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MINDWHEELS: MOBILITY POWERED BY EEG BASED BCI TECHNOLOGY

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ABSTRACT
This project presents the development and implementation of a Brain-Controlled Wheelchair system, designed to enhance mobility for individuals with motor disabilities. The process begins with EEG data capturing, utilizing medical-grade conductive paste to secure electrodes on the scalp. A cue-based experimental paradigm prompts users to perform distinct mental tasks, facilitating the collection of EEG data synchronized with task performance. Signal processing techniques, including bandpass filtering and FFT, are employed to isolate relevant brainwave frequencies and extract features for classification. Machine learning algorithms, specifically the Voting ensemble method, are utilized to enhance classification accuracy by combining predictions from diverse classifiers. The system is integrated with a user-friendly interface, leveraging Cython for efficient data processing and real-time translation of EEG signals into wheelchair commands. This interface provides prompt and accurate responses to user intentions, ultimately offering promising solutions for improved mobility and quality of life for individuals with motor impairments.

Keywords:
Brain Computer Interface, Motor Imagery, Brain Controlled Wheelchair

INTRODUCTION

The human brain, with its intricate network of approximately 100 billion neurons and trillions of synaptic connections, serves as the foundation for groundbreaking developments in assistive technology. Electroencephalography (EEG), now the foremost noninvasive tool for studying dynamic brain signatures, offers insights into neural activity through voltage fluctuations at the scalp. These signals, originating from dendritic inputs to large pyramidal cells in the neuropil, provide a window into cognitive processes, emotions, and motor intentions [1-5]. EEG categorizes brain waves into distinct frequency bands, ranging from delta to gamma, and has become indispensable in various applications, including clinical diagnosis and Brain-Computer Interface (BCI) systems [8-14].
Motor Imagery (MI), a cognitive process wherein individuals mentally rehearse physical movements without execution, holds significant promise for BCI technology [15-17]. By engaging similar neural circuits as those involved in actual movement, MI tasks produce distinct EEG patterns that can be decoded to translate intention into action. Through MI-based BCIs, users can interact with external devices solely through their thoughts, offering a pathway to increased independence and autonomy.
The integration of BCI, Motor Imagery, and EEG represents a symbiotic relationship aimed at revolutionizing assistive technology. By harnessing the power of the mind, individuals with motor disabilities can transcend physical limitations and engage with the world in ways previously unimaginable. As research continues to push the boundaries of neuroscience and engineering, the potential for BCI-driven solutions to enhance human capabilities and improve quality of life remains boundless.

Components used for Proposed System

- EEG Electrodes: Utilizing multiple non-invasive dry electrodes, eliminating the need for uncomfortable conductive gel or paste. EEG electrodes can be categorized as wet, semi-dry, or dry electrodes. Wet electrodes require gel or paste between the electrodes and the skin, while semi-dry electrodes need only a small amount of conductive gel. Dry electrodes eliminate the need for gel or skin preparation altogether, enhancing user comfort and convenience [15-17].

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- Raspberry Pi: Serving as the core processing unit in the prototype, offering versatility and flexibility for embedded systems and IoT projects.
- ADS1299: A specialized analog front-end (AFE) tailored for biomedical signal acquisition, particularly EEG applications. With eight high-resolution analog-to-digital converters (ADCs) boasting low-noise performance, the ADS1299 enables simultaneous acquisition of multiple channels of bioelectric signals. Configurable gain settings, flexible filtering options, and built-in safety features ensure robust and precise signal acquisition for medical devices, research purposes, and brain-computer interface (BCI) systems like brain-controlled wheelchairs.
- L298N: Serving as the motor driver integrated circuit (IC) in the prototype, specifically designed for controlling DC motors and stepper motors. Capable of bidirectional control for two DC motors or precise control for one stepper motor, the L298N offers versatility in motor control applications. Its wide range of supply voltages and high current capabilities make it suitable for robotics, automation, and motorized vehicles. Built-in protection features such as thermal shutdown and overcurrent protection ensure safe and reliable operation in various environments.
- Custom PCB: Designed and fabricated specifically for EEG signal acquisition, amplification, and digitization using the ADS1299 as the main component. The custom PCB integrates necessary components and circuitry to ensure optimal signal quality and compatibility with the Raspberry Pi and other system components. This tailored approach allows for efficient and reliable EEG data acquisition, essential for the successful implementation of the brain-controlled wheelchair prototype. Fig. 1 and Fig. 2 shows the schematic of the board.

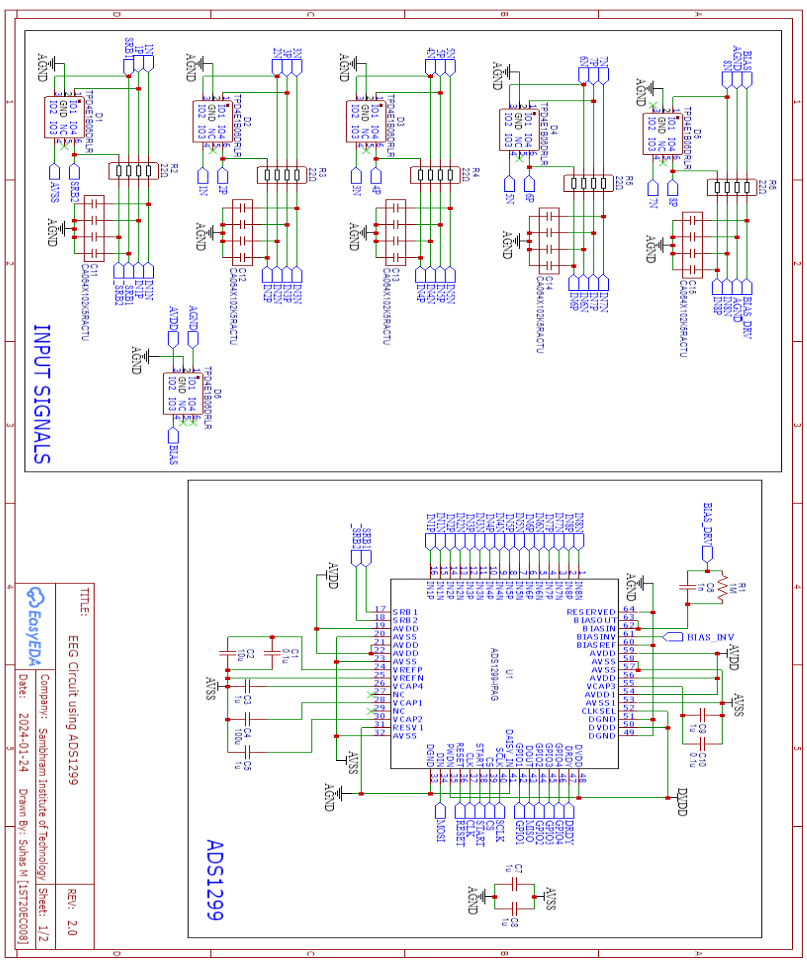

Fig. 1PCB Schematic Sheet 1/2

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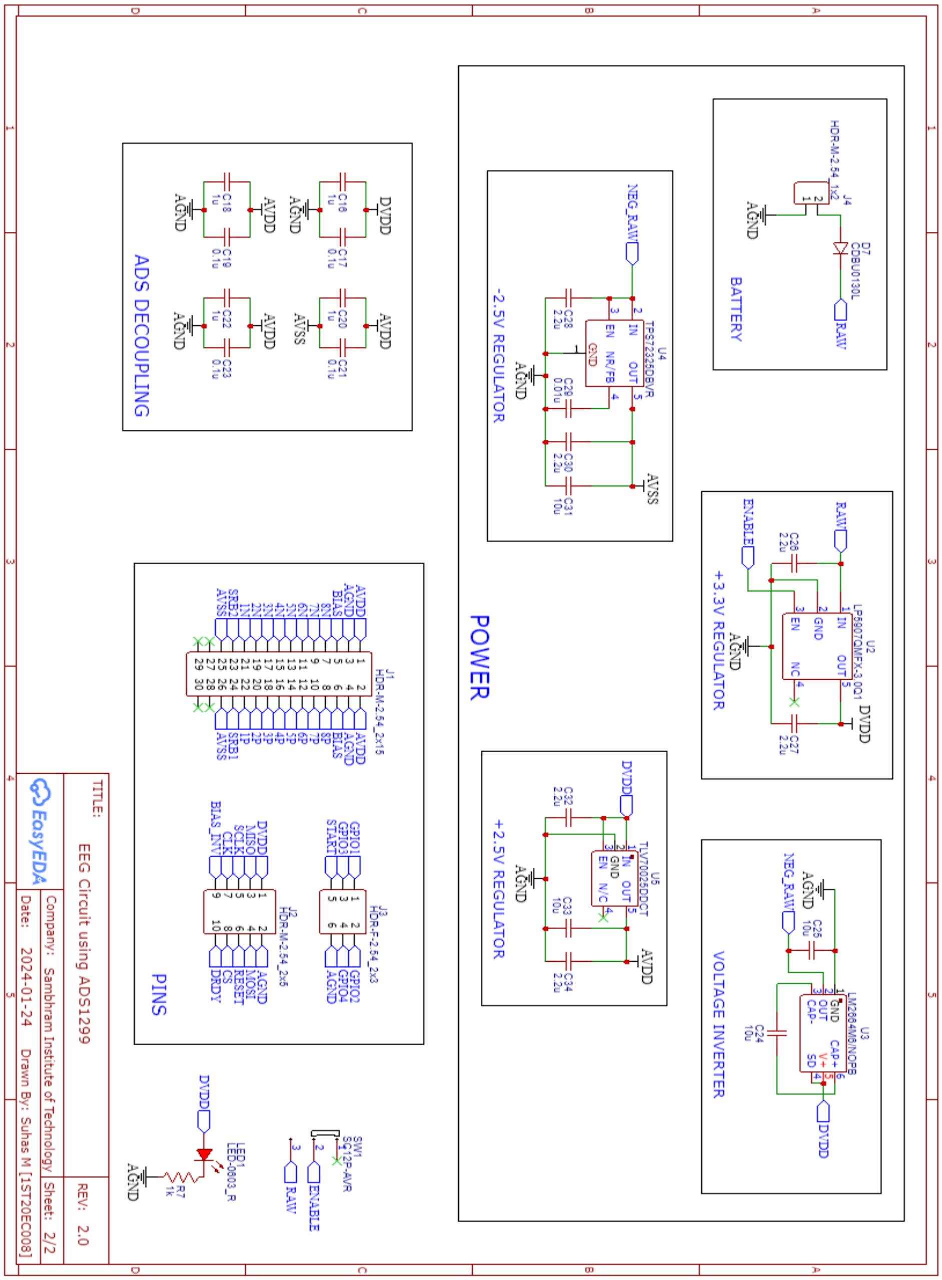

Fig. 2: PCB Schematic Sheet 2/2

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METHODOLOGY

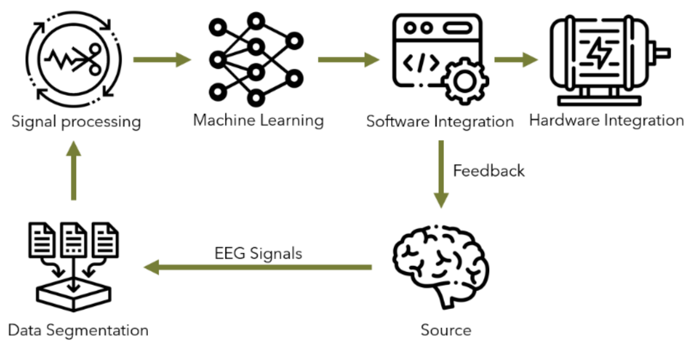

Fig 3: Block Diagram

1. Data Capturing

Medical grade Ten20 EEG conductive paste was used to secure electrodes directly onto the scalp of the participant. The four electrodes used to collect MI data were placed along the sensorimotor cortex. Two reference electrodes were placed on the subject's two ears. C1, C2, C3, and C4 channels were used, as recommend for the detection of the optimal rhythm. Red are references electrodes

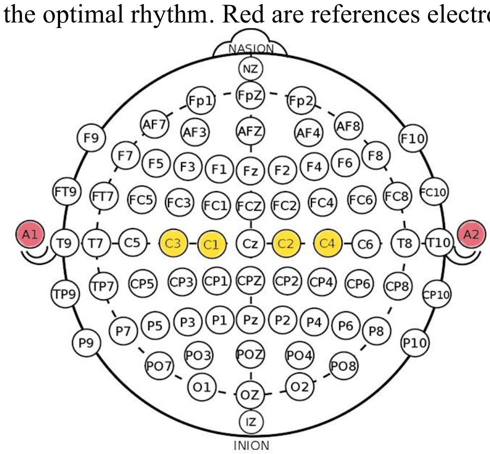

Fig 4: Placements of EEG electrodes on the scalp

To obtain optimal data, we designed a cue-based experimental paradigm with three MI tasks. The custom built software interface prompts the participant to imagine a certain state using visual cues (left arrow, right arrow, and sleep for rest). EEG data labelling is done synchronously with the collection process. Task design involved defining specific mental tasks that the user can perform to control the wheelchair. These tasks (imagining moving the left hand, right hand, rest position) are distinct and easily distinguishable in the EEG signals. User undergo training sessions to familiarize themselves with the tasks and improve their ability to generate distinguishable EEG patterns. Machine learning algorithms are employed to adapt to individual user variations and enhance system accuracy. The feedback is provided to users during task performance which is essential for

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learning and improving control. Visual feedback reinforce successful task execution and guide users toward achieving desired brainwave patterns.

2. Signal Processing:
The raw EEG signals contain a broad range of frequencies, including both relevant brainwave frequencies and unwanted noise. The preprocessing step facilitates the removal of low-quality data without altering the clean data to drive effective wheelchair control based on the user's cognitive signals. Bandpass filters are applied to isolate the specific frequency bands associated with motor imagery tasks. Our targeted frequency range is the alpha rhythm (8-12Hz) when the subjects are at rest and beta rhythm (13-36Hz) when the subjects blink their eyes. To process real-time data, we sampled at 250 Hz with a time window of two seconds. The signal was first notched-filtered at 60 Hz and 120 Hz to remove the power-line noise across all eight electrodes. After the data pre-processing, we used Power Spectral Density (PSD) to extract the power of with respect to frequency. FFT was found effective method for stationary signals. It transforms signals from the time domain to the frequency domain and implements spectral analysis. In this method, features are extracted by using mathematical tools to calculate the PSD. The estimation of PSD for the alpha band (8-12Hz) and the beta band (13-36 Hz) computed with FFT, which uses non-parametric methods such as Welch's method.

3. Machine Learning:
In our research, we've found the Voting ensemble method to be a highly effective approach for improving classification accuracy in machine learning models. By combining predictions from multiple diverse classifiers, this method consistently outperforms individual models. Its simplicity and robustness make it a practical choice for enhancing predictive power across various datasets and problem domains. This ensemble method aggregates the predictions from various base classifiers, such as decision trees, support vector machines, or logistic regression models, and uses a majority vote (for classification tasks) or an average (for regression tasks) to determine the final prediction. n our ensemble, we've combined the predictions of three distinct classifiers: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Linear Regression

4. Software Integration
We created a user-friendly interface for the Brain-Controlled Wheelchair system, prioritizing accessibility and precise conveyance of the machine learning model's predictions. To overcome the inherent processing limitations of Python, we leveraged Cython, a powerful tool for optimizing Python code, ensuring efficient execution of data processing tasks. This interface seamlessly translated EEG signals into actionable wheelchair commands in real-time, facilitating rapid responsiveness to user intentions. Through meticulous optimization for low latency and continuous data processing, supported by advanced signal processing algorithms, we achieved prompt and accurate system responses. A linear regression is used to classify, in real-time, the motor imagery state of the wheelchair user. The feature used in the regression is the average mu band power, given as the average of the frequencies of interests (8-12Hz) for all time points. The linear regression then gives a motor imagery state for every given time point. The direction with the most occurrence within a 3 second time-window is the final decision output and is fed to the wheelchair. If no motor imagery signals are detected and jaw-clenches are sustained, the wheelchair will go into a stop. Sustaining jaw clenches again will bring the wheelchair to move forward. Refer Fig. 5.

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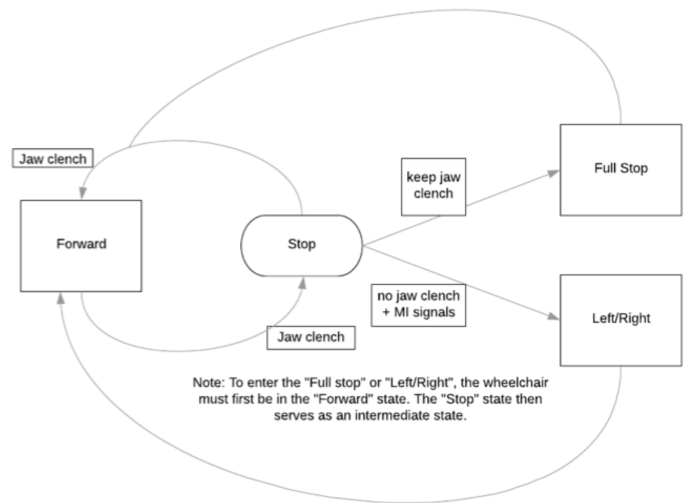

Fig 5: State transition

CONCLUSION

In conclusion, the EEG-Powered Wheelchair project embodies a pioneering endeavor at the confluence of neuroscience, assistive technology, and artificial intelligence. By harnessing the intricate signals of the human brain, this project endeavors to redefine mobility for individuals grappling with severe motor disabilities, offering a pathway to heightened independence and enhanced quality of life.

The project's systematic methodology, spanning EEG signal acquisition, sophisticated signal processing, machine learning integration, software development, and hardware integration, underscores a holistic approach to crafting a dependable Brain-Computer Interface. Notably, the project not only tackles technical hurdles associated with translating cognitive signals into wheelchair commands but also prioritizes user experience, safety, and adaptability.

Continual advancements in EEG technology, signal processing algorithms, and machine learning techniques promise ongoing refinement and improvement. As the field progresses, future iterations may yield even more precise, user-friendly, and universally accessible solutions, fostering inclusivity and societal integration.

The potential applications of the EEG-Powered Wheelchair extend across diverse medical conditions and rehabilitation scenarios, offering transformative benefits for individuals with paralysis, spinal cord injuries, and other severe motor impairments. The technology's adaptability, real-time processing capabilities, and adaptive learning features position it as a frontrunner among assistive mobility solutions.

Nevertheless, as with any innovative endeavor, challenges and considerations abound. Addressing issues such as user training, hardware reliability, and ethical concerns regarding privacy and data security will be paramount to realizing the full potential of this groundbreaking technology.

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