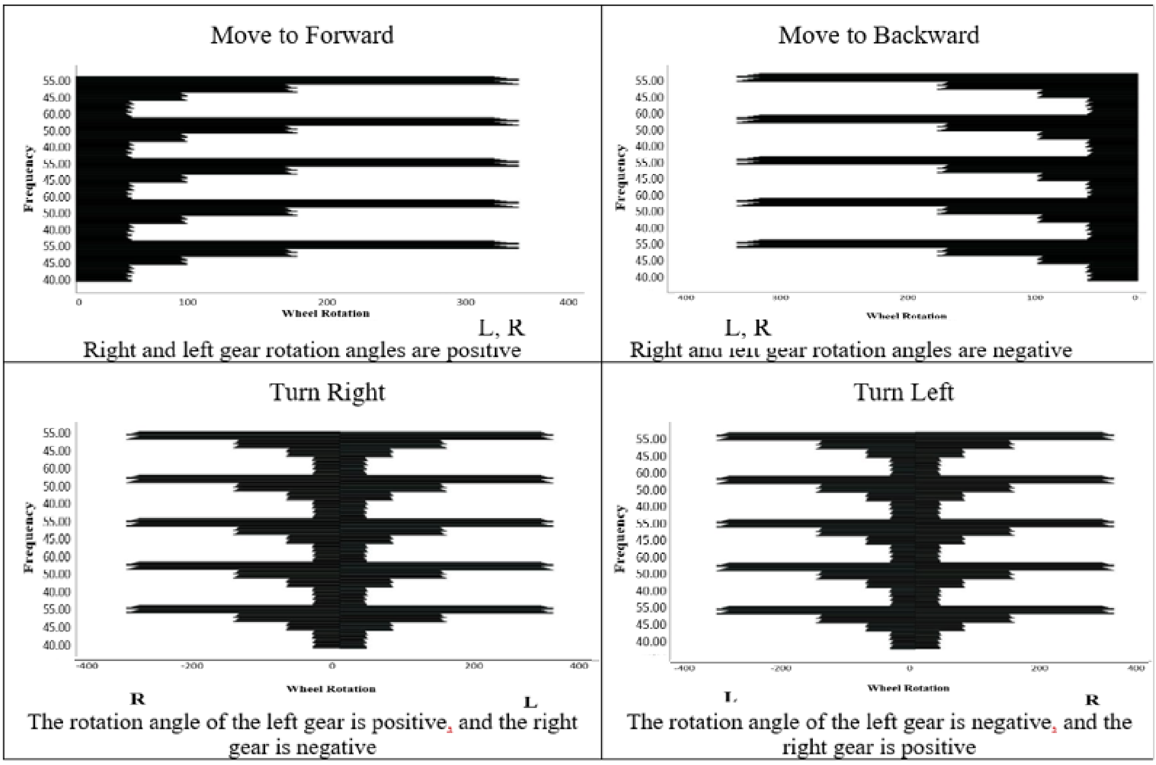

Figure 7. Synchronize the rotation angle of the right and left gears with VUX

The test aims to determine the suitability of the commands carried out with the direction of rotation of the DC motor following the desired direction. According to the test results that have been carried out in Table 4, it is found that the direction of rotation of the right and left motors is in accordance with the commands carried out. The results of the movement of the wheelchair simulator are also appropriate without any obstacles in the wrong direction or direction malfunction.

Table 4. Testing DC motor rotation and wheelchair movement direction

No	Commands performed	Directional movement of the DC motor		Wheelchair direction
		Right motor	Left motor	
1	Forward	Forward rotation	Forward rotation	Forward
2	Backward	Backward rotation	Backward rotation	Backward
3	Right	Backward rotation	Forward rotation	Right
4	Left	Forward rotation	Backward rotation	Left
5	Stop	Slow to silence	Slow to silence	Silent

3.3. Functional testing of voice recognition and kinematics work

Functionality testing was carried out in two stages, namely the stage of setting the wheel movement angle based on the voice command data given, as shown in Table 5. Testing the wheel rotation speed based on the voice frequency of the command given, both without load and with a load of 60 kg, with a distance of 2 meters for the forward and backward direction, and a distance of 0.5 meters for the right and left direction as many as 10 trials with a performance comparison as in Table 6. After knowing the travel time and speed in each test, the average speed is calculated in all directions of wheelchair movement. From the experiments that have been carried out, it is known that the speed during testing without a different load and with a good load for the direction of movement forward, backward, right, and left results in different results. The load affects the power of the motor, so it affects the speed of the wheelchair simulator. The difference in speed can also be caused by the strength of the battery which begins to decrease due to repeated trials, this can be seen from the difference that occurs during the first trial to the 10th trial, where battery life is still stable until the 6th test for no load while testing with battery power loads is still stable until the 5th test for all directions of electric wheelchair movement.

Table 5. Wheel position and rotation angle based on voice recognition

Command	Left Wheel Angle (rad)	Right Wheel Angle (rad)	Position X (m)	Position Y (m)	Theta (rad)
Forward	0.50	0.50	0.30	0.00	0.00
Backward	-0.50	-0.50	-0.30	0.00	0.00
Left	0.00	0.50	0.00	0.30	0.50
Right	0.00	-0.50	0.00	-0.30	-0.50
Stop	0.00	0.00	0.00	0.00	0.00

Table 6. Testing the forward direction of the electric wheelchair as a whole

Trial	Without Load						With Load					
	Time	Speed (m/s)					Time	Speed (m/s)				
	(s)	Forward	Backward	Right	Left	Stop	(s)	Forward	Backward	Right	Left	Stop
1	6	0.35	0.34	0.35	0.35	0.34	7.2	0.33	0.27	0.33	0.33	0.32
2	6	0.35	0.34	0.35	0.35	0.34	7.2	0.33	0.33	0.33	0.32	0.33
3	6	0.35	0.34	0.35	0.35	0.34	7.2	0.33	0.33	0.33	0.32	0.33
4	6	0.35	0.34	0.35	0.35	0.34	7.2	0.33	0.33	0.33	0.32	0.33
5	6	0.35	0.34	0.35	0.35	0.34	7.2	0.33	0.33	0.33	0.32	0.33
6	6	0.35	0.34	0.34	0.34	0.34	7.3	0.29	0.27	0.30	0.30	0.29
7	6.4	0.34	0.31	0.34	0.34	0.34	7.5	0.29	0.27	0.30	0.30	0.29
8	6.6	0.33	0.30	0.33	0.33	0.32	7.6	0.28	0.26	0.27	0.27	0.26
9	6.8	0.33	0.29	0.33	0.33	0.32	7.6	0.26	0.26	0.27	0.27	0.26
10	7	0.33	0.28	0.32	0.33	0.32	7.6	0.26	0.25	0.26	0.26	0.26
	Average	0.343	0.322	0.341	0.342	0.334	Average	0.305	0.266	0.305	0.301	0.300

3.4. Subjective usability testing

Subjective testing of user satisfaction with the prototype's performance was conducted using an assessment research method using a questionnaire. The evaluation was conducted using a Likert scale ranging from 1 to 5, and then the average score for each category was calculated. The results of the 15 subjective tests were obtained, as shown in Table 7.

Usability testing subjectively provides a user's cognitive assessment of the usability of an electric wheelchair design, with a direct assessment by the user. Table 7 shows that the cognitive load perceived by the user is very low. In addition, the test also showed a very high level of usability, where the high level of ease of learning, attractive aesthetics, and very easy navigation played the role of the principle of human-machine interaction in design based on VUX data, with an average usability level of 93%.

Table 7. Usability test of application design

Assessment Aspects	Indicators	Rating scale (1-5)	Average score
Ease of navigation	speech, movement suitability	1: Very difficult - 5: Very easy	4.8
Aesthetics of instruments	Microphone Position	1: Not interesting - 5: Very interesting	4.5
System responsiveness	Response time	1: Slow – 5: Very fast	4.7
Ease of use	Quickly, users understand the functions of the machine	1: Very difficult – 5: Very easy	4.6
Overall satisfaction	Overall experience	1: Dissatisfied – 5: Very satisfied	4.65

4. CONCLUSION

This study successfully develops an electric wheelchair optimized for individuals with quadriplegia by integrating VUX and a kinematic-based wheel rotation system. Implementing voice recognition and machine learning ensures high accuracy in recognizing and executing movement commands. The kinematic model effectively enhances maneuverability, allowing users to navigate confined spaces efficiently. Performance testing demonstrates a 92.82% accuracy in word recognition and 94.48% accuracy in frequency and amplitude detection, ensuring reliable functionality. The wheelchair achieves stable movement at an average speed of 0.343 m/s without a load and 0.305 m/s with a 60 kg load. These findings indicate that the proposed system significantly improves accessibility, ease of use, and independence for individuals with quadriplegia. Future research may explore the refinement of noise-canceling techniques in voice recognition and the integration of advanced AI-driven adaptability to further enhance user experience and mobility.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration

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C : **C**onceptualization
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P : **P**roject administration
Fu : **Fu**nding acquisition

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. Due to ethical and privacy considerations, certain data may be restricted to protect participant confidentiality. Alternatively, if applicable the datasets generated and analyzed during this study are publicly available at *https://docs.google.com/spreadsheets/d/15M1hwMJpSVRafWWgvZPa6o-JSuHlfdye/edit?usp=sharing&ouid=102693883183634282270&rtpof=true&sd=true*.

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