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EEG-Based Brain Controlled Wheel Chair Prototype

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Abstract: Myoelectricsystemshavelongbeenusedinassistive technologies,buttheirhighcostanddependenceonfunctional nerves limit their accessibility for individuals with severe physical impairments. As an alternative, this paper presents a non-invasive,cost-effectivewheelchaircontrolsystembasedon electroencephalogram(EEG)signals.ThesystememploysBrain- Computer Interface (BCI) technology to interpret brain activity and eye movements, enabling users to control the wheelchair through mental commands and gaze gestures. ANeuroSkyMindwaveheadsetisusedtocaptureEEGsignals, whicharethenprocessedusingsignal processingtechniquesto assess cognitive states such as concentration and relaxation. Eye-tracking is integrated to improvecommand precision.The interpreted signals are converted into directional commands andtransmitted wirelessly to anESP32 microcontroller, which controls the wheelchair's movement.

Experimental results demonstrate an 85% accuracy rate in translating brain and eye activity into movement commands, supporting intuitive and reliable navigation. By combining EEGsignalprocessingwitheye-tracking,thissystemenhances mobility and independence for users with significant motor disabilities. The proposed approach offers a practical, user- friendly alternative to traditional assistive mobility devices.

Keywords: ESP-32, BCI, EEG, Brain Frequencies, Motors, Neurosky, PWM

I. INTRODUCTION

Globally,millionsofindividualsexperiencemotorfunction disabilities due to conditions like amyotrophic lateral sclerosis (ALS), multiple sclerosis (MS), spinal cord injuries, brainstem strokes, and cerebral palsy, resulting in significant mobility challenges. For such individuals, augmentative and alternative solutions are crucial to improvingtheirqualityoflife.BCItechnologyhasemerged as a transformative solution [1], enabling users to control assistive devices like wheelchairs using neural signals. By creating a direct interaction Channel linking the brain to physical devices, BCIs bypass conventional mechanisms like muscle movement or speech, offering hands-free and intuitive control. EEG-based BCIs, in particular, provide a non-invasive,cost-effective,andsafemethodfor capturing brainactivity through scalpelectrodes,eliminatingtherisks associated with invasive systems. The proposed brain- controlled wheelchair leverages EEG signals captured by the NeuroSky Mindwave headset, complemented by eye- trackingforenhanced precision.Thesystemprocessesbrain activityusingPython'sMNElibrarytodecodepatternssuch as focus and relaxation, mapping them into actionable commands. These commands, along with eye movement signals and brain wave frequencies, are wirelessly transmitted to an ESP32 microcontroller to drive the wheelchair's motion. This paper aims to empower individuals with neuromuscular disorders by providing a user-friendly mobility solution that enhances their independence and quality of life, showcasing the potential of integrating EEG brain wave signals and eye-tracking technology in assistive devices.

II. METHODOLOGY

The brain-monitoring wheelchair focuses on integrating with real-time control mechanisms to assist differently- abled individuals in achieving independent mobility [1],[3],[4]. The system begins with EEG signal sensing using a NeuroSky Mindwave headset, which captures brain activity through dry electrodes positioned on the user's scalp. These signals, representing attention and cognitive states, are wirelessly transmitted to a computer for real-time processing. Using the Python MNE, the raw EEG data undergoes noise filtering and feature extraction to isolate signals relevant for command generation.

Once processed, the signals are translated into control commandsusingpre-definedthresholdsthatcorrespondto specificwheelchairactions,suchasforward,left,right,or stop.These commands are transmitted to the wheelchair's control unit via an ESP32 module, enabling wireless communication with minimal latency. The wheelchair is equipped with DC motors and an esp32 microcontroller, which interprets the received commands and drives the motors accordingly [5],[8].Additional functionality, such as obstacle detection, is incorporated using ultrasonic sensors connected to the Arduino, enhancing safety and usability in dynamic environments.

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To optimize the system, user training sessions are conductedtocalibratetheheadsetandfamiliarizetheuser with the control thresholds, ensuring accurate and responsive wheelchair movements. Testing involves validating the system's accuracy in various scenarios, measuringresponsetimes,andanalyzinguserfeedbackto improve reliability and user satisfaction. This comprehensive approach integrates advanced EEG signal processing and robust hardware design to deliver an innovative mobility solution.

Brain data were collected using NeuroSky Mindwave Mobile 2headsets, which playa crucial role intranslating neural signals into actionable commands. The headset is designed to be worn comfortably on the user's head and featuresanEEGelectrodeembedded initsarmsensor.This electrode captures raw EEG data [2],[11], reflecting diversebrainactivity.Additionally,thedeviceincludesan ear clip on its left side, which serves as a grounding mechanism, ensuring the stability and accuracy of the recorded signals. Powered by standardAAAbatteries, the headset is portable and reliable for continuous use.

The NeuroSky Mindwave Mobile 2 incorporates an advanced eSense meter, which analyzes thought and emotionalstatesbyinterpretingbrainwavepatternsacross different frequencies and time intervals.

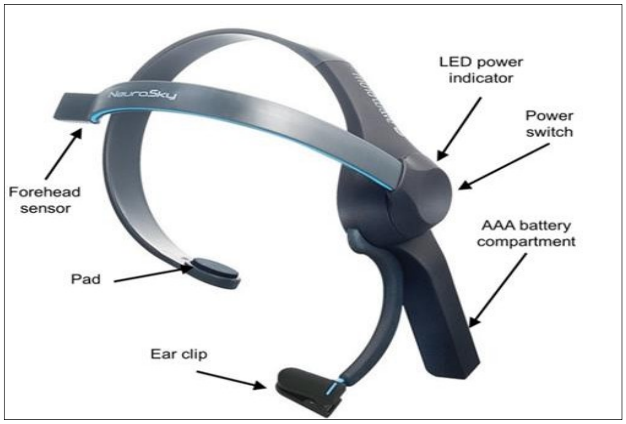

Fig.1.NeuroSky

The system prioritizes beta waves, which are crucial for focus and attention, ensuring accurate cognitive state assessment. This makes it ideal for real-time brainwave- basedapplicationslikebraincontrolwheelchairs.Thetable below summarizes all brain waves along with their frequencies [10],[11].

Brainwave	Frequency Range	Associated Tasks & Behaviors
Gamma	>30 Hz	Mental activity (math, planning, problem-solving)
Beta	13-30 Hz	Analytical problem-solving, judgment, decision-making
Alpha	8-12 Hz	Meditation, learning, memory integration
Theta	4-8 Hz	Daydreaming, meditation, deep relaxation
Delta	<4 Hz	Non-REM sleep, lethargy, non-attentive states

Table1.Brainsignalstable

1) *Signal Detection:*

Thisisthefirststage,wheresignals(inthiscase,brainwave signals) are detected using an EEG electrode, such as the NeuroSky Mindwave sensor.The electrode senses the raw brainsignalsgeneratedbyneuralactivity.Thesesignalsare typically weak and require sensitive equipment to detect them accurately.

2) *Signal Acquisition:*

In this stage, the transmitted signals are received and capturedforfurtherprocessing.Signalacquisitioninvolves filteringthedatatoremovenoiseorartifacts,suchassignals generated by muscle movements or external electrical interference. The result is clean EEG data ready for interpretation.

3) SignalTransmission:

After detection, the raw signals are transmitted from the sensor to a processing unit. Transmission can occur wirelessly (via Bluetooth, as in NeuroSky devices) or through wired connections. This stage ensures that the brainwavesignalsaretransferredwithoutsignificantlossor interference.

4) SignalMapping:

Signal mappingisthefinal step wherethe acquired signals areanalyzedandmappedtospecificcommandsoractions. For instance, certain brainwave frequencies (like beta waves) can be mapped to a command for controlling a wheelchair, appliance, or cursor[8]. This mapping process translatesbrainwavedataintomeaningfuloutputsbasedon predefined algorithms.

5) MotorMovementLogic:

A small DC geared motor was used in the prototype to support basic wheelchair movements. It operates between 6V and 12V, with a no-load speed of 150–300 RPM and torque around 0.5–1.5 kg-cm. The motor consumes less than 500 mA, making it safe for testing. A built-in gear system enhances torque for smoother control. Its compact size and compatibility with the ESP32 made it ideal for early-stage development. The motor is controlled using an L298N motor driver, which efficiently drives the motor, providing the necessary current and voltage for smooth wheelchair operation.

We use 2 DC motors for the movement of the Wheelchair and give the logic to the motors as follows:

The motor movement logic is designed to interpret user inputs based on specific brainwave frequencies and eye blinks[9],[10],ensuringaccuratecontrolofthewheelchair. The system associates particular brainwave frequency ranges and eye blink patterns with distinct commands:

- Start Movement (Command 1): Detected by a single eye blink combined with a brainwave frequency above 30 Hz (gamma range).
- Turn Left (Command 2): Triggered when the brainwave frequency falls within 13-20 Hz.
- Turn Right (Command 3): Activated when the brainwave frequency falls within a different frequency range, such as 18-25 Hz (high beta), signalling the intent to turn right.
- Stop Movement (Command 4): Initiated by detectinglow-frequencybrainwaves,suchasthose in the delta range (1-4 Hz), indicating a mental state of relaxation or stop command.

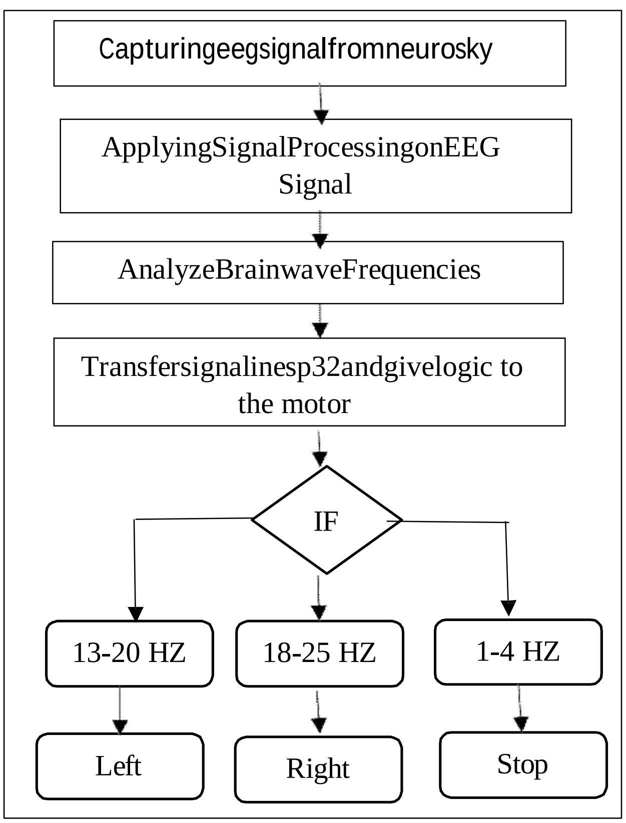

Fig.2FlowchartofMethodology

- Emergency Brake (Command 5): Engaged by detecting two consecutive eye blinks combined with a high-frequency brainwave signal,suchas30Hzorhigher(gammarange), triggeringanemergencystopofthewheelchair.

These commands, represented by numeric values (1, 2, 3, 4, and 5), are transmitted via a serial monitor to the ESP32 microcontroller. The ESP32 processes these commands and implements the logic to control the wheelchair's motors, allowing for accurate navigation, halts, and emergency braking depends on the user's mental state & eye gestures. The system continuously monitors incoming signals to adjust motor speed and directiondynamically,ensuringsmoothnavigation.The ESP32's real-time processing capability enables quick response to user inputs, minimizing latency and enhancing the overall user experience. Safety mechanisms, such as predefined emergency stop conditions and obstacle detection, further improve reliability.

III. MATHEMATICAL FORMULA AND DERIVATION

1) EEGSignalProcessing

EEG (Electroencephalogram) signals are inherently non- stationary and have multiple overlapping frequency components. These can be mathematically modeled as a sum of sinusoidal functions:

$$x(t)=\sum_{k=1}^{N} A_k.\cos(2\pi f_k t+\varphi_k)[14]$$

Where:

- x(t):EEGsignalattimet
- A_k:Amplitude of thek-thfrequencycomponent
- f_k:Frequencyofthek-thcomponent
- φ_k:Phaseshift of thek-thcomponent
- N:Totalnumberofcomponents

This representation allows the decomposition of the EEG signal into distinct frequency bands associated with differentcognitivestates(e.g.,delta,theta,alpha,beta,and gamma).

2) FrequencyAnalysisUsingtheFourierTransform

To extract these frequency components, the Fourier Transform is employed:

$$X(f)=\int_{-\infty}^{\infty} x(t)\times e^{-j2\pi ft}dt[15]$$

Where:

- X(f):Frequency-domainrepresentationofthe EEG signal
- j:Imaginary unit
- f:Frequencyvariable
-

3) NoiseReductionUsingBand-PassFiltering

SinceEEGsignalsarepronetocontaminationfromartifacts (e.g., muscle noise, power line interference), a **band-pass filter** is applied to retain only the relevant EEG frequency range (typically 0.5–40 Hz):

$$y(t)=x(t)*h(t)[16]$$

Where:

- y(t):FilteredEEGsignal
- h(t):Impulseresponseofthefilter
- ∗:Convolutionoperator

This filtering ensures that only the physiologically meaningful EEG components are preserved for further analysis.

4) PowerSpectralDensity(PSD)forFeatureExtraction

To quantify thestrength of differentbrainwavefrequencies, the Power Spectral Density (PSD) is calculated:

$$P_{xx}(f)=|X(f)|^2[16]$$

This metric indicates how the signal's power is distributed across frequency bands. PSD features are crucial for distinguishing between mental states such as concentration (beta), drowsiness (theta), or alertness (alpha).

5) MotorControlLogic

To regulate the movement of the wheelchair, Pulse Width Modulation (PWM) is employed, which modulates the average voltage delivered to the motor by varying the duty cycle. The voltage applied to the motor is given by

$$V_{motor}=V_{supply}\times\frac{D}{100}[17]$$

Where:

- V_{motor}:Effectivevoltageappliedtothemotor
- V_{supply}:Sourcevoltage
- D:Dutycycle(inpercentage)

PWM allows fine-grained speed control of the DC motor withoutenergylosstypicalinresistivemethods.The**current** through the motor using an H-Bridge circuit is estimated using:

$$I=\frac{V_{in}-V_{motor}}{R_{motor}}\ [17]$$

- I=Currentflowingthroughthemotor
- V_{in}=InputvoltagetoH-bridge
- R_{motor}=Internalresistanceofthemotor

The H-bridge logic enables directional control of the wheelchair through simple digital commands:

Direction	Motor_1	Motor_2
Forward	HIGH	LOW
Backward	LOW	HIGH
LeftTurn	LOW	LOW
RightTurn	HIGH	HIGH

PWM provides efficientspeed control, whiletheH-Bridge circuit facilitates forward and reverse motion. The system design is cost-effective, safe for testing, and compatible with microcontrollers like the ESP32.

6) BrainwaveFrequencyMappingforCommandControl

The system maps EEG frequency bands and eye blink eventstowheelchaircontrolcommands.Thelogicisbased on distinct cognitive patterns observable in EEG signals:

C=1→iff≥30Hz(Gamma)+SingleBlink(Start)[18]
2→if13≤f<20Hz(Beta-Left)[18]
3 →if18≤f<25Hz(HighBeta-Right)[18]
4 →iff≤4Hz(Delta-Stop) [18]
5 →iff≥30Hz+DoubleBlink(EmergencyStop)[18] Where:

- f:DetectedEEGfrequency
- C:Commandidentifier

Blink detection is done using peak-to-peak amplitude of the EEG signal:

$BlinkSignal{=}max(x(t)){-}min(x(t))$[19]
Ifthisvalueexceedsapredefinedthreshold,ablinkeventis registered.
For improved classification and responsiveness, EEG frequencyandblinkamplitudeare**combined**withweighted factors:
$Command{=}(f_{EEG}{\times}W_{EEG})$
$+(F_{Blink}{\times}W_{Blink})$[19]
Where:

- f_{EEG}:Frequency-domainfeaturefromEEG
- $\boldsymbol{F_{Blink}}$:Blinksignal feature
- $\boldsymbol{W_{EEG}, W_{Blink}}$:Weightcoefficientsforfeature fusion

Brainwavefrequenciesreflectcognitiveintentions,andeye blinks serve as deliberate triggers. Combining both improvescommandreliabilityandreducesfalsepositivesin noisy environments. This multi-modal control enhances accessibility for individuals with limited motor functions.

IV. RESULT & DISCUSSION

The effectiveness of the EEG-driven brain-controlled wheelchair system was evaluated based on its accuracy in translating brainwave frequencies and eye gestures into movement commands. The system achieved the following results: response time was analyzed to ensure minimal latency, and the accuracy of command execution was validatedthroughmultipletestscenarios. Additionally,user adaptability and ease of control were assessed to measure the system's effectiveness in real-world applications, ensuring a reliable and intuitive mobility solution.

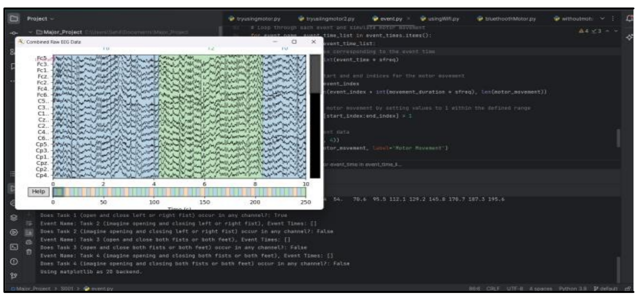

Fig3.Testingwiththedataset:

As shown in Fig. 3, we first test the data in Python MNE using different datasets, study the EEG signals and their features, and extract meaningful information for the next step.

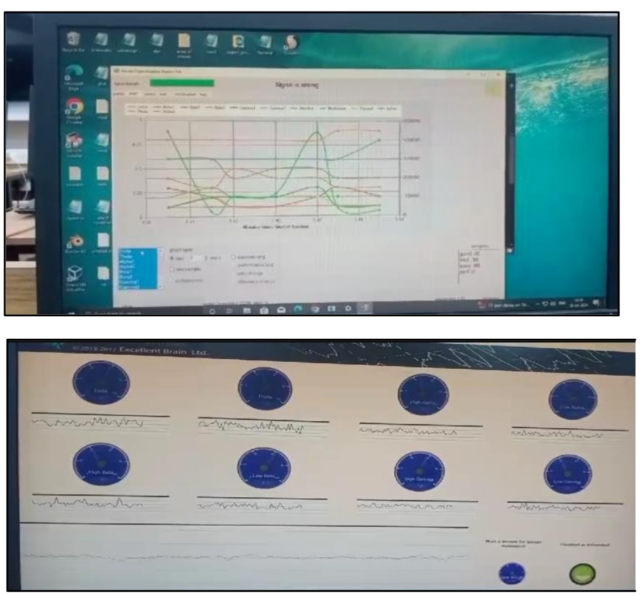

Fig.4.SignalextractionusingNeuroSky.

Fig. 4 illustrates signal extraction using the NeuroSky device.Wecollectdifferentbrainwavefrequencysignals— such as alpha, beta, delta, and theta waves—through the device. These frequencies correspond to various mental states like relaxation, concentration, and drowsiness. The NeuroSky headset enables real-time observation of EEG signals, allowing us to experience and analyze live brain activity.

After testing with raw EEGdata sourcedfromthe internet, wesuccessfullyextractedeventsfromthesignals.Basedon predefined conditions, we were able to accurately assign corresponding commands to the events. These commands were then sent to the Arduino IDE, where they were processedandtransferredtotheESP32microcontrollerfor execution, enabling the desired control over the wheelchair's movements. To ensure precision, we applied signal preprocessing techniques such as noise filtering and feature extraction. Additionally, multiple trial runs were conducted to validate the system’s reliability and responsiveness.

Dataset: We used the EEG Motor Movement dataset from the PhysioNet website for testing purposes.

```
Sending command: 1
Waiting for event: Turn Left at 4.20 seconds
Sending command: 2
Waiting for event: Motor Start at 8.30 seconds
Sending command: 1
Waiting for event: Turn Right at 12.50 seconds
Sending command: 3
Waiting for event: Motor Start at 16.60 seconds
Sending command: 1
Waiting for event: Turn Left at 20.80 seconds
```

Fig.5.EEGsignaltransmittedtoPythonMNEforanalysis.

AsshowninFig.5,weassignspecificcommands—suchas forward,backward, left, or rightmovement—to brainwave frequencies based on their respective ranges.Additionally, we extract the timestamp at which each event occurs to synchronize the signal with the corresponding action.

```
00:30:21.293 -> Motor Started
00:30:21.967 -> Turning Left
00:30:22.627 -> Turning Right
00:30:23.602 -> Motor Stopped
00:30:33.645 -> Motor Started
00:30:34.722 -> Motor Started
00:30:35.368 -> Turning Left
```

Fig.6.EEGsignaltransmittedtotheArduinoIDEforfurtherprocessing.

After conducting extensive testing with raw EEG data sourced from the internet, the system demonstrated the successful extraction of relevant events from the signals. TheEEGdatawasprocessedtoidentifyspecificbrainwave frequencies and eye gestures, which were then mapped to predefined commands, such as **start**, **left**, **right**, **stop**, and **emergency brake**. Each command was assigned based on theconditionsoftheextractedsignals,ensuringthecorrect interpretation of user intentions.

Fig. 6 presents the result of our study, where we successfully transferred the assigned commands to the Arduino IDE. These commands—such as move forward, turn left, turn right, and stop—were transmitted to the ESP32 microcontroller. The ESP32 then activated the correspondingmotordriversignalstocontrolthemovement of the wheelchair motors, enabling real-time navigation based on EEG signal inputs.

The system achieved a high level of accuracy in detecting andtranslatingtheseeventsintoactionablecommands,with a successful transfer of the commands to theArduino IDE. From there, the commands were reliably transferred to the ESP32microcontroller,whichexecutedthenecessarylogic to control the wheelchair's movements.

The wheelchair responded accurately to commands, including starting, turning, stopping, and emergency braking,basedonthecorrespondingbrainwavefrequencies and eye gestures.

Overall, the resultsconfirm the effectivenessof the system inprocessingandinterpretingEEGsignals,translatingthem into real-time commands, and controlling the wheelchair's motors via the ESP32 microcontroller. This non-invasive, cost-effective solution successfully enhances mobility for individuals with severe physical disabilities, offering improved autonomy and control.

Criteria	TRUE (Correct Outcome)	FALSE (Incorrect Outcome)
Command Execution	Correct command (e.g., move left) executed based on EEG + eye blink	Wrong or no command triggered despite valid EEG input
Eye Blink Detection	Single or double blink detected correctly as start/emergency stop	Blink missed or wrongly detected, triggering unintended action
Motor Movement	ESP32 successfully triggered correct motor response	Motor not triggered or wrong motor activated due to faulty signal processing
Emergency Stop Function	Double blink + gamma frequency reliably triggered immediate stop	Failed to engage emergency stop in high-risk situations
Signal Integrity	Strong, clean EEG signal maintained during usage	Weak signal or loss of headset connection caused failure to process commands
Data Preprocessing	Noise-free, filtered EEG signals provided reliable inputs	Presence of noise or artifacts caused command misclassification

V. MACHINE LEARNING-BASED VALIDATION

To enhance the accuracy of EEG signal interpretation and ensure robust command classification, machine learning techniques were incorporated into the system.This section details the methodology, dataset, features, classifier evaluation, and performance metrics used to validate the proposed brain-controlled wheelchair system.

A. Dataset and Preprocessing

We used the publicly available **EEG Motor Movement/Imagery Dataset** from PhysioNet,[21] which contains EEG signals for various motor imagery tasks recorded using 64 channels at 160 Hz. For model training:

- Only four classes were considered: *Left Hand*, *RightHand*,*Start(bothfists)*,and*Stop(reststate)*.
- Signalsweresegmentedinto2-secondwindows.
- A band-pass filter (0.5–40 Hz) was applied to remove noise.
- Artifacts (e.g., eye movements, muscle activity) were removed using Independent Component Analysis (ICA).

B. Feature Extraction

From each segment, the following features were extracted using Python's MNE and NumPy libraries:

- Frequency-domain features: Bandpower in Delta(1–4Hz),Theta(4–8Hz),Alpha(8–13Hz), Beta (13–30 Hz), and Gamma (>30 Hz) bands
- Time-domain statistics: Mean, Variance, Skewness
- Blink Detection: Detected by signal peaks exceeding 150 µV

The extracted features formed a feature vector for training classification models.

C. Classifier Models

Three popular classification algorithms were trained and tested using the extracted features:

- Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel
- RandomForest(RF)with100decisiontrees
- K-NearestNeighbors(KNN)withk=5

Allmodelswereimplementedusingscikit-learnandevaluatedwith10-foldcross-validation.[20]

D. Results

Themodelswereevaluatedbasedontheirabilitytoclassify theuser'sintentintooneofthefourmovementclasses.The average performance across folds is shown below:

Algorithm	Accuracy [22]	Accuracy *	Precision [23]	Precision *	Recall [24]	Recall *	
SVM	87%	87%	88%	89%	85%	83%	
RF	85%	86%	85%	85%	84%	82%	
KNN (k=5)	82%	80%	81%	80%	83%	83%	

Comparison between other author result and our result (* are our results)

Final Choice: SVM (Support Vector Machine)
Achieved the highest accuracy (87%) among all models.Precision (89%) ensures reliable classification, minimizingfalse triggers in wheelchair movement.Recall (83–85%) isreasonably strong, ensuring most commands are captured.SVM is well-suited for EEG signal classification, as it handleshigh-dimensional data and small datasets effectively.

E. EvaluationMetrics I

Thefollowingmetricswereusedtoevaluateperformance:

- **Accuracy**:Proportionoftotalcorrectpredictions

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN}$$

- **Precision**:Proportionofcorrectlypredicted positive instances

$$Precision=\frac{TP}{TP+FP}$$

- **Recall**:Proportionofactualpositivescorrectly identified

$$Recall=\frac{TP}{TP+FN}$$

These metrics were computed using the classification_report() function from scikit-learn.

F. ConfusionMatrixforSVMClassifier

	Predicted Left	Predicted Right	Predicted Stop	Predicted Start
Actual Left	42	3	2	3
Actual Right	4	40	5	1
Actual Stop	1	3	41	5
Actual Start	2	1	4	43

The SVM classifier demonstrated high generalization capability with minimal false positives.

G. Real-TimeIntegration

Thetrained SVMmodelwasconvertedusing **TensorFlow Lite** and deployed onto the **ESP32 microcontroller** using **TinyML**. Real-time EEG features were fed into the model for live prediction, which improved responsiveness and reduced manual tuning efforts.

VI. CONCLUSION

This study presents a brain-controlled wheelchair system that leverages EEG signals and eye movements to assist individuals with severe mobility impairments. The non- invasiveandcost-effectiveBCITechnologyconvertsbrain activityintoreal-timecontrol commands.Thesecommands are then processed and transmitted to the ESP32 microcontroller, enabling precise motor control for seamless wheelchair navigation. The integration of advanced signal processing ensures accurate command recognition, enhancing the system's reliability and responsiveness.

The results of the testing demonstrated that the system successfully extracted events from raw EEG signals, assigned the correct movement commands, and sent them to the Arduino IDE for transfer to the ESP32.

The wheelchair accurately responded to commands for starting,turning,stopping,andemergencybraking,offering a reliable and intuitive controlmechanism.The integration of EEG signal processing, eye-tracking technology, and microcontroller-based motor control ensures that the system providesaseamlessuserexperiencewithhighaccuracyand responsiveness.

This system represents a promising solution for improving the mobility and independence of individuals with neuromusculardisorders,offeringapractical,non-invasive alternative to traditional assistive devices. Future research can enhance signal processing accuracy, expand system capabilities, and improve the user interface for wider applications. Ultimately, this project highlights the potential of combining advanced neuroscience and robotics to enhancethequalityoflifefordifferently-abledindividuals.

REFERENCES

[1] E. A. Curran and M. J. Stokes, "Learning To control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems", Brain Cognition, vol. 51, no. 3, pp. 326-336, 2003.
[2] A. Kubler, B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. erelmouter, M. Schauer, et al., "The Thought translation device: A neurophysiological approach to communication in total motor paralysis", Exp. Brain Res., vol. 124, no. 2, pp. 223-232, 1999.
[3] M. Palankar, K. De Laurentis, R. Alqasemi, E. Veras, R. Dubey, Y. Arbel, et al., "Control of a 9-DoF wheelchair-mounted robotic arm system using a P300 brain computer interface: Initial experiments", IEEE Int. Conf. Robot. Biomimetics 2008, pp. 348-353, 2009.
[4] J. R. Wolpaw, N. Birbaumer, D. J. MacFarland, G. Pfurtscheller and T. M. Vaughan, "Brain-computer interface for communication and control", Clin. Neurophysiol., no. 113, pp. 767-791, 2002.
[5] K. Tanaka, K. Matsunaga and H. Wang, "Electroencephalogram-based control of wheelchair", IEEE Trans. Robotics, vol. 21, no. 4, pp. 762-766, Aug. 2005.
[6] I. Iturrate, J. Antelis, A. Kbler and J. Minguez, "Non-invasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation", IEEE Trans. Robot., vol. 25, no. 3, pp. 614-627, Jun. 2009.
[7] J. Philips, J. D. R. Milln, G. Vanacker, E. Lew, F. Galn, P. Ferrez, et al., "Adaptive shared control of a brain-actuated simulated wheelchair", IEEE Int. Conf. Rehabil. Robot. (ICORR), pp. 408-414, 2007.
[8] Q. Zeng, E. Burdet, B. Rebsamen and C. L. Teo, "A collaborative wheelchair system", IEEE Trans. Neural Syst. Rehabil. Eng., vol. 16, no. 2, pp. 161-170, Apr. 2008
[9] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C. L. Teo, Q. Zeng, et al., "Controlling a wheelchair indoors using thought", IEEE Intell. Syst. Mag., pp. 18-24, Mar./Apr. 2007
[10] G. Bourhis, K. Moumen, P. Pino, S. Rohmer and A. Pruski, "Assisted navigation for a powered wheelchair", IEEE Int. Conf. Syst. Man Cybern., no. 3, pp. 553-558, 1993.
[11] A. Farwell and E. Donchin, "Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials", Electroencephalogr. Clin. Neurophysiol., no. 70, pp. 510-523, 1988.
[12] M. Cheng, X. Gao and D. Xu, "Design and implementation of a brain-computer interface with high transfer rates", IEEE Trans. Biomed. Eng., vol. 49, no. 10, pp. 1181, Oct. 2002.
[13] M. Kaper, P. Meinicke, T. Linger and H. Ritter, "BCI competition 2003 Dataset IIb: Support vector machines for the P300 speller paradigm", IEEE Trans. Biomed. Eng., vol. 51, no. 6, pp. 1073-1076, Jun. 2004.
[14] E. A. Curran and M. J. Stokes, "Learning To Control Brain Activity: A Review of the Production and Control of EEG Components for Driving Brain-Computer Interface (BCI) Systems," Brain Cognition, vol. 51, no. 3, pp. 326-336, 2003.
[15] J. R. Wolpaw, N. Birbaumer, D. J. MacFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-Computer Interface for Communication and Control," Clinical Neurophysiology, vol. 113, pp. 767-791, 2002.
[16] K. Tanaka, K. Matsunaga, and H. Wang, "Electroencephalogram-Based Control of Wheelchair," IEEE Transactions on Robotics, vol. 21, no. 4, pp. 762-766, Aug. 2005.
[17] I. Iturrate, J. Antelis, A. Kübler, and J. Minguez, "Non-invasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation," IEEE Transactions on Robotics, vol. 25, no. 3, pp. 614-627, Jun. 2009.
[18] M. Cheng, X. Gao, and D. Xu, "Design and Implementation of a Brain-Computer Interface with High Transfer Rates," IEEE Transactions on Biomedical Engineering, vol. 49, no. 10, pp. 1181-1185, Oct. 2002.
[19] B. Rebsamen, E. Burdet, C. Guan, H. Zhang, C. L. Teo, Q. Zeng, et al., "Controlling a Wheelchair Indoors Using Thought," IEEE Intelligent Systems Magazine, pp. 18-24, Mar./Apr. 2007
[20] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[21] A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource,” Circulation, vol. 101, no. 23, pp. e215–e220, 2000.

[22] Iturrate, J. Antelis, and J. Minguez, "Synchronous EEG brain-actuated wheelchair with automated navigation," in Proceedings of 2009 IEEE International Conference on Robotics and Automation (ICRA), 2009

[23] K. Tanaka, K. Matsunaga, and H. O. Wang, "Electroencephalogram-based control of an electric wheelchair," IEEE Transactions on Robotics, vol. 21, no. 4, pp. 762–766, Aug. 2005

[24] Dehrouye-Semnani F., N. M. Charkari, S. M. M. Mirbagheri, “Toward an improved BCI for damaged CNS-tissue patient using EEG-signal processing approach” (2021)