NeuroWarn BCI: Enhancing Safety in EEG-Controlled Wheelchairs with an RNN-Based Warning System

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In Partial Fulfillment

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Bachelor of Science in Computer Science

by

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March 2025

Approval Sheet

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Abstract

This study introduces Neurowarn BCI, a smart wheelchair system designed to assist individuals with mobility impairments by utilizing EEG-Insight to interpret brainwave signals for controlling the wheelchair’s movement and direction. Additionally, a Recurrent Neural Network (RNN) machine learning model is integrated to predict the wheelchair’s path, specifically in Forward, Neutral, and Backward directions. The model demonstrated an average accuracy of 95%, ensuring reliable performance. The system's effectiveness was evaluated based on ISO 9241-11 usability standards, where the results indicated that it successfully meets user needs, particularly in terms of ease of use, efficiency, and overall satisfaction. These aspects were rated as "Very Good", confirming the system’s high usability. The Neurowarn BCI represents a significant advancement in the biomedical field, offering a promising solution to enhance mobility and independence for individuals with paralysis.

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CHAPTER 1 INTRODUCTION TO THE STUDY

Background of the Study and Conceptual Framework

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As of the 2013, US Paralysis Prevalence & Health Disparities Survey, nearly 5.4 million individuals endure paralysis, often stemming from stroke or spinal cord injuries [1]. Quadriplegia (also known as tetraplegia) occurs in approximately 60% of traumatic spinal cord injury cases, rendering all four limbs and the trunk paralyzed [2]. Given the absence of a cure for complete paralysis, various alternative treatments exist, ranging from physical and occupational therapy to mobility aids.

A mobility aid that has gained considerable academic interest is employing an EEG (electroencephalogram) device to control a smart wheelchair [3]. A smart wheelchair is a powered wheelchair that has been modified by adding necessary sensors and instruments that can read, collect, and send information that can be used to modify the status of the wheelchair, as well as interact with the environment or the user [4].

By employing an EEG device to control a smart wheelchair, users can engage with their surroundings without relying entirely on assistance from others [5]. One study has reported a 70% success rate, thus proving the feasibility of the approach [6]. However, safety remains a primary concern, particularly in accurately detecting cerebral signals and the establishment of secure navigation protocols within unfamiliar surroundings [7-8].

Building upon the promising potential of Brain-Computer Interfaces (BCIs) for movement control in individuals with paralysis, researchers are actively exploring methods to analyze the dynamic nature of brainwave signals [9]. Recurrent neural networks (RNNs) offer a promising approach for handling this task due to its ability to capture the sequential dependencies present within these signals. Unlike traditional models, RNNs possess internal loops that enable them to consider not only the current information but also the context provided by past inputs. This unique characteristic allows them to effectively model the complex patterns of brain activity, making them well-suited for analyzing ongoing brain signals in real-time [10].

This study aims to integrate Recurrent Neural Networks (RNN) into current Brain-Computer Interface (BCI) control frameworks to anticipate user intention. The objective is to create a warning mechanism based on predictions made by the model and sensor data retrieved from a custom-built smart wheelchair. This warning mechanism can detect unseen obstacles and consequently prevent collisions, thereby enhancing the safety of BCI-controlled wheelchairs.

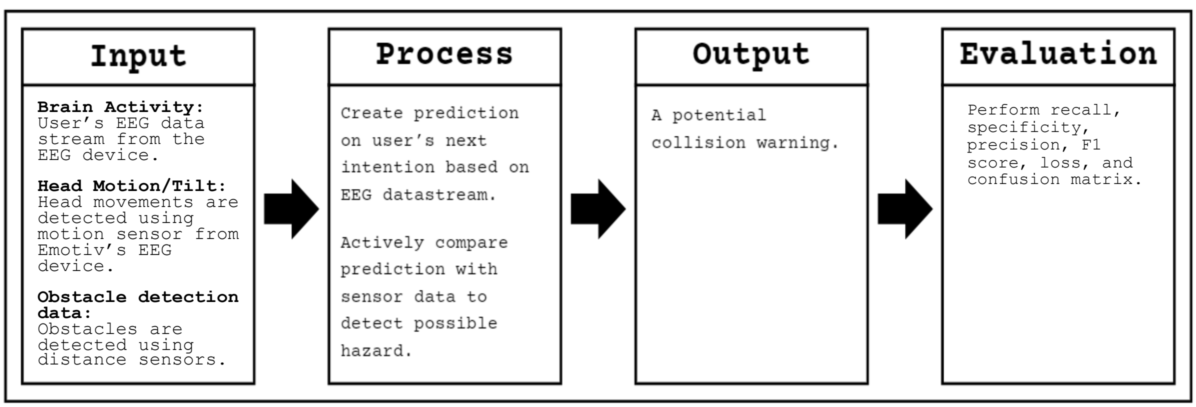

Figure 1. Conceptual Framework

Objectives of the Study

This research generally aims to enhance the safety of BCI (Brain-Components Interface) system-controlled smart wheelchairs.

Specifically, this study is expected to:

1. design a smart wheelchair that utilizes Emotiv's Mental Command Suite for wheelchair motor controls and Light Detection and Ranging (LiDAR) sensors for obstacle avoidance.
2. utilize Recurrent Neural Network - Long Short-Term Memory (RNN-LSTM) to predict the user's intended direction while avoiding obstacles.
3. develop a user interface that will send visual and auditory prompts to the user if an obstacle is detected in the predicted intended direction.
4. evaluate the performance of the algorithm using recall, specificity, precision, F1 score, loss, and confusion matrix.

5. assess the usability of the warning system through user testing, following the human-system interaction principles outlined in ISO 9241-11.

Significance of the Study

The results of this study will be useful to the following:

Tetraplegic Patients. The findings of this study could directly contribute to the advancement of EEG-controlled smart wheelchairs thus enhancing the mobility and quality of life of Tetraplegic Patients.

Doctors and Therapists. This research could provide them with insights into the treatment of tetraplegic patients. By understanding how Recurrent Neural Network can better analyze brainwave signals for wheelchair control, neurologists can potentially tailor EEG-based therapies for improved patient outcomes.

Researchers. This study could contribute to the advancement of Brain-Computer Interface (BCI) technology. The implementation of RNNs in predicting brainwave patterns is not limited to wheelchair control. Researchers could leverage the findings of this study to develop more effective and efficient BCI implementations.

Engineers. This study could provide valuable insights into the practical application of Brain-Computer Interface (BCI) technology. Engineers could utilize the findings to enhance the design and development of responsive, real-time systems that rely on brainwave data, including those requiring better and faster obstacle detection for safer and more efficient navigation.

Developers. This study could serve as a valuable reference for developers, offering approaches they can leverage to build more intelligent, real-time applications that respond to neural input. The implementation strategies are not limited to wheelchair control. They can be extended to software for accessibility, gaming, health monitoring, and other interactive BCI-driven platforms

Delimitation of the Study

This study focused on the application of Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) units to predict user-intended directions in a Brain-Computer Interface (BCI) controlled smart wheelchair. The system utilized Emotiv's Mental Command Suite to interpret the user's mental commands to control the smart wheelchair. However, this study did not investigate or elaborate on the underlying mechanisms and algorithms of the Emotiv framework itself. This research was constrained to utilizing the pre-existing capabilities of the Emotiv system without modifying or enhancing its functionalities. Additionally, the system developed within this study was designed to operate effectively only if the two specific mental commands (push, and pull) have been trained and recognized by the Emotiv Mental Command Suite. These two commands are important parameters that were used by the RNN-LSTM model. Any exploration beyond these two commands is outside the scope of this research.

Moreover, the study included the modification of an existing electric wheelchair, transforming it into a smart wheelchair equipped with LIDAR sensors, and ultrasonic for obstacle detection and an Arduino for the control. The modifications to the wheelchair was strictly based on the system requirements, which include controlling the wheelchair using the Mental Command Suite and incorporating an obstacle detection system. No additional modifications or enhancements to the wheelchair were undertaken beyond these specified requirements. The primary goal was to develop a comprehensive warning system that synergizes the RNN-LSTM based prediction of the user's next intended direction with the data obtained from the LIDAR sensors. This warning system was expected to improve the safety and reliability of the smart wheelchair, offering a practical solution for users who rely on BCI for mobility. However, the study did not extend to the development of new hardware or the exploration of alternative sensor technologies beyond what was specified.

Definition of Terms

For better understanding, the following terms were defined conceptually and operationally:

Arduino Mega 2560: A microcontroller board with many I/O pins, suitable for projects needing numerous inputs and outputs, such as robotics. It is versatile and widely used in the maker and electronics communities.[39]

In this study, this refers to the software application designed to analyze the EEG data in real-time and generate warnings to the user about potential hazards or critical situations based on the anticipated control commands.

BCI (Brain-Computer Interface): BCI enables direct brain-to-device communication, allowing control and interaction based on brain signals. This technology holds promise for enhancing communication and mobility for individuals with disabilities.[40]

In this study, this refers to the system that translates brain signals from the EEG into control commands for the wheelchair and potentially generates warnings through the NeuroWarn BCI.

Electroencephalography (EEG): EEG records brain electrical activity. This is used in neuroscience and clinical settings for diagnosing disorders and studying brain function. It is non-invasive and provides real-time insights into brain activity.[41]

In this study, this refers to the measurement of brain electrical activity used to control the wheelchair and potentially trigger warnings from the NeuroWarn BCI system.

Emotiv Mental Command Suite: A brain-computer interface framework developed by the company Emotiv can classify user intention through training.[42]

In this study, this refers to the control framework that was utilized to control a wheelchair.

LSTM (Long Short-Term Memory): LSTM is an advanced RNN designed to preserve information over long sequences, ideal for tasks with long-term dependencies like natural language processing. It is particularly effective in capturing context and relationships in sequential data.[43]

In this study, this refers to a specific type of RNN (Long Short-Term Memory) chosen for its ability to learn complex patterns in the EEG data and anticipate the user's intended control commands for the wheelchair.

NeuroWarn BCI: The expected warning system application to be developed in this study. NeuroWarn BCI serves as the communication interface between the system and the user.

In this study, it refers to the software application designed to analyze the EEG data in real-time and generate warnings to the user about potential hazards or critical situations based on the anticipated control commands.

Quadriplegia (Tetraplegia): A paralysis that affects all four limbs and the trunk, often due to cervical spinal cord injury.

It can result in significant physical challenges and require assistive mobility devices.[44]

In this study, this refers to the medical condition of the target users who were piloting the EEG-controlled wheelchair.

RNN (Recurrent Neural Network): RNN is a neural network type that retains information through cycles, often used in sequence modeling tasks like time series prediction. It is effective for capturing patterns in sequential data.[45]

In this study, this refers to the type of artificial neural network used to analyze the EEG data and anticipate potential control commands from the user.

Time-of-Flight (ToF) sensors: these are used for a range of applications, including robot navigation, vehicle monitoring, people counting, and object detection. ToF distance sensors use the time that it takes for photons to travel between two points to calculate the distance between the points.[50]

In this study, this refers to the sensors used for real-time detection of obstacles and measurement of distances in the wheelchair's environment. These sensors were integrated with the EEG-based control system to enhance safety by providing the wheelchair with information about its surroundings.

CHAPTER 2 REVIEW OF RELATED STUDIES

Review of Existing and Related Studies

Current Systems

The typical human brain contains approximately 86 billion neurons [15], and the communication among these neurons is the fundamental activity of the brain. These neurons are excitable cells that possess inherent electrical properties, and their activity generates both magnetic and electrical fields. These fields can then be detected and recorded through the use of specialized recording electrodes [16].

Motor control enables the stabilization and movement of the body and its extensions in a deliberate manner. Researchers in this field primarily investigate actions such as walking, reaching, facial expressions, speech, typing, and writing [62]. Studies suggest that motor commands for limb movements derive from a limited set of fundamental motor patterns, known as muscle synergies. These synergies activate groups of muscles simultaneously, helping to manage the body's many movement possibilities more efficiently [63].

Two promising approaches for restoring movement in individuals with permanent paralysis are neural stem cell therapy and motor neuroprosthetics. Neural stem cell therapy aims to repair damaged neural pathways, while motor neuroprosthetics allow patients with intact cognitive function to control external devices using their thoughts or "motor intentions," bypassing the damaged pathways. Motor neuroprosthetics function by detecting electrical activity in the brain associated with movement intention and converting these neural signals into commands for external devices. In simple terms, a brain-computer interface (BCI) acts as a substitute for nerves and muscles, using neural signals along with specialized hardware and software to generate movement [64].

Electroencephalography (EEG) is a tool that records the electrical signals produced by the brain, allowing healthcare professionals and researchers to study and understand how the brain operates and the neural processes underlying various cognitive functions [17]. Electrodes detect the micro-Volt-sized signals that result outside the head due to the synchronized neuronal action within the brain. Present monitoring methods typically fall into two categories: inpatient, which occurs within a tertiary care facility and involves time-locked video monitoring with the patient usually confined to a bed due to wires connecting electrodes and recording equipment; or ambulatory, where the recording device is portable, allowing the subject to carry on with their regular daily activities [18]. Unlike other electrical recording devices that require inserting electrodes into the brain hence calling for surgery, EEG electrodes are simply attached to the scalp therefore it is considered a non-invasive procedure [17].

Common application areas are sleep studies, epilepsy, brain-computer interface, and augmented cognition. Sleep disorders impact over 70 million individuals in the United States. The typical diagnostic approach involves polysomnography (PSG), which simultaneously monitors various bodily functions such as brain activity (via electroencephalography or EEG), heart rate (via electrocardiography or ECG), and respiratory function during sleep. However, the requirements for wearable EEG devices used in sleep studies differ somewhat from those employed in epilepsy studies [18]. Epileptic seizures are characterized by a burst of electrical activity usually originating from a particular area within the brain [17], and as of 2024, approximately 50 million people worldwide have it—making it one of the most common neurological diseases globally [19]. By monitoring EEG signals, healthcare professionals can determine whether an epileptic seizure is taking place, and if so, identify its type [17]. Brain-computer interface (BCI), on the other hand, is a new technology with multidisciplinary connections including materials, neuroscience, signal processing, and so on [20]. Traditionally, brain-computer interface (BCI) technology utilizing electroencephalography (EEG) has been employed to assist individuals with severe motor impairments, enabling them to communicate and control devices through their brain signals. However, recent advancements have expanded the applications of BCI beyond this realm. Emerging trends indicate that BCI can now be utilized in various domains such as entertainment, industrial settings, and even language and clinical research that investigate EEG patterns in individuals with aphasia. [16,20,21,22].

Multichannel EEG is generally used in brain-computer interfaces (BCIs), whereby performing EEG channel selection improves BCI performance by removing irrelevant or noisy channels, and enhances user convenience from the use of lesser channels [21]. The main purpose of applying channel selection is to reduce computational complexity while analyzing EEG signals, improve classification accuracy by reducing over-fitting, and decrease setup time. Baig and Aslam assert that channel selection algorithms enable comparable classification performance while utilizing fewer EEG channels. In certain instances, channel selection can even boost system performance by eliminating noisy channels that may adversely impact the analysis. Their study demonstrates that, in most cases, a reduced set of 10 to 30 channels can achieve the same level of performance as utilizing the full channel array [23]. In a study about real-time control of unmanned aerial vehicles (UAVs) that used non-invasive BCI headsets from Emotiv, called EPOC+ (14-channel) and INSIGHT (5-channel), the EPOC+ had 98.8% in overall classification accuracy while 84.5% for the 5-channel. However, one of the main difficulties in monitoring electroencephalography (EEG) data is identifying and removing unwanted signals or artifacts. These artifacts can originate from factors related to the subject being monitored, such as body movements, sweating, electrical activity from the heart (ECG), and eye movements. Additionally, technical artifacts can arise from external sources like electrical interference at 50/60 Hz frequencies and issues with the monitoring equipment itself. Addressing these various types of artifacts requires different approaches and techniques [24].

A separate study explored the use of a single-channel electroencephalography (EEG) device, the NeuroSky MindWave Mobile-2 headset, in conjunction with an Arduino Uno microcontroller for wheelchair control. The system was designed to enable maneuvering in various directions such as start, turn left, turn right, and stop. The researchers employed recurrent neural networks trained on non-sequential data for this purpose. However, instead of utilizing a full-sized wheelchair, the study was conducted using a miniature wheelchair model. The authors acknowledged that the use of only a single EEG channel resulted in reduced accuracy compared to systems with more channels [28]. Others have developed and implemented a platform that enables control of a wheelchair system through a brain-computer interface (BCI) and automated navigation within indoor environments. The experimental results demonstrated that the user could successfully stop the wheelchair at high success rates across two experiments (Experiment A = 94.7% success rate, Experiment B = 92% success rate) [29]. Another study that used Emotiv INSIGHT and Arduino for BCI-controlled Smart Wheelchair successfully maneuvered 'forward', 'backward', 'left', and 'right' using the commands from the integrated BCI unit with a negligible time of 2s delay. Performing simultaneous changes in direction from opposing directions will cause a slightly larger delay of 5s [30]. Moreover, the Emotiv Mental Command Suite offers a user profile feature that allows individuals to personalize their experience with EEG technology. By creating a user profile, individuals can tailor the settings of the EEG device to their specific needs and preferences, enhancing the overall effectiveness and comfort of the system.[41] This feature is particularly beneficial in applications such as brain-computer interfaces (BCIs), where individualized settings can improve the accuracy and efficiency of brain signal interpretation.

The use of electroencephalography (EEG) has created new opportunities not only for technological innovation but also for helping people who thought they could no longer regain mobility. In a relevant existing system that used artificial intelligence (AI) algorithms, specifically recurrent neural networks (RNNs), helped the researchers choose the most suitable algorithm for their study. Although the system was tested on a small-scale wheelchair model, it used RNNs trained on non-sequential EEG data. This provided useful information on how well the algorithm could read brain signals for real-time movement control. While the system's accuracy was lower due to using only one EEG channel, the study still showed that simple and affordable EEG-based brain-computer interface (BCI) systems could support mobility.

Related Systems or Solutions

Conventionally, the most widely employed methods for reducing noise in signals are wavelet transform (WT) denoising, independent component analysis (ICA) denoising, and empirical mode decomposition (EMD) denoising [25]. However, among these techniques, the wavelet transform (WT) has emerged as the most prevalent and effective approach for removing noise from non-stationary signals, such as those obtained from electroencephalography (EEG) and electrocardiography (ECG) recordings [26]. In 2020, a study about EEG signal-driven brain-computer interface for disabled wheelchair users even used a combined wavelet transformation and recurrent neural networks (RNN) approach, where the wavelet transform extracted time-frequency features and the RNN classified four drone movement directions and focus/non-focus status, achieving 79.6% accuracy [35].

While the number of EEG channels impacts accuracy, training is also crucial for enhancing the performance and precision of mental commands used to control systems like wheelchairs. Proper training can help improve accuracy even when using a limited number of channels [30]. While there may be some concerns surrounding the emerging trend of smart wheelchairs, the integration of algorithms can provide assistance and contribute to safe navigation for these systems [27]. For instance, a research study introduces a long short-term memory deep learning (LSTM) network to recognize emotions using EEG signals [31]. The brainwaves from a user of a BCI-controlled smart wheelchair are susceptible to emotions which may lead to the malfunctioning of the device since the EEG will be suffering from too much noise [24], however with the help of the integration of LSTM into the system, the classification of four negative class of emotions using genres sadness, disgust, angry, and surprise along with the classification of three basic class of emotions i.e., positive, negative, and neutral, brainwave noise may be reduced [31]; hence improves safety navigation other than purely depending on obstacles as risk factors [27].

RNN, one of the promising deep learning (DL) models, can predict future information based on past and present data. However, in the RNN structure, it is difficult to learn stored data for a long time because of the gradient vanishing issue or gradient exploding issue. A model that fundamentally solved this problem of RNN is LSTM [33], making it one of the most advanced networks to process temporal sequences [34]. Another paper employed deep learning models, specifically long short-term memory (LSTM) and gated recurrent neural networks (GRNN), for the task of classifying motor imagery from electroencephalography (MI-EEG) data. As mentioned earlier, the LSTM architecture was designed to mitigate the vanishing gradient problem, while GRNN allowed each recurrent unit to adaptively capture dependencies across different time scales. The experimental results demonstrated that GRNN and LSTM achieved higher classification accuracies compared to existing approaches [32]. Furthermore, in another separate study, LSTM was implemented for a brain-computer interface (BCI) controlled smart wheelchair using simple eye open/close commands. This approach achieved higher accuracy ranging from 77.61% to 92.14% compared to traditional classifiers (59.71%), with an optimal time window of around 7 seconds for user tasks. Real-world testing revealed a trade-off between accuracy and response time was necessary to ensure reliable detection [36]. These findings suggest that such recurrent neural network (RNN) models can be beneficial for further research and applications involving the processing of MI-EEG signals [32].

As for object detection, Papageorgiou and T. Poggio present a powerful system for detecting objects like faces, people, and cars in still images. It uses a technique called Haar wavelets combined with a machine learning algorithm called support vector machines. This allows very accurate detection with very few false positives. For face detection, it achieves 90% accuracy with only 1 false positive per 100,000 images processed. For people detection, it gets 90% with 1 false per 10,000 images. This is the first people detector that is purely based on pattern recognition without using motion tracking or assumptions about the scene. However, the study finds detecting cars more challenging due to viewpoint variations, so the researchers utilized a component-based approach—identifying parts like headlights and wheels, which turned out to be better [46].

Robots can be useful in dangerous situations where it's not safe for humans [49]. A three-wheeled autonomous navigational robot with efficient modular architecture by Balasubramanian, et. al. has the key capabilities of obstacle detection, pattern recognition, and obstacle avoidance. The robot can successfully identify and selectively pick up balls of a particular color while ignoring other objects. The design utilizes a single-board computer as the central controller, communicating with ultrasonic sensors, motors, and multiple microcontrollers to control motion; a Java program running on the onboard computer that communicates with the master microcontroller through RS232; a modified H-bridge circuit that efficiently drives the DC motors of the base unit; and Hough transform algorithm for object detection that executes in real-time Java in just 1 second compared to 4 minutes in Matlab. The modular architecture also allows easily adding various modules to enhance functionality [47]. Although robots generally use various sensors to detect obstacles and determine their own position, conventional sensors have limitations in range, resolution, and complexity. So Hutabarat, et. al. developed an autonomous mobile robot that uses a LiDAR (Light Detection and Ranging) sensor to avoid obstacles. It moves according to the Braitenberg vehicle strategy. A single Raspberry Pi 3 computer board runs the sensor data collection and control algorithm. Experiments showed that LiDAR can consistently measure distances, without being affected by an object's color or ambient light levels. The mobile robot could avoid different-sized colored objects. However, it could not detect and avoid transparent objects. Overall, this autonomous robot can navigate safely inside a room, avoiding walls and obstacles [49].

Sakic, et. Al also proposed a solution for determining the distance to obstacles by combining data from a camera and a LIDAR sensor. The algorithm uses the camera images for object detection and the LIDAR's point cloud data to calculate the position of detected objects. Based on the position of the nearest object in front, the motion planning module can control the vehicle's movement. During validation, this approach showed good results in accurately estimating obstacle distances while meeting real-time processing requirements. However, the current implementation has some limitations. It only considers the area directly in front of the vehicle rather than the true trajectory. It is also necessary to add time synchronization between data obtained from different sensors so the algorithm will be able to process samples from different sensors—which originate from the synchronized time moment with a certain threshold. Crucially, if the camera fails to detect an object, the LIDAR data is also ignored[48].

Distance measurement sensors based on the Time of Flight (ToF) principle have been increasingly adopted lately due to their cost-effectiveness and precision. These sensors are likely to play a crucial role in obstacle detection systems going forward [50]. Garcia, et. al. showcased the reliability and effectiveness of ToF technology in diverse environments, demonstrating its potential to enhance safety and efficiency in obstacle detection applications by designing and rigorously evaluating a robust object detection system that integrated ToF sensors. The study used 150 images to obtain 660 samples, with 210 samples containing a curb and 450 without a curb. Various window sizes, feature vectors, filters, classifiers, and amplitude and depth images from the camera were tested to find the best performance using the leave-one-out cross-validation method. The KNN classifier performed best, with 98.333% accuracy and an AUC ROC of 0.9987. This result used a 20x40 pixel window size, median filtering to reduce noise, and HOG features extracted from the amplitude and distance window with a 4x4 cell size, resulting in a 2592-value feature vector. A method was developed to measure the distance between the vehicle and the curb. When tested on 30 new images not used for training, the classifier correctly classified 24 images but made errors on 6 images, achieving 80% performance [51]. Another research study employed an innovative 3D range camera for obstacle detection and segmentation algorithms to be used in Automated Guided Vehicles (AGVs). This 3D range camera operates on the Time-of-Flight (ToF) principle, enabling it to simultaneously capture intensity images and range data of targets in indoor environments. The range camera is particularly attractive for obstacle detection in industrial applications due to its relatively low cost compared to similar sensors. Additionally, it can deliver range and intensity images at a rate of 30 frames per second, with an active range of 7.5 meters, and it has no moving parts, unlike many off-the-shelf laser sensors that incorporate spinning mirrors. However, after the implementation, researchers analyzed some outdoor data, and the preliminary results show good promise in using this sensor for outdoor forest environments, in other areas that are shaded, and in night conditions—indicating that it's not limited to indoor settings anymore [52]. The development of

ToF sensors has also been driven by advancements in machine learning and computer vision technologies. Modern ToF sensors are increasingly used in computer vision systems, including augmented reality and 3D object reconstruction. These advancements enable ToF sensors to provide real-time information about objects in space, making them valuable components in obstacle detection systems for applications such as car parking assistance, mobile robotics, and workplace safety enhancement [50].

It just goes to show that this study on developing a mind-controlled wheelchair using electroencephalography (EEG) and recurrent neural networks (RNNs) is supported by previous research that addresses two key challenges: reducing noise in EEG signals and improving navigation safety. EEG signals are often affected by noise, especially from the emotional state of the user, which can lower the accuracy of brain-computer interface (BCI) systems. Earlier studies have shown that traditional methods like wavelet transform (WT) are effective in filtering out noise from non-stationary signals such as EEG. In addition, using long short-term memory (LSTM) networks—a type of RNN—helps the system recognize and manage emotional patterns, which reduces brainwave noise and improves the clarity of the signals. This supports more accurate and stable control of the wheelchair. For navigation, systems that use object detection techniques like Haar wavelets with support vector machines (SVMs), along with sensor fusion from cameras and LIDAR, have been shown to improve safety. These technologies allow the wheelchair to detect nearby obstacles and take appropriate action, even if the brain signal is delayed or unclear. These findings support our study by showing how signal processing, and smart navigation systems can work together to build a safer and more reliable mind-controlled wheelchair.

Related Studies

Relevant research was conducted on using the 5-channel Emotiv INSIGHT electroencephalography (EEG) headset to control a wheelchair intended for elderly individuals and those with motor impairments. Despite the limited number of EEG channels, the study determined that accurate wheelchair control was highly feasible with this system. The wheelchair incorporated a drive motor to enable safe navigation. It integrated a 10.525 GHz Doppler radar detector (40 mA) and a microwave sensor (HB100) to detect obstacles in the surrounding environment. These sensors, coupled with a custom algorithm developed by the researchers, issued collision warnings to the user, thereby assisting in obstacle avoidance [27].

Path planning involves charting the trajectory to reach a target location from the wheelchair's current position while accounting for potential obstacles. Ferracuti et al. [37], employed the Dynamic Window Approach (DWA) navigation algorithm for indoor obstacle avoidance in their study. However, their smart wheelchair was limited to indoor environments. During indoor navigation toward a desired destination, obstacles along the planned path can elicit electroencephalography (EEG) potentials when detected by the user. These potentials could serve as supplementary inputs to the navigation algorithm, facilitating trajectory modification to uphold safety. Their research demonstrated the feasibility of real-time feedback between the smart wheelchair and the brain-computer interface (BCI) acquisition system, enabling users to actively contribute to trajectory control by circumventing environmental factors that may compromise their security [37].

Contrary to the previously mentioned studies that used RNN, Kocejko et. al. utilized convolutional neural network (CNN) models for signal classification acquired from sixteen EEG channels for the implementation of an obstacle detection system and its integration with a brain-machine interface with movement activity commands 'LEFT', 'RIGHT', 'RELAX', and 'BREAK'. The system employed the on-board camera to capture RGB images, which were transmitted to a server for inverse depth estimation using the Pytorch MiDaS v3.1 dpt_beit_large_512 model. The model provided relative depth information from the input images. The inverse depth outputs were segmented into left, right, and center sections, with the bottom portions cropped to minimize floor misidentification as obstacles. The mean depth of each section was computed and compared against a predefined threshold tailored to detect large obstacles like walls or trash cans. For smaller obstacle detection, each section underwent grid subdivision, with the mean value of each grid cell calculated and tallied if exceeding a specified threshold. The integration of a collision detection system employing movement imagery and a 16-channel electroencephalogram (EEG) proved beneficial in augmenting conventional robot control. A subject-dependent approach yielded significantly higher accuracy, as a brain-computer interface's (BCI) effectiveness hinges on individual factors such as cognitive capabilities, attention span, and the ability to volitionally modulate brain activity. Notably, users require extensive training to attain proficiency in controlling a BCI system via neural signals. The achieved 83% accuracy is comparable to state-of-the-art solutions, albeit with a limited participant group and some unintended vehicle movements. Nonetheless, the results underscore the real-world applicability of the proposed solution while emphasizing the need for continued refinement and comprehensive investigations to facilitate seamless integration into larger-scale applications [38].

The study proposes an autonomous system that integrates an electroencephalogram (EEG) interface to capture the user's desired movement direction while incorporating robust object detection and avoidance capabilities. A key innovation lies in the integration of an informative warning system that provides visual feedback to the user, transparently communicating reasons for stopping or confirming safe conditions for intended turns rather than abruptly halting upon encountering an obstacle. This transparent communication enhances the user experience and situational awareness. By coordinating cutting-edge assistive technologies like EEG control with advanced environmental mapping and obstacle avoidance algorithms, the research undertakes the development of an autonomous system that can effectively navigate environments while prioritizing user agency and safety throughout the process.

These studies support the development of a mind-controlled wheelchair by demonstrating the feasibility of using EEG data, whether from low or high-channel systems, for reliable movement control and obstacle avoidance. They show that EEG signals can provide both directional commands and responsive feedback to enhance navigation safety. The integration of neural networks, such as RNNs and CNNs, improves signal classification and decision-making accuracy. Additionally, combining EEG with real-time environmental sensing, like object detection, contributes to safer mobility solutions. These findings validate the potential of RNNs with EEG for creating an efficient and user-responsive wheelchair system.

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

Description of the Proposed Study

This study investigates the integration of real-time movement prediction and obstacle detection to develop a warning system for Brain-Computer Interface (BCI) controlled smart wheelchairs. It employed Emotiv Insight, a 5-channel electroencephalogram (EEG) headset that was used to capture continuous time series electroencephalographic data from the user. The same EEG headset was also used to control a customized smart wheelchair using Emotiv's existing control framework called Mental Command Suite.

The main objective is to predict the user's intended direction using Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units. The researchers, therefore, trained the model using brainwave data collected from the five channels of the EEG device that was accessed through Node-RED. The model worked alongside the Emotiv Mental Command Suit. The Emotiv Mental Command Suite was responsible for the wheelchair control while the RNN-LSTM model analyzed the extracted features and predicted the user's intended movement (forward, backward, right, left).

To demonstrate the performance of the developed warning system, researchers modified an electric wheelchair, transforming it into a smart wheelchair. The said wheelchair was equipped with a microcontroller, motor drivers for control, and Light Detection and Ranging (LiDAR) and ultrasonic sensor for obstacle detection. The system utilized both predictions from the developed RNN model and obstacle detection sensors to create a simple logic. If the predicted movement direction matches with an obstacle, the wheelchair receives a "stop" command and sends a warning prompt to the user. However, if the path is clear, the predicted command is executed. Furthermore, a control laptop was attached to the wheelchair which acted as both the main processing unit and the user interface for the warning system.

Methods and Proposed Enhancements

Target

The study was conducted to investigate the integration of real-time prediction using RNN-LSTM and an obstacle detection system to create a warning system for EEG-controlled smart wheelchairs. Ten participants, six male and four female, aged between 18 and 25 years old, were involved in the training, testing, and validation of the developed system. The researchers conducted this study within a controlled environment in their private homes.

Data Gathering Instrument

This study utilized the following instruments to gather data:

1. Emotiv Insight - 5-Channel Wireless EEG Headset

    This study used the Emotiv Insight, a 5 Channel Wireless EEG Headset. It is a non-invasive brain-computer interface (BCI) headset. The device measured electrical activity within the brain and converted it to electroencephalography (EEG) data. It then sent this data to a control laptop for classification and training.

2. Control Laptop

A control laptop was attached to the custom-built smart wheelchair. The device received and processed data from the EEG Headset. The laptop served as both the processing component and user interface of the system.

3. Node-RED

The researchers extracted brainwave data from the EEG device using Node-RED. Node-RED utilized Emotiv’s Cortex API to extract data from the EEG device. It provided a user-friendly interface ideal for this study.

4. Obstacle detection sensors (LiDAR and Ultrasonic Sensor)

The study incorporated a LiDAR (Light Detection and Ranging) sensor equipped with Time of Flight (ToF) technology and ultrasonic sensor for obstacle detection. The LiDAR emitted laser pulses and measured the time it took for these pulses to bounce back from objects in the wheelchair's surroundings. Meanwhile, the ultrasonic sensor used the same technique but with sound. This allowed these sensors to detect obstacles in the surrounding environment.

Procedure

The researchers mainly utilized Python for the main program. A local web application run on Javascript was used for the user interface. The following steps were:

a. Emotiv Mental Command Suit Training

Before extracting the continuous EEG data for RNN training, participants must first train the existing control system provided by Emotiv called Mental Command Suite. In this process, the participants trained the Mental Command Suite framework to classify push, and pull. The Mental Command Suit Framework was responsible for the movement controls of the smart wheelchair.

b. Data Collection

After training Emotiv's Mental Command Suite, the researchers collected a time-series EEG data using Node-RED. The participants recorded a time series of data using the three commands of the mental command suite (push, pull, neutral) for a specific timeframe. Node-RED automatically wrote the comma-separated values (CSV) file used to train the neural network model. This approach enabled researchers to streamline the data collection, ensuring that the model receives suitable data for its purpose.

c. Data preprocessing

The collected time series data were then split into a training and testing set. Seventy percent of the data collected were used for training the RNN-LSTM model. The remaining thirty percent were used to test the algorithmic performance of the neural network model.

d. Model Training

This study utilized the RNN-LSTM neural network model. Long Short-Term Memory (LSTM) networks, which are a form of Recurrent Neural Network (RNN), excel at predicting sequential input such as movement intentions. LSTMs solved the vanishing gradient problem in RNNs by making use of memory cells that can learn long-term dependencies. These cells regulated the flow of information through gates, allowing the network to store important past information for future predictions.

The following were the components of a Long Short-Term Memory (LSTM) network:

1. Activation Function

   A softmax function is a good choice for the output layer as it maps internal activations to probabilities between 0 and 1, ideal for predicting the four-movement categories (Left, Right, Forward, and Backward).

$$s\left(x_i\right) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Figure 2. Softmax Activation Function Formula [53]

Figure 2 illustrates the formula of a softmax activation function. It takes a vector of real numbers as input and converts them into a probability distribution of K possible outcomes, where K is the number of classes. In the RNN-LSTM model, K would represent four possible movements: forward, backward, left, and right. The function takes a vector of activation values (x_i) from the neural network's final layer, representing each movement class (forward, backward, left, right). It exponentiates each value (e being the base of the natural logarithm), then divides them all by the sum of those exponentials. This transforms the activations into a probability distribution ($s(x_i)$) where the output for each class signifies the likelihood of that class being the correct prediction. This normalization step guarantees that the output values sum to 1, which is a crucial property of a probability distribution.

2. Loss Function

Categorical cross-entropy is a common loss function for multi-class classification problems. It measures the difference between the predicted probability distribution and the actual distribution of the movement class.

$$CE = -\sum_{i}^{C} t_i log(f(s)_i)$$

Figure 3. Cross Entropy Function Formula [54]

Figure 3 illustrates the cross entropy function formula. It measures the difference between the model's predicted probability distribution (f(s)) for movement categories (forward, backward, left, right) and the actual intended movement (t) in a given sequence. The lower the CE, the better the model's predictions align with reality. f(s) represents the probability scores assigned by the model to each movement category. The formula (log(f(s))) calculates a penalty for assigning a low probability to the correct movement across multiple training examples. By minimizing this penalty, the LSTM model learns to adjust its internal parameters and improve its predictions for intended movements.

3. Optimizer

   Adam (Adaptive Moment Estimation) is a popular optimizer due to its efficiency in handling sparse and noisy data, potentially encountered with movements.

Unlike regular RNNs, LSTMs can learn long-term dependencies within the data due to their internal gating mechanism. The following are the gating mechanism and their description:

1. Forget Gate

   Decides what information from the previous cell state (memory) to discard.

2. Input Gate

   Selects what new information from the current input to store in the cell state.

3. Output Gate

   Determines what information from the current cell state to output.

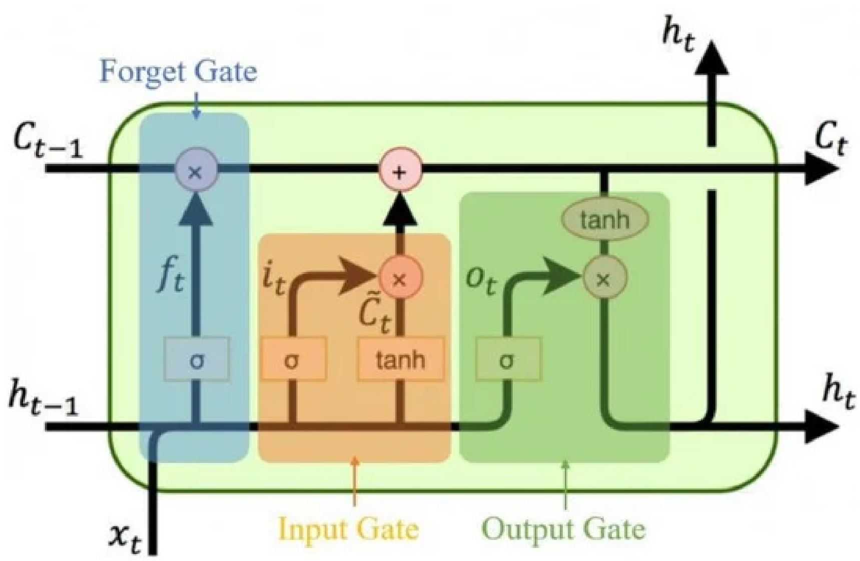

Figure 4. LSTM Model [55]

These gates allow LSTMs to learn complex temporal patterns in movement thought data.

The time window defines the amount of historical movement through the data that the LSTM considers for prediction. The researchers experimented with different values (e.g., 0.5 seconds, 1 second) to find the optimal window that captures relevant patterns without introducing unnecessary noise.

The window size is the number of data points within the time window. It should be large enough to capture the relevant movement thought sequence but not excessively long to avoid computational inefficiency. The researchers also experimented with the values to find the optimal value for the accuracy of the model with a reasonable size and adjust this based on the data characteristics.

e. Smart Wheelchair Modification

To showcase the system's functionality, researchers modified a smart electric wheelchair with the essential control components and sensors needed for the warning system. The following figure illustrates the blueprint for the smart wheelchair and its components;

Figure 5. Wheelchair Blueprint

1. Electric wheelchair

An electric wheelchair featuring a 24-volt 250-watt Brushless DC Motor, an onboard motor driver, and a 12-volt battery with a 20-kilometer range, served as the foundational platform for the smart wheelchair. The researchers replaced the control system and integrated the essential sensors needed for the warning system.

2. BTS7960 Motor Driver

   The BTS7960 Motor Driver allowed the researchers to control the existing onboard motor driver in the electric wheelchair through an Arduino microcontroller.

3. Arduino Mega

   This microcontroller served as the communication interface between the warning and control system in the laptop computer and the components and sensors within the wheelchair.

4. Obstacle Detection Sensors

   This study employed 2 kinds of obstacle-detecting sensors

   a. LiDAR - Time-of-Flight (ToF) sensors - this sensor was used to detect obstacles in front of the wheelchair due to its long range.
   b. Ultrasonic Sensor - this sensor was used to detect obstacles behind the wheelchair.

5. Control Laptop

This laptop functioned as both the processing unit for the entire system and the interface facilitating interaction between the user, the system, and the smart wheelchair. It controls the movement of the wheelchair, processes sensor data, runs the developed RNN model, and displays the output of the warning system.

6. Laptop Mount

This was used to mount the control laptop into the wheelchair.

f. Software Development

The study developed a simple local web application to act as the visual interface for the warning system. This program collected data from the wheelchair sensors and predictions from the RNN model. The program displayed the location of the obstacle using the wheelchair sensors and issued a warning—it halts the wheelchair if the predicted direction of its movement coincides with the location of the obstacle, otherwise, it will continue to move in the user’s desired direction.

g. System testing

The researchers ensured that the system demonstrated the capacity to predict EEG brain wave data accurately and efficiently by testing and evaluating the necessary components in the system. The algorithm was tested using recall, specificity, precision, F1 score, loss, and confusion matrix. The usability was then accessed using the ISO 9241:11 usability standards.

Proposed Enhancement

The advantages of the proposed warning systems are the following:

a. Reduced Cognitive Load

Automating obstacle detection and issuing warnings reduces the cognitive load for users. This allows them to focus on controlling the wheelchair and navigating their surroundings.

b. Enhanced Safety

The system significantly reduces the risk of collisions and accidents by providing timely warnings about potential obstacles. This approach provides a greater sense of security for the users.

Improvements in EEG-controlled wheelchair technology make it more dependable, helping users trust that it would work well and minimize risks. As these advancements develop further, users can feel more confident in relying on these systems to operate smoothly and safely.

Components and Design

System Architecture

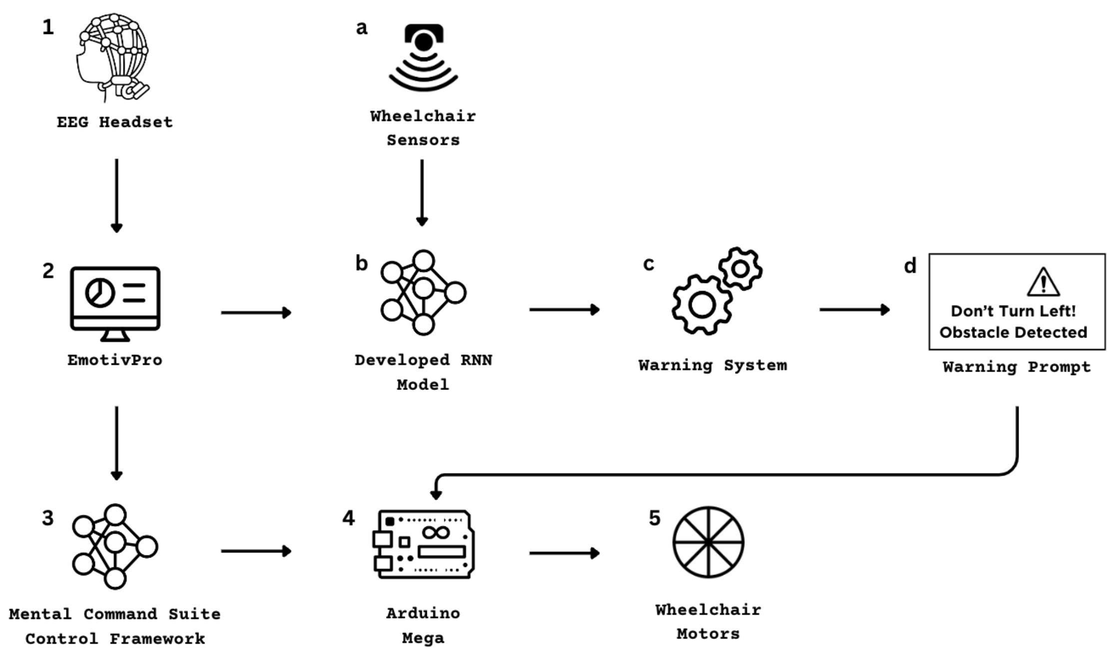

Figure 6. System Architecture

As depicted in Figure 6, the proposed system employs a multi-layered architecture to safeguard against wheelchair collisions. A portable EEG headset (1) acts as the initial point of contact, capturing the user's brain activity. This data is then wirelessly transmitted via Bluetooth to the EmotivPro application (2). Here, the system leverages Emotiv's Mental Command Suite Control Framework (3) to establish communication with the Arduino Mega (4) and transmit control commands for maneuvering the wheelchair. Concurrently, the EmotivPro application transmits data to a specifically developed RNN-LSTM model (b) for analysis. This model generates predictions that are passed to the warning system (c). The warning system functions by continuously monitoring these predictions alongside sensor data received from the wheelchair (a). If a sensor detects an impending obstacle that aligns with the model's prediction of a potential collision, the system springs into action. A warning prompt (d) is activated to alert the user, while a stop command is simultaneously transmitted to the Arduino Mega (4). This immediate halt ensures the safety of the user by preventing the wheelchair from colliding with the obstacle.

Software Architecture

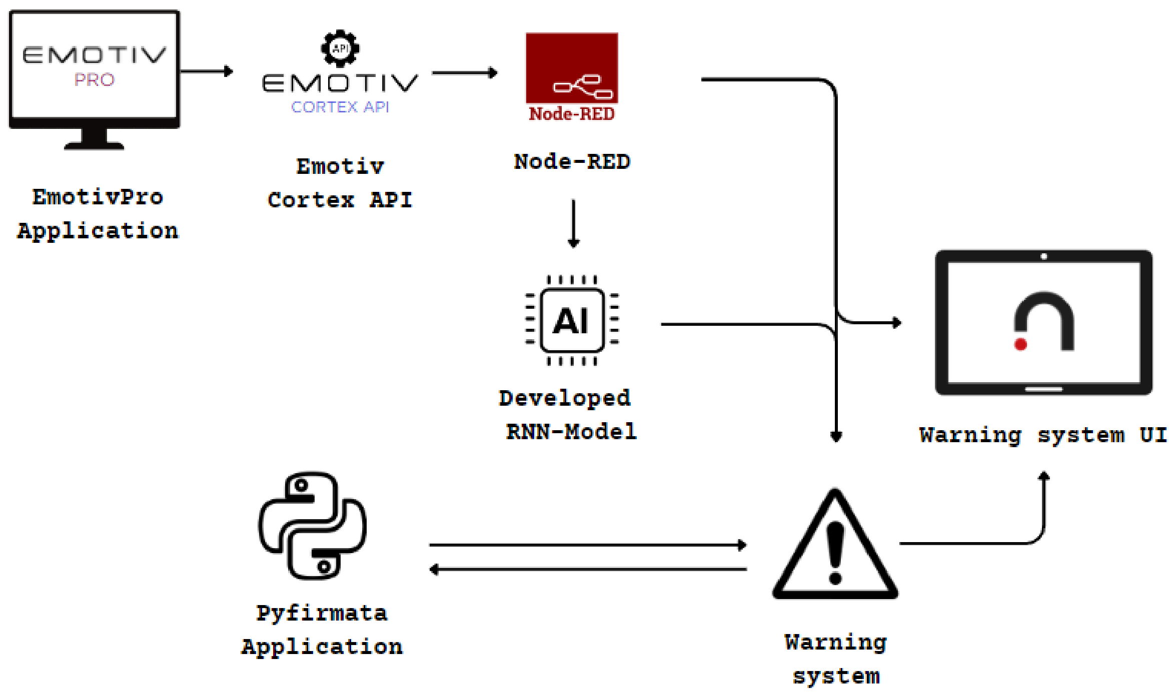

Figure 7. Software Architecture

Figure 7 illustrates the software architecture of the warning system. The first stream of data comes from the EmotivPro application. It sends that data to the developed RNN model through the Node-RED. The prediction of the model is then sent to the developed warning system. Simultaneously, the Pyfirmata application continuously sends sensor data into the warning system. The warning system then compares these sensor data with the model prediction. If the predicted direction coincides with an obstacle, the warning sends a command back to the Pyfirmata application to stop, and send a warning message through its user interface. If not, the command will execute.

Procedural Design

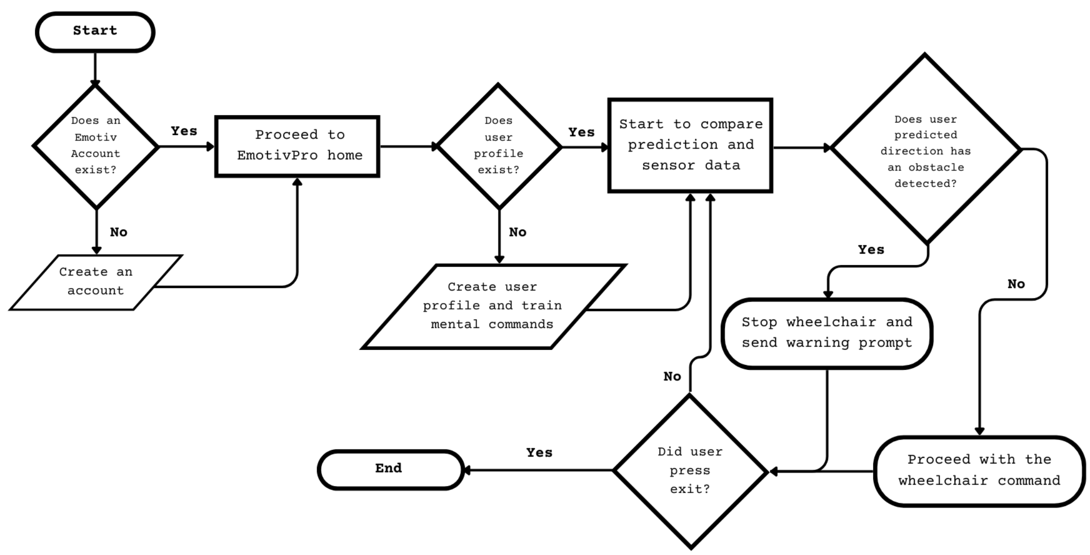

Figure 8. Procedural Design

Figure 8 illustrates the procedures of the proposed system. Upon launching the application, it first checks if the user has an Emotiv Account. If the user has no account, it will require the user to create one. If the user has an account, it will proceed to the home screen. From there, the system will check if the user has a user profile. If the system doesn’t find a user profile, it will require the user to create one and briefly train the mental commands. If the system finds a user profile, it will begin creating predictions and compare them to obstacle sensor data. Once the predicted direction and an obstacle match, the system will send a prompt and stop the wheelchair. However, if the predicted direction is clear of obstacles, the desired command will be executed. This comparison will actively continue until the user decides to exit.

Object-Oriented Design

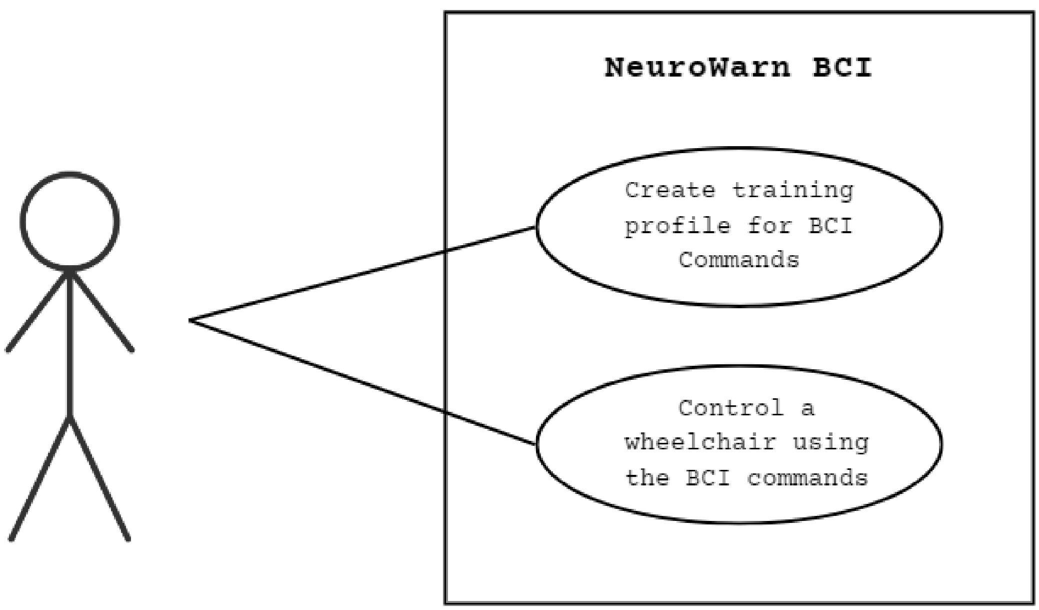

Figure 9. Object-Oriented Design

Figure 9 shows the use case diagram of the system. The user primarily used the system to control the smart wheelchair. However, the user must first create a user profile in the EmotivPro application for training.

Process Design (DFD)

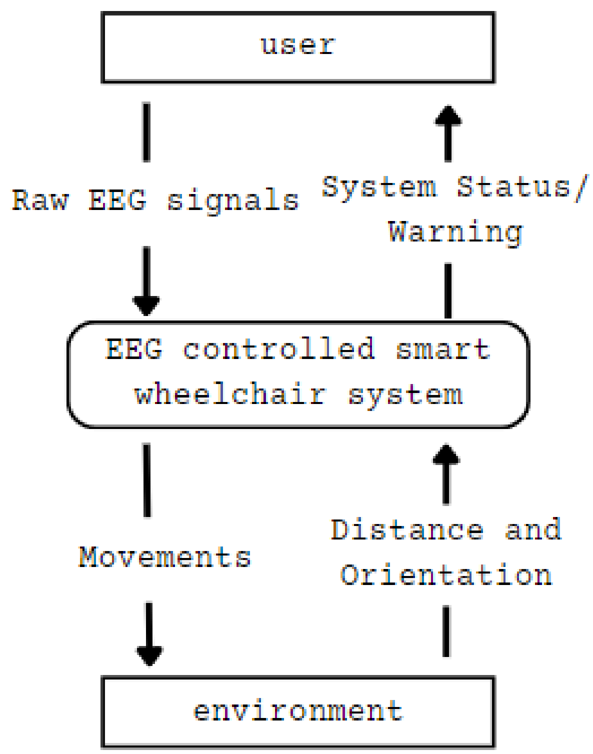

Figure 10. Data Flow Diagram Level 0

Figure 10 offers a high-level view of this EEG-controlled smart wheelchair system. It uses a square to represent the User, who provides raw EEG signals. Another square depicts the

Environment, in which sensor data is derived. The core of the system is represented by a rounded rectangle, encompassing all internal processes.

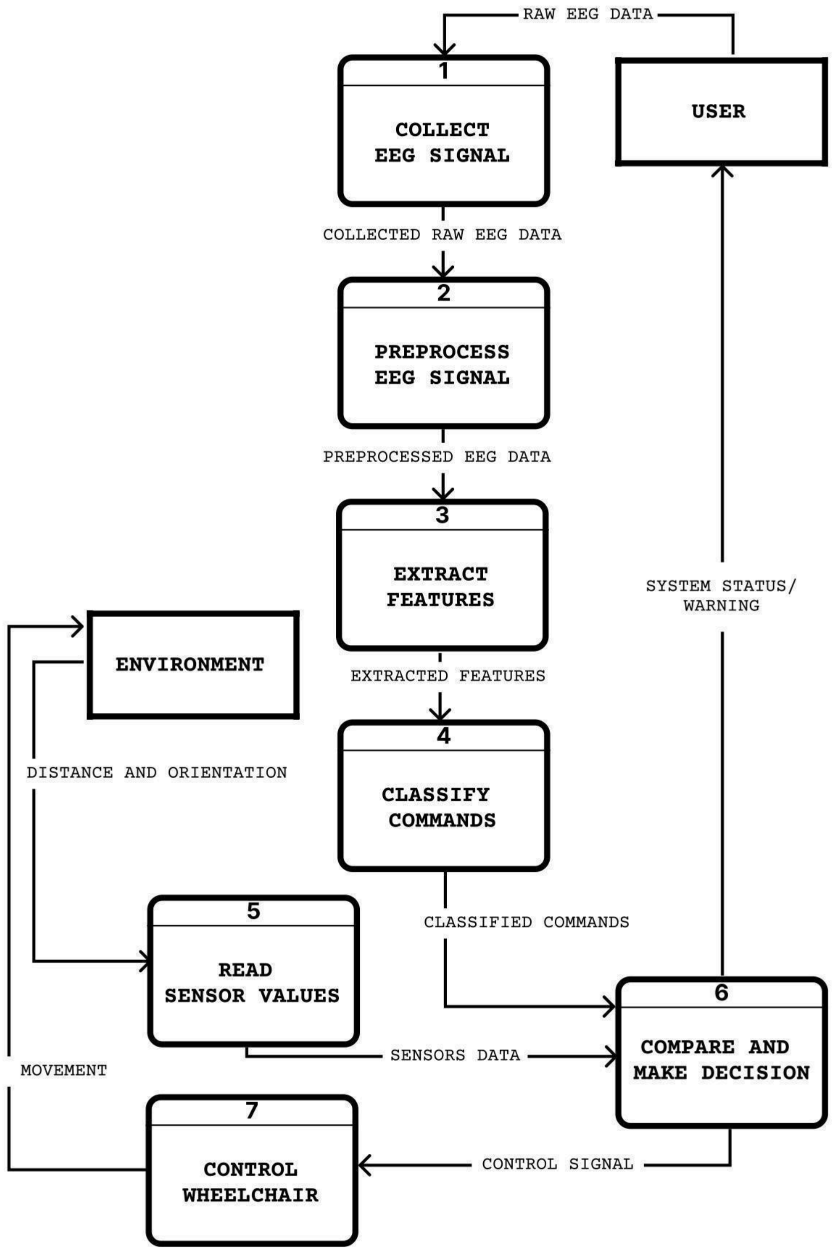

Figure 11. Data Flow Diagram Level 1

The Level 1 DFD illustrates how the EEG-controlled smart wheelchair system translates the User's intent from EEG signals into movements within the surrounding environment. Also, with the integration of sensors to monitor the terrain, the system can match the intent of the user and the actual terrain to decide if proceeding with the action would be safe. Then if the system considers the proceeding action to be dangerous, it sends a warning to the user prompting it to stop.

Methodology

System Development Life Cycle

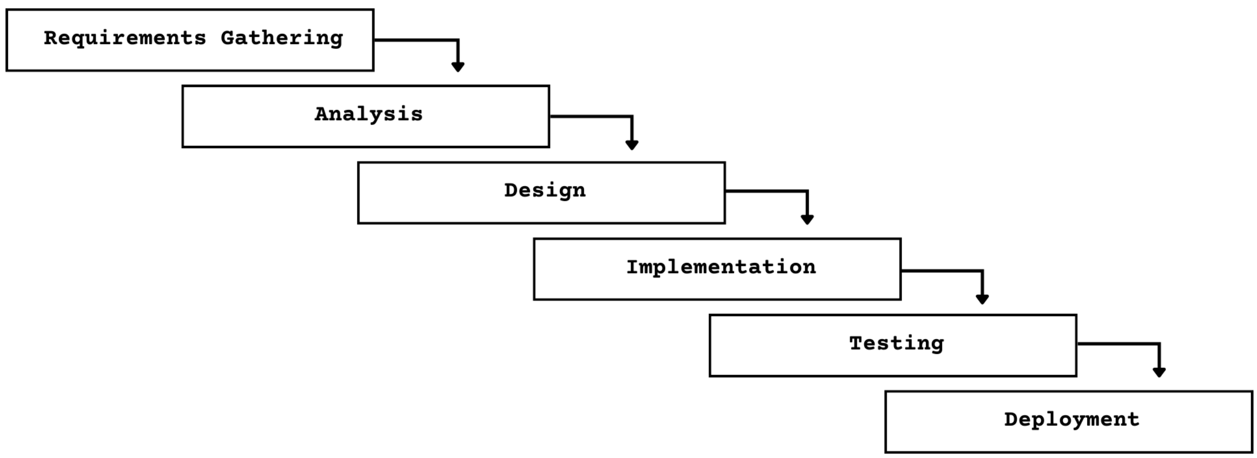

Figure 12. System Development Life Cycle

The researchers utilized the Waterfall System Development Life Cycle to identify the project goals. The following are the phases in the Waterfall development method:

a. Requirements Gathering

In this phase, the researchers looked into the existing landscape of BCI-Controlled Smart Wheelchairs. This is done by exploring various academic papers that discuss the concept and implementation of BCI-Controlled Wheelchairs. The researchers explored algorithms, methodologies, research gaps, and any possible system limitations.

b. Analysis

The researchers then analyzed the collected requirements. In the case of this study, it was identified that current BCI-Controlled Smart Wheelchairs lack safety protocols. Hence it was decided that the research group would develop a warning system to enhance safety.

c. Design

The researchers planned out the architecture of the warning system. This integrated an RNN-LSTM architecture into the existing BCI control framework and created a prediction. The prediction was then integrated with obstacle-detecting sensors to develop a warning system. A local computer application was then developed for the implementation of the warning system.

d. Implementation

The researchers started the development of the warning system based on the identified design and specifications. The warning system was implemented in the developed BCI-controlled wheelchair.

e. Testing

A random sampling technique was implemented to select test cases for the evaluation of the warning system's performance. The system's overall usability and user experience were then assessed in accordance with the standards outlined in ISO 9241-11.

f. Deployment

Following the development phase, the researchers deployed the warning system onto the BCI-controlled wheelchair. This process involved integrating the developed system into the wheelchair's existing infrastructure.

CHAPTER 4 RESULTS AND DISCUSSION

Implementation

Development Tools

The development of the NeuroWarn BCI system focused on three main components: the BCI wheelchair control system, the warning system interface, and the RNN-based prediction model. Each component worked together to create a cohesive system aimed at enhancing mobility and safety for wheelchair users through advanced control and situational awareness.

The BCI wheelchair control system was designed to enable wheelchair movement through mental commands processed by EmotivBCI. EmotivBCI software provided the necessary framework to train and interpret these mental commands, which the user could then use to control the wheelchair’s movement. A Python program acted as the intermediary between EmotivBCI and the wheelchair’s hardware, retrieving mental command data from EmotivBCI and transmitting it to the Arduino hardware via serial communication. This communication ensured that each mental command was promptly translated into motor responses.

To manage the hardware control, the Arduino IDE and Arduino language (C++) were employed. The C++ code on the Arduino interpreted the movement data received from the Python program and directly controlled the wheelchair motors, resulting in a responsive and smooth movement that aligned with the user's mental input.

The second component, the warning system interface, was developed as a local web application to provide real-time safety alerts based on data from sensors and the RNN prediction model. The interface was built using HTML, CSS, and JavaScript, with JavaScript leveraging WebSockets for real-time data transmission. This application continuously received input from a time-of-flight sensor programmed through Arduino, which monitored the wheelchair's surroundings to detect potential obstacles. In addition, the web application used WebSockets to gather input from the EEG device and the BCI control system, ensuring it remained synchronized with the user's mental commands.

A NodeJS runtime environment powered the local server, managing WebSocket connections to integrate data from the neural network model. This model predicted the wheelchair's potential path based on the user’s commands and environmental input. The combined data from the BCI system, sensor feedback, and predictive model allowed the web application to deliver timely alerts, enhancing the user’s awareness of surrounding hazards and supporting safer navigation.

For the third component, the RNN-based prediction model, Node-RED was used to collect and process data from the user’s interactions and surroundings. The RNN model was coded and trained in Python, using this data to predict the user’s likely path based on the current environment and mental commands. This predictive capability improved the system’s ability to anticipate and mitigate potential obstacles, reinforcing safety measures through proactive navigation assistance.

Together, these three components form an integrated system called NeurowarnBCI.

Hardware Requirements

The Neurowarn BCI system requires four hardware components. The primary component is the EEG headset. The headset reads the user's electrical brainwave data and transmits it to the NeuroWarn BCI system for interpretation. The system is only compatible with Emotiv EEG headsets because the system relies on Emotiv’s mental command framework. In this study, the Emotiv Insight, a five-channel EEG headset, was used. However, any headset in the Emotiv product line was expected to be compatible with the system.

Figure 13. Emotiv Insight

The second hardware component is a smart wheelchair or a BCI-controlled wheelchair. In this study, an electric wheelchair was modified into a smart wheelchair. The motor driver of the electric wheelchair was replaced with a BTS7960 motor driver. This approach enables the control of the wheelchair motors via an Arduino. The Arduino was then connected to a control laptop which allows the NeuroWarn system to control the movement of the wheelchair.

Figure 14. Smart Wheelchair

To enable the NeuroWarn BCI to detect obstacles, the modified wheelchair was equipped with obstacle-detecting sensors. Specifically, a total of four sensors were installed with two facing forward and two facing backward. The front-facing sensor utilized in the modified wheelchair was a time-of-flight sensor. It was capable of detecting obstacles, for this use case the researcher utilized a range of 1,500 millimeters in a 20-27-degree field of view. These sensors were positioned at the front corner of the wheelchair at an angle of 13.5 degrees facing up and 5 degrees on the side to cover the center. The rear-facing sensor was an ultrasonic sensor with a utilized detection range of 1 meter in a 15-degree field of view. These sensors were positioned in the rear corners of the wheelchair at an angle that covers a range approximately the same size as the width of the wheelchair. This configuration enabled the wheelchair to detect obstacles in its path both ahead and behind as illustrated in the following figure.

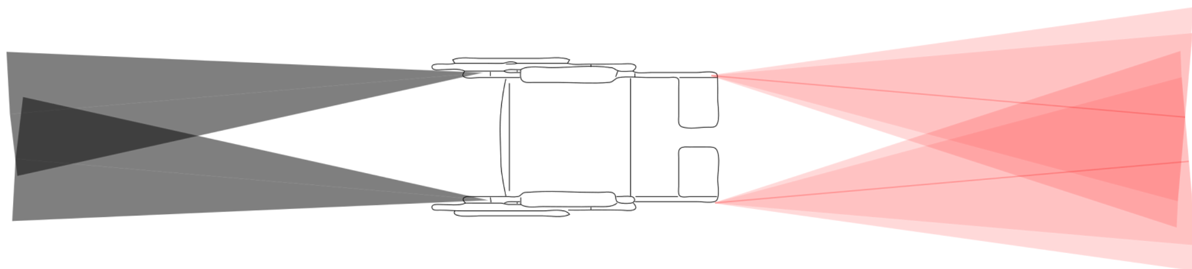

Figure 15. Top View of the Detection Zones of the Obstacle Detecting Sensors

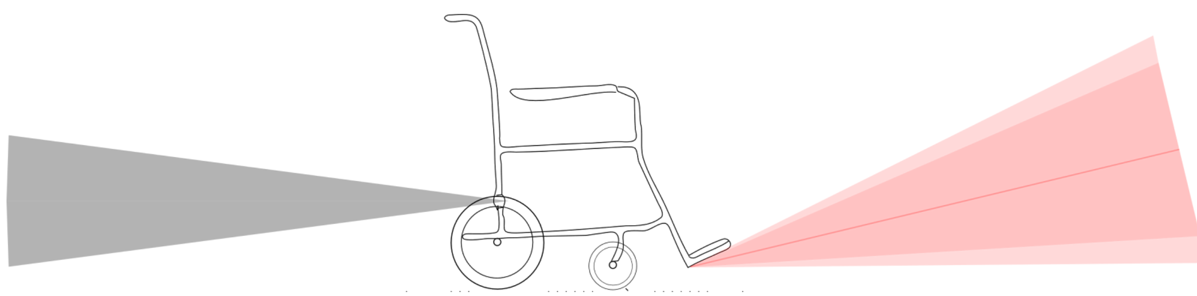

Figure 16. Side View of the detection Zones of the Obstacle Detecting Sensors

Figures 15 and 16 illustrate the coverage and range of the obstacle-detecting sensors. The area colored red is the coverage of the LiDAR sensor while the area in gray is the coverage of the ultrasonic sensor.

The modified electric wheelchair was converted into a smart wheelchair using two Arduino circuits. One controlled the wheelchair's motor, while the other collected sensor data. The following was the circuit diagram for the Arduino circuits.

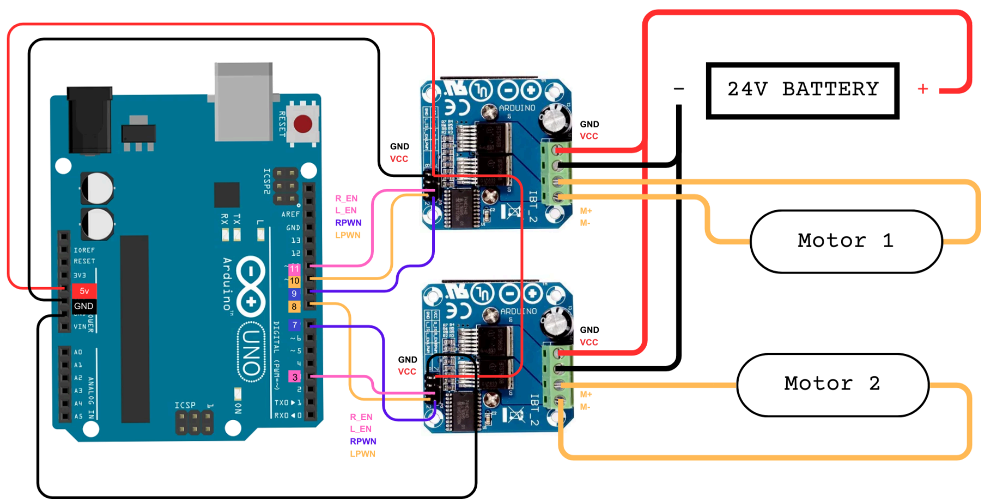

Figure 17. Arduino Circuit Diagram for the Electric Motor Driver Control

Figure 17 shows the Arduino circuit diagram for the electric motor driver control. To transform the standard electric wheelchair into a smart wheelchair, the existing motor driver was replaced with a BTS7960 electric motor driver. This motor driver was selected for its capability to handle high-amperage motors. Two BTS7960 drivers were used, one for each motor.

The first BTS7960 driver was connected to the Arduino, with pin 7 linked to the driver's RPWM pin and pin 8 connected to the LPWM pin. These pins controlled the motor's rotation direction. To regulate motor speed, pin 3 of the Arduino was connected to the driver's L_EN and R_EN pins. For power, the Arduino's 5V pin was connected to the driver's VCC pin, and GND was linked to the ground. The driver was then connected to Motor One and its 24V battery.

For the second BTS7960 driver, pin 9 of the Arduino was connected to the driver's RPWM pin, and pin 10 was connected to the LPWM pin to control the motor's direction. Pin 11 was linked to the L_EN and R_EN pins for speed control. The driver was powered by connecting it to the Arduino's 5V and GND pins. It was then connected to the second motor of the wheelchair and the motor battery for power.

This circuit enabled the control laptop to manage the wheelchair's motor movement, allowing the NeuroWarn system to control the wheelchair's physical motion.

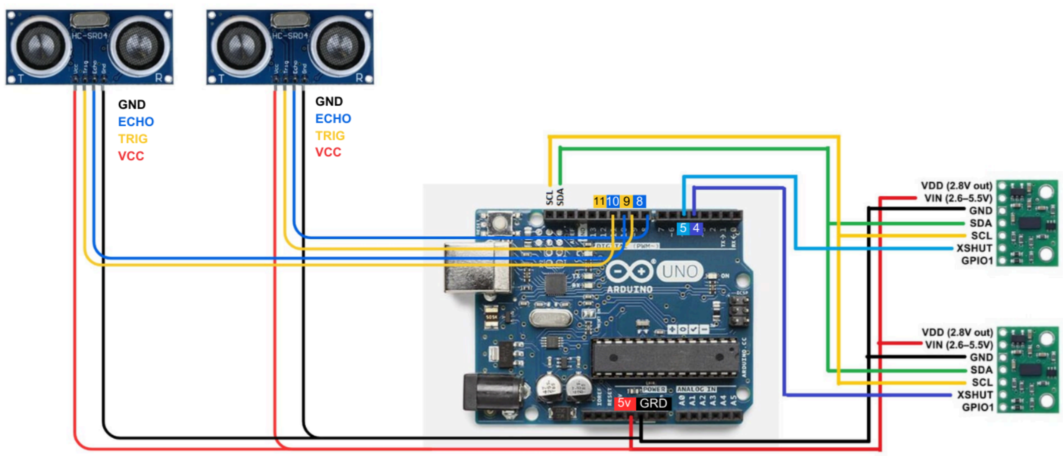

Figure 18. Arduino Circuit Diagram for the Obstacle Sensors

Figure 18 illustrates an Arduino microcontroller connected to 2 ultrasonic sensors (HC-SR04) and 2 time-of-flight sensors (VL53L1X) for distance measurement. The HC-SR04 sensors are powered by the Arduino's 5V and GND pins, with their trigger and echo pins connected to separate digital pins for measuring distance using ultrasonic waves. Meanwhile, the VL53L1X sensors are interfaced via the I2C bus, with their SDA and SCL lines connected to the Arduino’s SCL and SDA pins, respectively, while the XSHUT pins are assigned to different digital pins to manage individual sensor addresses. These sensors receive power from the 5V pins of the Arduino. This setup satisfies the distance sensing requirement, utilizing

VL53L1x attached on the front ensures real-time sensing capability.

Software Requirements

The following are the software requirements to run NeurowarnBCI:

1. EmotivBCI - is an application developed by Emotiv for their EEG headset. This is where users can train Mental Command. Mental Commands are used in this study as the input control for wheelchair movement and a target variable for the RNN prediction.

2. Node-RED - is an open-source flow-based programming tool that allows users to connect devices, APIs, and services through a visual interface. In this study, Node-RED was used as the tool to collect EEG data. This data is used to train the prediction of the RNN Model.

3. Neurowarn BCI - is the software developed in this study. It integrates both the control system for the BCI-controlled wheelchair, and RNN-based warnings for obstacle avoidance and safety.

Input and Outputs of the Study

The study receives input from the user through an EEG headset, which reads the user's brainwave activity and transmits the data to the system for interpretation. The system has two outputs: wheelchair movement and a warning system. To achieve this functionality, there are several interactions between the user and the system.

Emotiv Mental Command Suite Training

The Emotiv Mental Command Suite is a brain-computer interface framework developed by the company Emotiv that can classify user intention through training [41]. It was chosen to be the main framework for this study due to its popularity and reliability in the BCI research community [56]. The mental command suite has fifteen commands. However, for this study, only two out of fifteen commands will be trained and used. These commands are the push (forward) and pull (backward). The EmotivBCI application provides an interface for training the Mental Command Suite.

Neutral State Training

Before training a command, the mental command suite first requires the user to train a neutral state. In this state, the user training the framework must be calm and quiet. This state serves as the baseline for classifying various kinds of commands. Figure 19 illustrates the user interface of EmotivBCI when adding a neutral state.

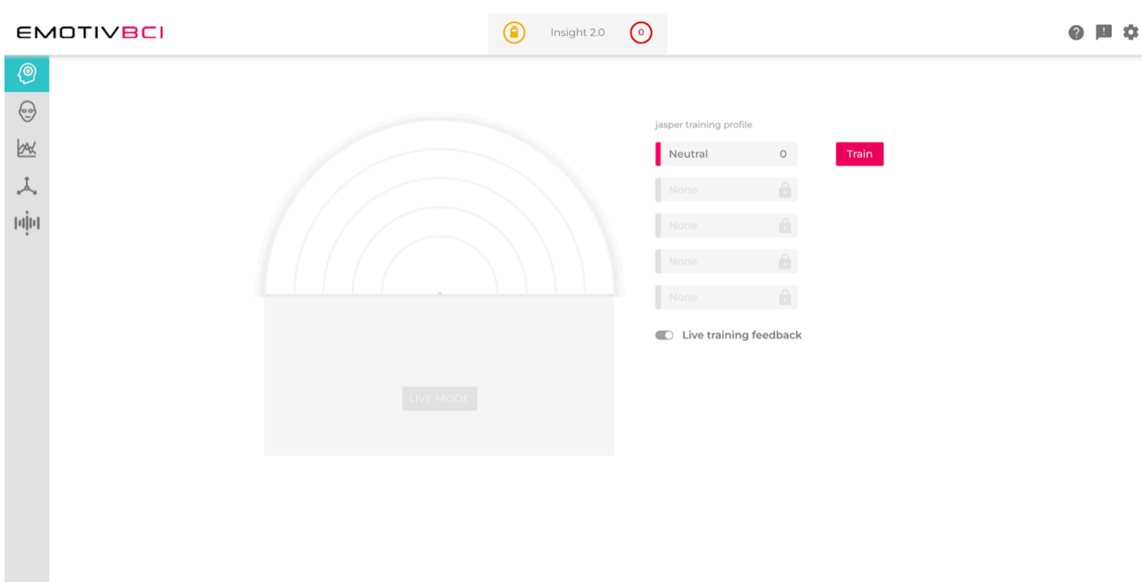

Figure 19: EmotivBCI’s User Interface when adding Neutral

Push (Forward) Command Training

To train the push command, the user must simply select the add command and choose push in the EmotivBCI application. Once the command is added, the user can start training.

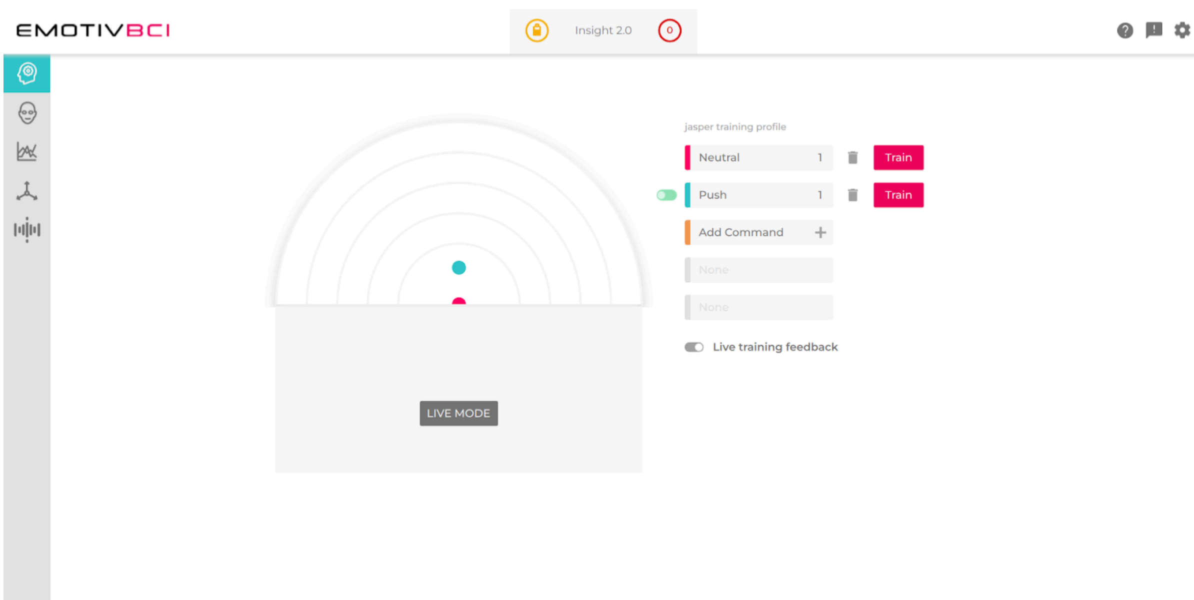

Figure 20. EmotivBCI's User Interface when adding push

When the user starts training, it should bring the user to a training interface where the user can start thinking of a specific thought that he/she wants to associate with the push command. Associating a facial muscle movement (e.g., smiling, raising brows, clenching teeth) with training mental commands is also possible, as this approach has proven highly effective in EEG classification [61].

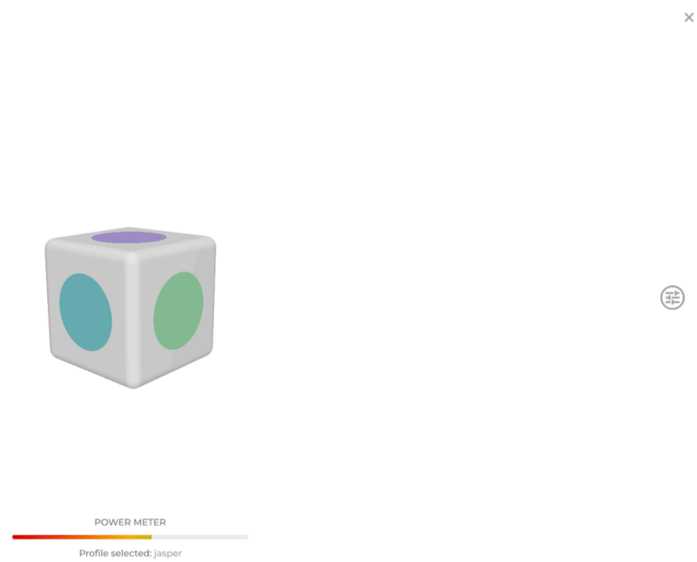

Figure 21. EmotivBCI's UI during pull training

The user can then continuously add training to the push command. The more training sessions recorded, the more accurate the framework can classify the registered command.

Pull (Backward) Command Training

Similarly to the push command, to train the pull command, the user must first add a new command and select pull. The user can then start training the pull command.

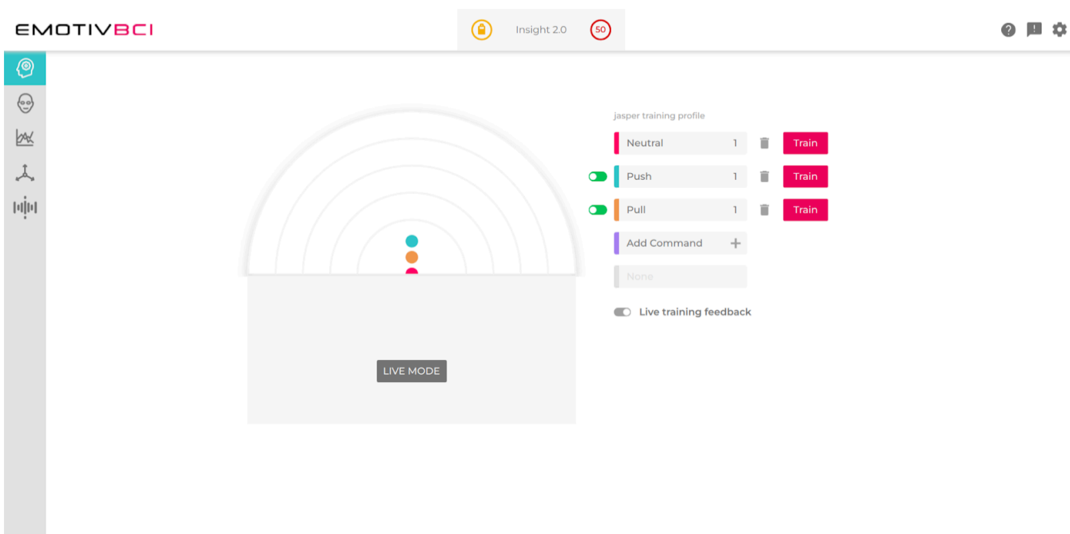

Figure 22. EmotivBCI's User Interface when adding pull

During training, the user is be taken to an interface like the previous command training. However, the user training the mental commands must think of a thought or facial muscle movement different from the thought or facial muscle movement he/she associated with the previous commands. This is to ensure that brainwave data differ and the MCS framework can classify it.

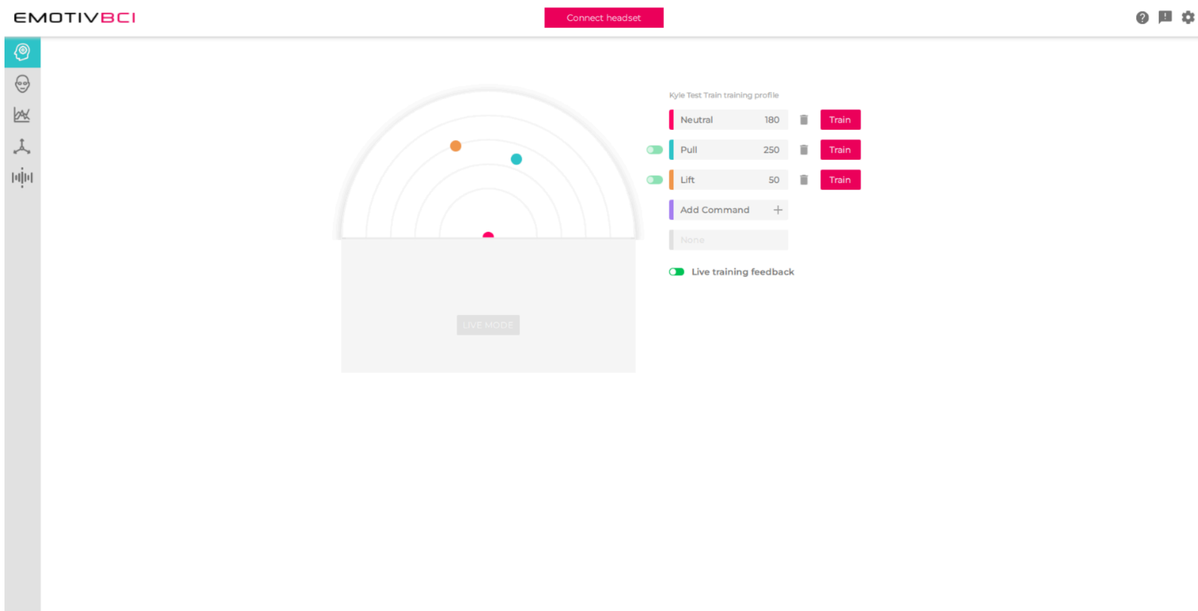

Figure 23. EmotivBCI's performance visualization

EmotivBCI features a simple visualization of the framework's performance in classifying commands as shown in the image above. Each circle represents a distinct mental command, and the greater the distance between these circles, the better the performance of the Mental Command framework. To achieve optimal results, users are encouraged to continually train their mental commands.

Once the mental command training is complete, the user can begin operating the BCI wheelchair control system.

The Neurowarn BCI wheelchair control system

The BCI wheelchair control system has five expected movements: stop, forward, backward, left, and right. However, due to the limitations of the five-channel EEG headset [57], only three movements (stop, forward, and backward) will be controlled using the mental command framework. For the left and right movements, the onboard gyroscope in the Emotiv Insight headset will be utilized as has been implemented in other BCI-controlled wheelchairs [58].

Additionally, each movement also triggers a response in Neurowarn’s user interface. A section of Neurowarn’s interface displays the current state or the direction of the wheelchair as shown in Figure 21.

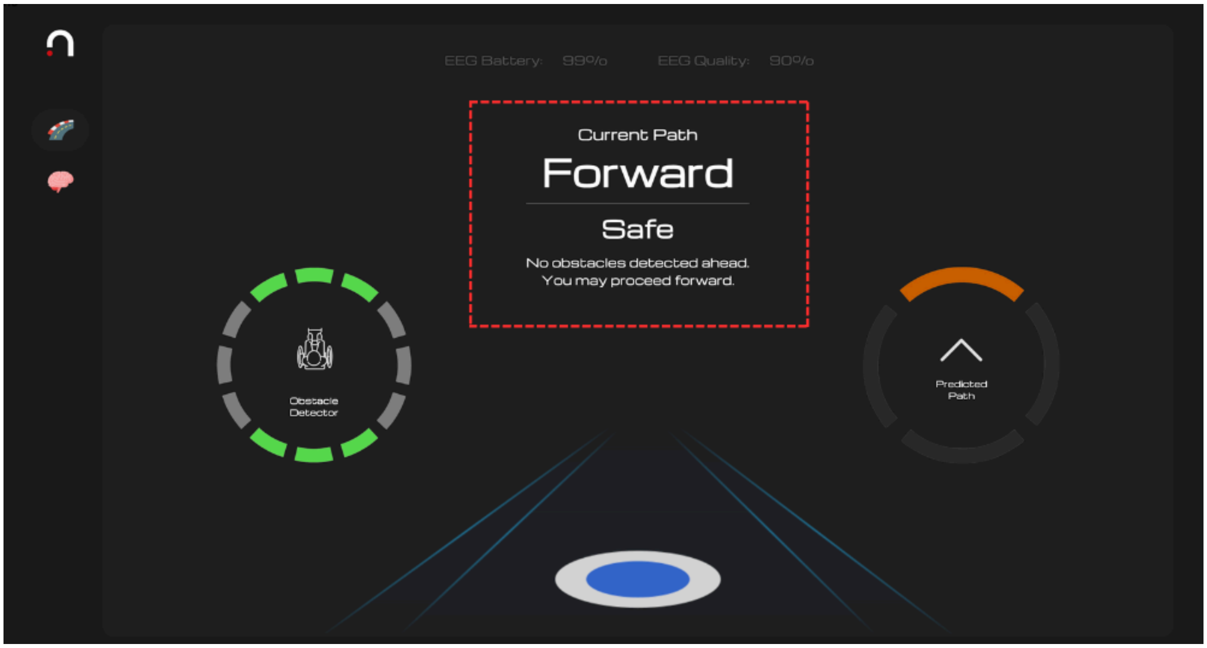

Figure 24. Neurowarn's UI section that shows the wheelchair state

The smart wheelchair's user interface (UI) displays both the current and predicted path, providing a direct visual representation of the wheelchair's movements. Additionally, the UI provides an assessment of the safety of these paths by utilizing the Obstacle Detection feature, located on the left side of the interface. If either the predicted or current path is deemed unsafe, the text indicator updates from "Safe" to "Not Safe." Furthermore, the interface also displays the status of the EEG battery and signal quality.

Moving Forward

To activate the forward output, the user must think of the trigger thought they practiced during the push training. This is expected to make the wheelchair move forward.

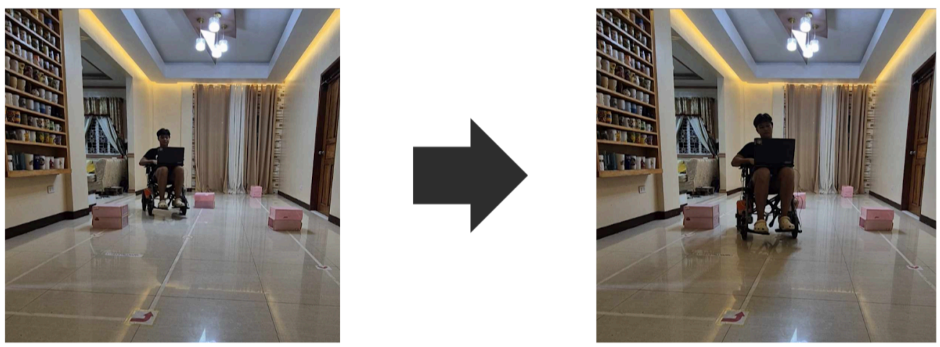

Figure 25. Before and after forward command

Figure 25 shows the output of the forward command. The image on the left is the position of the wheelchair before the forward command while the image on the right is after the forward command. Observe how the wheelchair moves forward after the forward command.

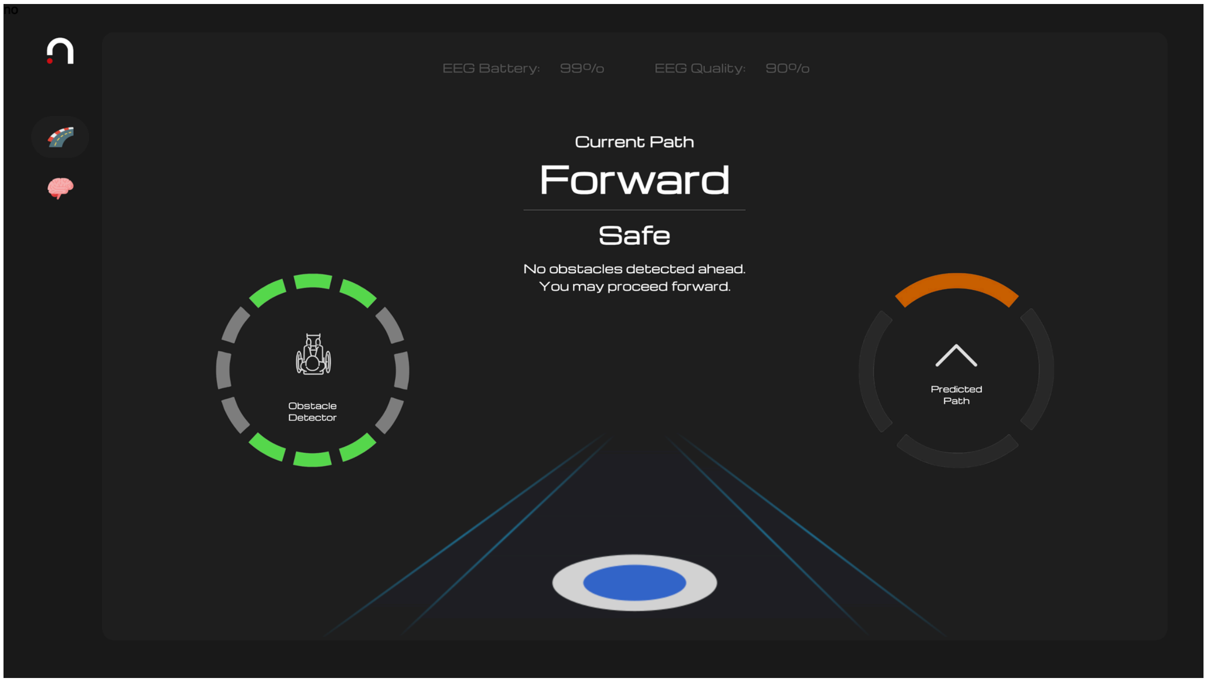

Figure 26. Neurowarn BCI's interface when moving forward

Additionally, when the forward command is triggered, a section of the warning system's user interface displays the message "Forward," as shown in Figure 26.

Moving Backward

To activate the backward output, the user must think of the trigger thought they practiced during the pull training. This is expected to result in the wheelchair moving backward.

Figure 27. Before and after backward command

Figure 27 shows the output of the backward command. The image on the left is the position of the wheelchair before the backward command while the image on the right is after the backward command. Observe how the wheelchair moves backward after the backward command.

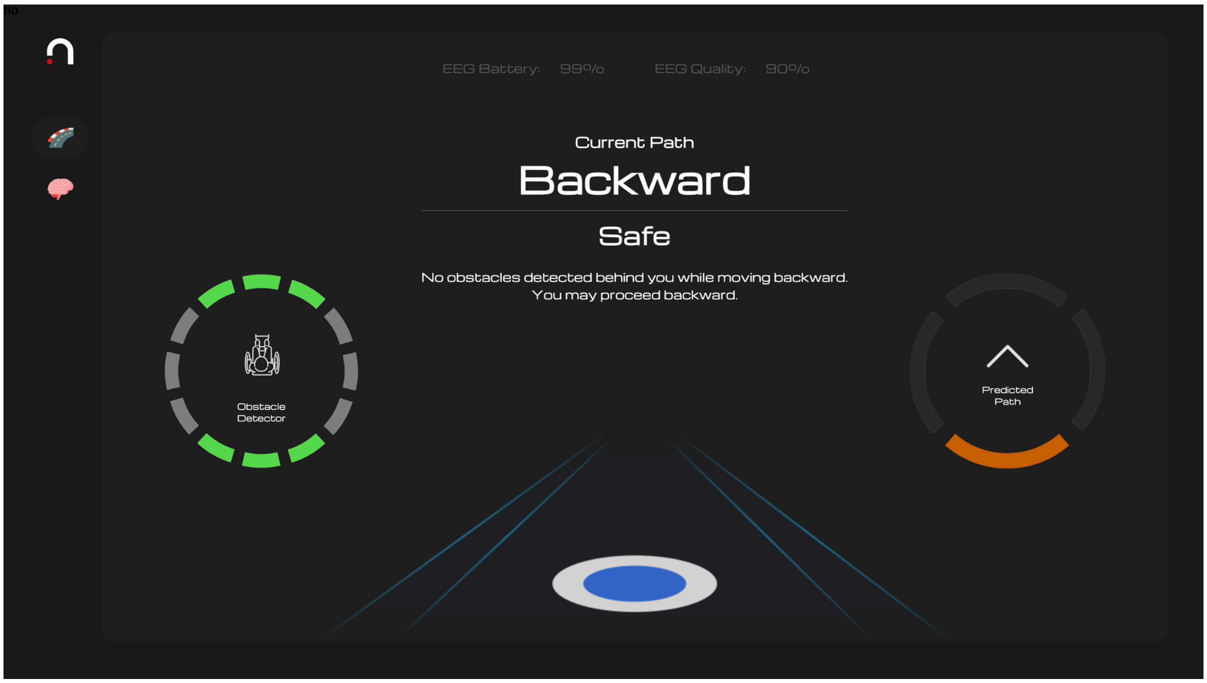

Figure 28. Neurowarn BCI's interface when moving backward

Similarly with move forward, when the backward command is triggered, a section of the warning system's user interface displays the message "Backward" as shown in Figure 28.

Turning Left

To activate the left output, the user must simply tilt their head to the left. This is expected to result in the wheelchair turning left.

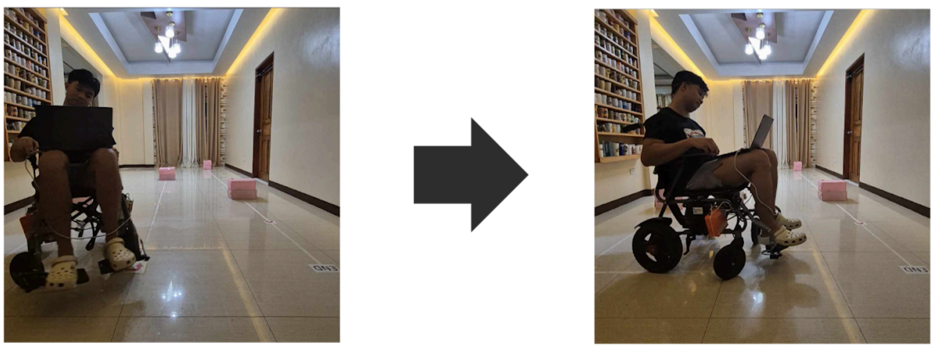

Figure 29. Before and after left command

Figure 29 shows the output of the left command. The image on the left is the position of the wheelchair before the left command while the image on the right is after the left command. Observe how the wheelchair turns left after the left command.

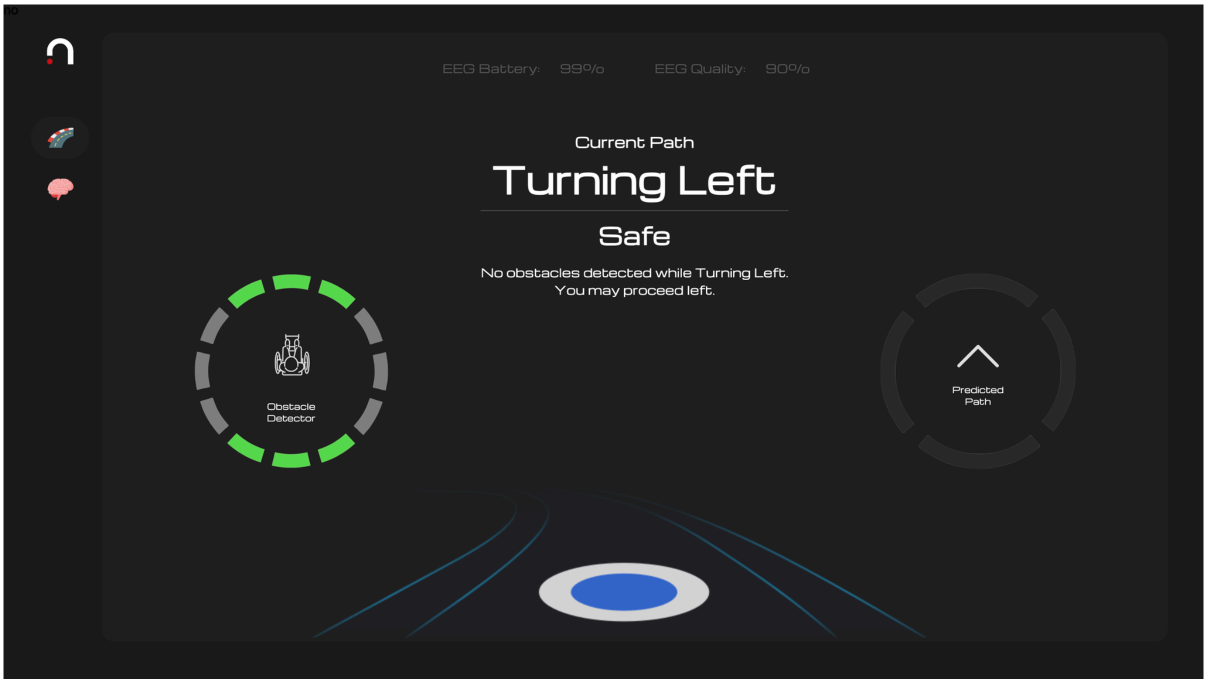

Figure 30. Neurowarn BCI’s interface when turning left

A UI response is also triggered when turning left. Neurowarn BCI’s interface displays the text “Turning Left” as seen in Figure 30.

Turning Right

To activate the right output, the user must simply tilt their head to the right. This is expected to result in the wheelchair turning right.

Figure 31. Before and after the right command

The images above show the output of the right command. The image on the left is the position of the wheelchair before the right command while the image on the right is after the right command. Observe how the wheelchair turns right after the right command.

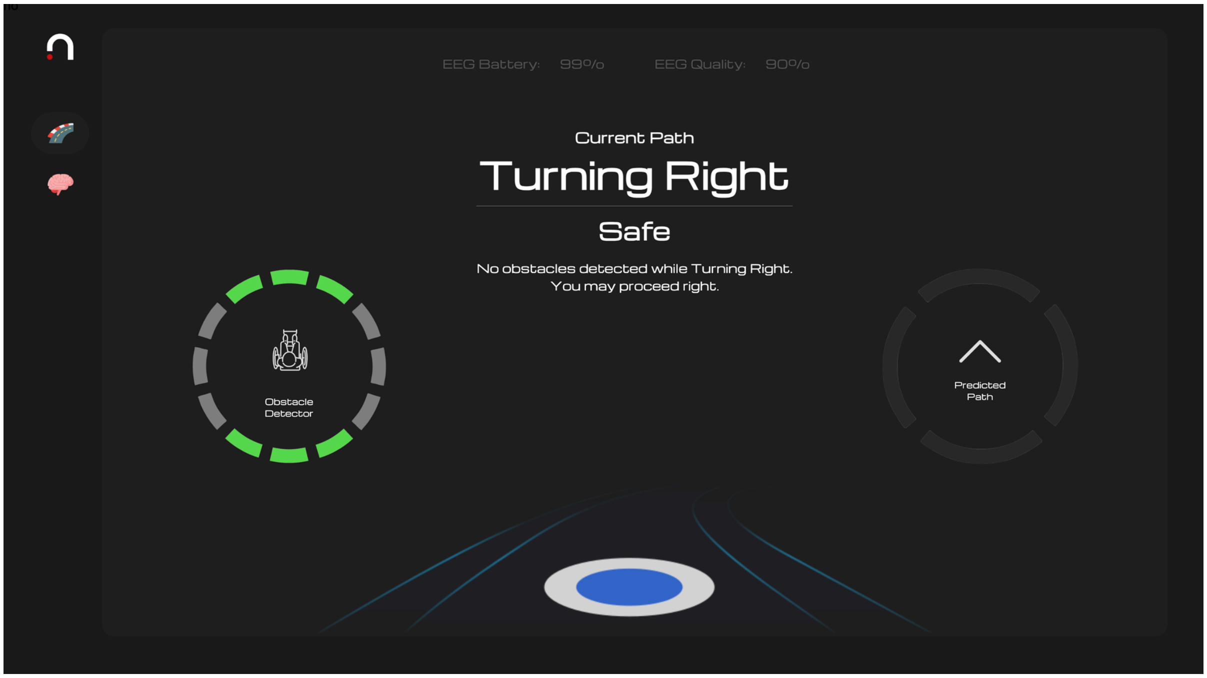

Figure 32. Neurowarn BCI's interface when turning right

When the right command is triggered, a section of the warning system's user interface displays the message "turning right" as shown in Figure 32.

Obstacle Detection output

The input from the obstacle detection sensors generates a corresponding output in the NeuroWarn user interface. A simple obstacle map within the UI displays the detected obstacle in a way that is easy for the user to understand.

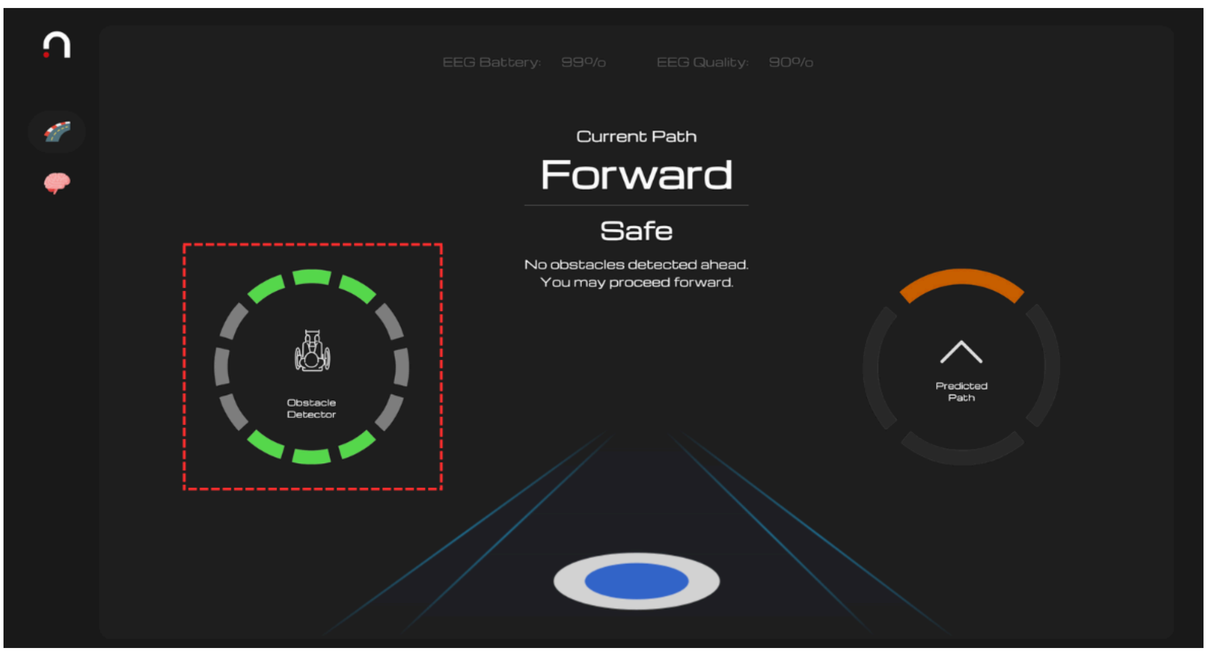

Figure 33. Neurowarn BCI's obstacle detector section

The obstacle map has an image of a wheelchair positioned in the center, with three bars displayed in front and three bars at the back as seen in the screenshot above. The bars appear green when no obstacles are detected, and they turn red when an obstacle is detected in that area as seen in the following examples.

Figure 34. The image shows a box positioned in front of the wheelchair to simulate an obstacle.

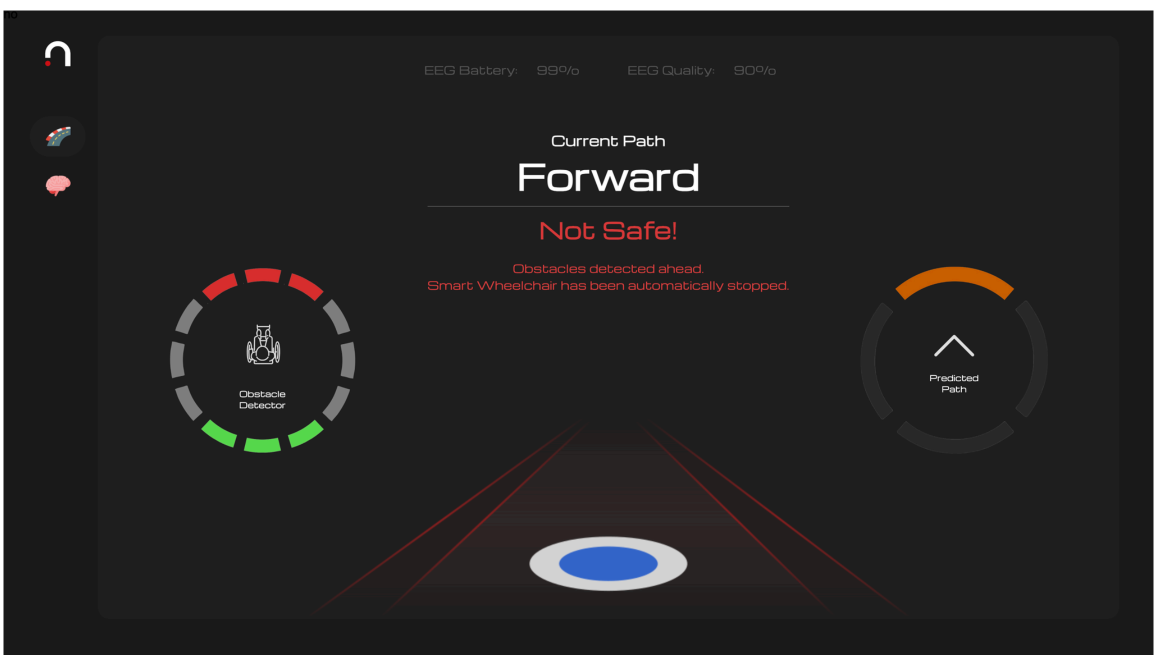

Figure 35. User interface when an obstacle is detected in front

In Figure 34, an obstacle is visible in front of the wheelchair. The wheelchair's front LiDAR sensor detects this obstacle and displays it on the user interface, as shown in Figure 35.

Figure 36. The image shows a box positioned behind the wheelchair to simulate an obstacle.

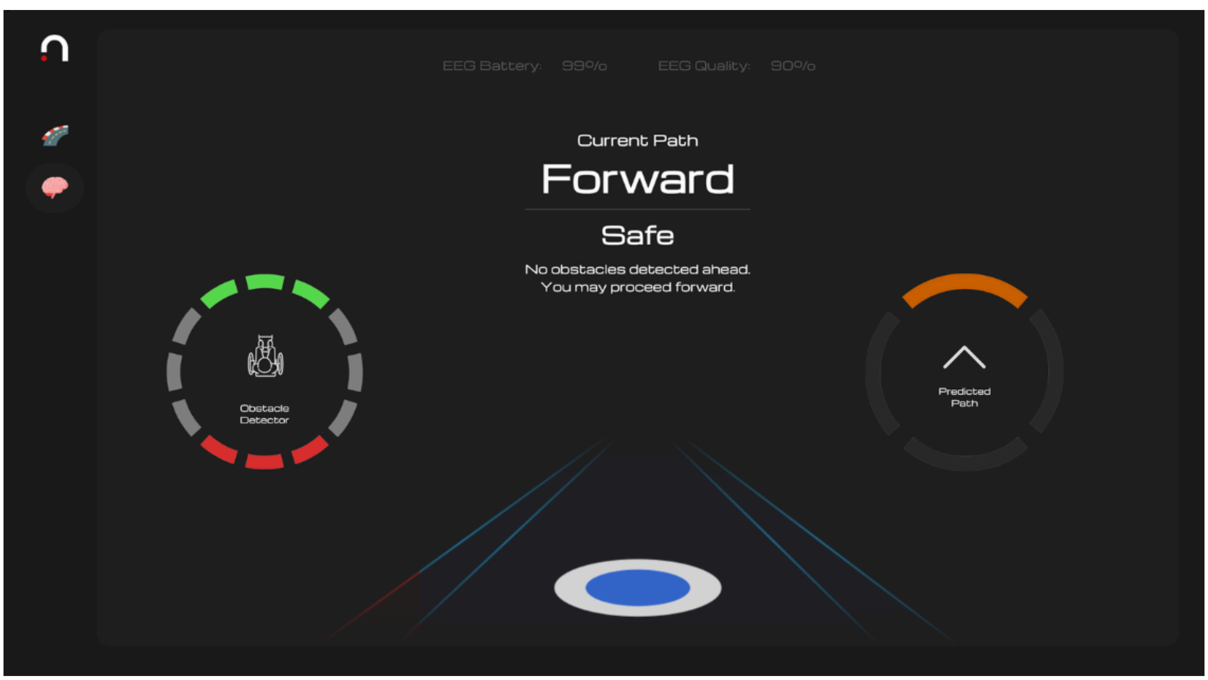

Figure 37. Neurowarn's UI interface when back obstacles are detected

In Figure 36, an obstacle is visible at the back of the wheelchair. The wheelchair's back LiDAR sensor detects this obstacle and displays it on the user interface, as shown in Figure 37.

Warning Outputs

Warning prompts accompanied by a warning sound are triggered when the predicted direction aligns with an obstacle. Additionally, the system also stops the motors to prevent a collision. Once the path is clear of obstacles, the warning prompt disappears, and the wheelchair motor is reactivated allowing the user to resume movement.

Figure 38. The image shows an obstacle in the path of the predicted direction

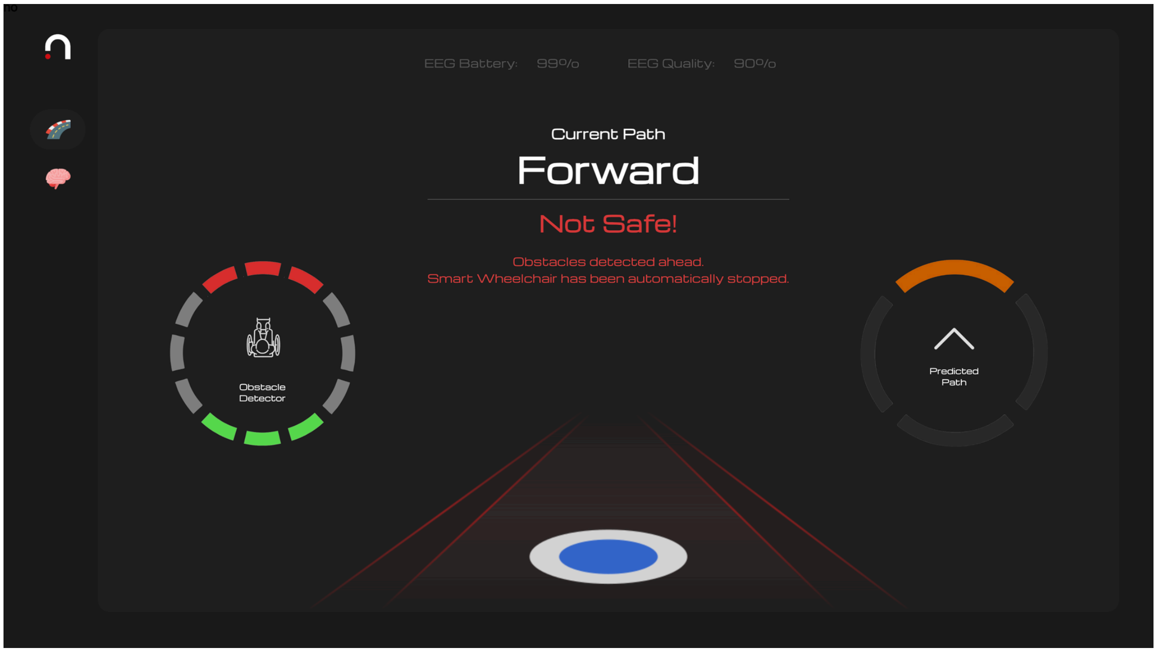

Figure 39. Warning prompt of forward

Figure 38 shows an instance where a participant triggered a warning. An obstacle was detected in front of the wheelchair while it was expected to move forward. Figure 39 displays the warning prompt generated by the user interface in response to the potential collision.

Results Interpretation and Analysis

The results and analysis focused on the performance of the LSTM neural network trained on EEG frequency band data to classify three commands: Neutral, Forward, and Backward. The model performance was evaluated using multiple metrics, including precision, sensitivity (recall), specificity, F1-score, and a confusion matrix. These metrics were derived from predictions on the test set, which was separate from the training set to ensure an unbiased evaluation of model performance.

Dataset

The dataset was composed of 25 features, which are the 5 frequency bands of each of the 5 probes of the EEG headset. The target variable would be one of three commands: neutral, forward, or backward. The data collection process used Node-RED to record the frequency band activities from the EEG headset and directly outputs them as a CSV file ready to be preprocessed and used for training in our LSTM Model.

Precision

The precision of the positive predictions is a measure of their accuracy. A 94.16% accuracy in this instance indicated that 94.16% of the samples that were predicted to be positive were, in fact, true positives. Given its high accuracy rate, the model appeared to be reasonably adept at preventing false positives. When false positives must be reduced, like in obstacle avoidance decision-making situations, high accuracy is essential.

Sensitivity/Recall

Sensitivity, or recall, measures the proportion of true positives correctly identified out of the total actual positives. A sensitivity of 93.95% meant that the model successfully identified 93.95% of all actual instances of each command. This high recall showed that the model was adept at capturing actual instances of commands, reducing the chance of missed detections (false negatives). This performance level is advantageous for applications in obstacle avoidance where it is important to identify as many true positives as possible, ensuring responsiveness to each command.

Specificity

Specificity measures the model's ability to correctly identify negative cases. A specificity of 96.70% implied that the model performs very well at avoiding false positives. High specificity further reinforces the model's reliability by ensuring that instances were not incorrectly classified as commands. This was critical for minimizing false alarms and ensuring that only genuine commands were acted upon, improving overall model robustness.

F1-Score

The F1-score provides a balanced view of the model's precision and recall by calculating their harmonic mean. With an F1-score of 94.05%, the model demonstrated strong overall accuracy in correctly identifying commands while balancing false positives and false negatives. The high F1-score indicated that the model was well-suited for applications where a balance between precision and recall is essential, making it effective in scenarios requiring both accurate command detection and minimal false classifications.

Overall Accuracy

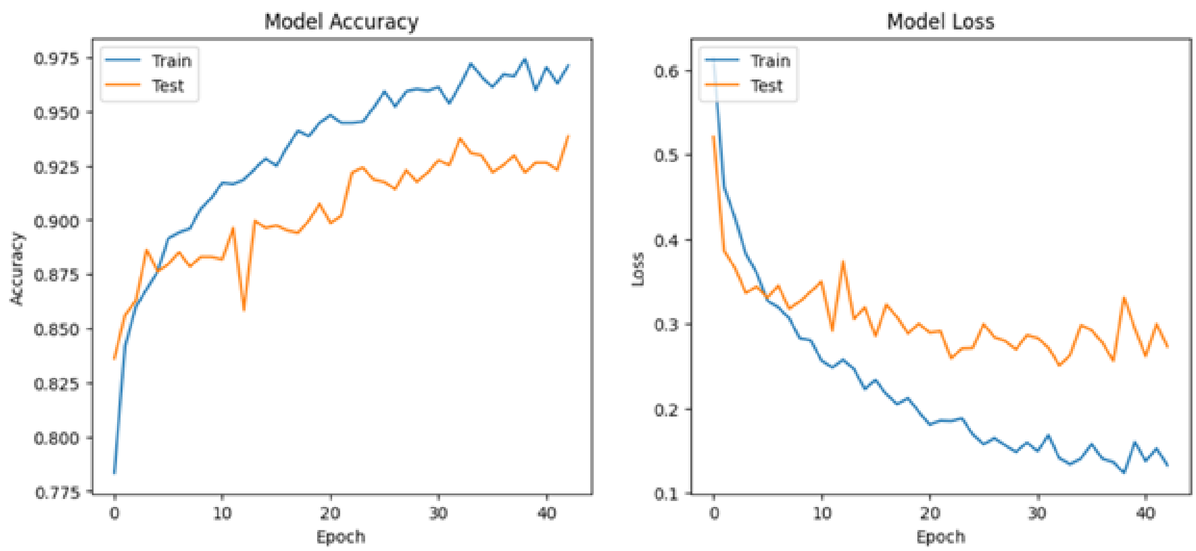

Figure 40. Model Accuracy

With an overall accuracy of 93.87%, a majority of the test set's samples were correctly predicted to be either Neutral, Forward, or Backward by the model. With a high degree of accuracy, this result shows that the model can consistently categorize EEG-based orders, indicating its overall efficacy in command identification. An accuracy of more than 93.87% indicates that the model has picked up on pertinent patterns in the data, but it could still be improved to pick up on more subtleties that might help lower mistakes even further.

Confusion Matrix

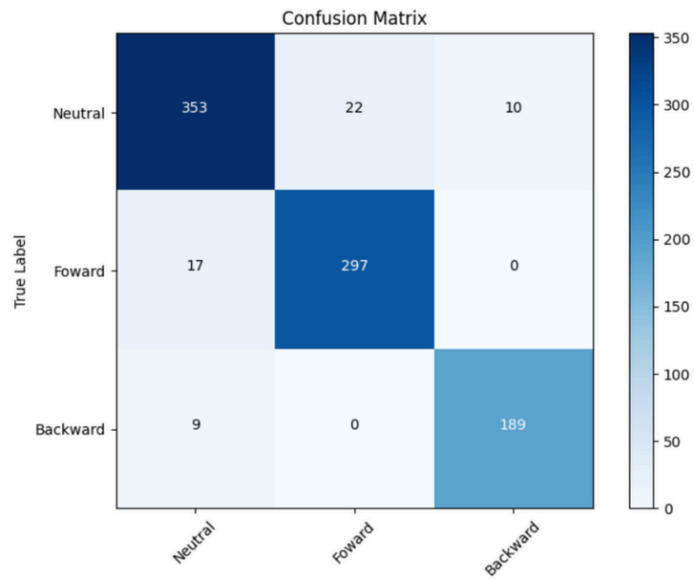

Figure 41. Confusion Matrix

The confusion matrix is a visualization tool used to evaluate the performance of your image classification model. It allows you to compare the actual target values (True Label) with the predicted values (Predicted Label) from your machine learning model. In this case, the target categories are 'Neutral', 'Forward', and 'Backward'.

a) Neutral: The model correctly classified 353 out of 375 neutral samples (94.1% accuracy). There were 22 false negatives (classified as Forward) and 10 false negatives (classified as Backward).

b) Forward: The model correctly classified 297 out of 310 forward samples (95.81% accuracy). There were 17 false negatives (classified as Neutral) and 17 false positives (classified as Backward).

c) Backward: The model correctly classified 189 out of 195 backward samples (96.92% accuracy). There were 6 false negatives (classified as Neutral) and 50 false positives (classified as Forward).

Overall, the model performed well in classifying all three classes with high accuracy (>94%). The lowest accuracy was observed for the Neutral class (94.1%) but all the accuracies were well above the chance level.

Here are some additional metrics to consider:

Metric	**Percentage**
Precision	94%
Recall (Sensitivity)	93%
F1-Score	94%
Specificity	96%

Table 1. Metrics

These metrics further confirm that the model is performing well on this classification task.

We can also see the loss and accuracy curves plotted over the epochs. The training accuracy increases steadily, and the validation accuracy follows a similar trend. This suggests that the model is learning well and generalizes well to unseen data. The loss curves show a similar trend where the training loss decreases and the validation loss follows a similar pattern. This again suggests that the model is learning well and not overfitting to the training data.

Effects of Methods and Enhancements

a) L2 Regularization: This regularization method reduces overfitting by penalizing large weights, helping the model generalize better to unseen data. This likely contributed to the high specificity and precision scores, which show the model's effectiveness on the test set.

b) Batch Normalization: Added after each LSTM layer, batch normalization helps stabilize and accelerate the training process, improving model convergence and reducing overfitting.

c) Dropout and Spatial Dropout: These methods were applied to prevent over-reliance on specific neurons by randomly disabling them during training. The dropout layers likely contributed to reducing overfitting, as suggested by the high scores on the test set.

d) Checkpoint and Early Stopping: These callbacks preserved the best-performing model and prevented further training when validation loss plateaued. This approach likely prevented overfitting, ensuring a model with strong generalization capabilities.

Observations and Significant Variables

1. Effect of Sequence Length (Window Size): The model's capacity to accurately capture temporal patterns may have been impacted by the window size of 5 used to create EEG sequences. Testing different sequence lengths turns up patterns that enhance F1-score and memory.

2. Hyperparameter Selections: The dropout rate and kernel

regularization parameter were set to certain values, however, they may still need to be adjusted further to improve the model's performance. The optimal value found to maximize the accuracy of the model was a dropout rate of 0.3.

3. Class Imbalance: If the number of samples for each instruction is unbalanced, recall or specificity may be impacted. Balancing the dataset or changing the class weights during training may further increase the model's sensitivity.

System Evaluation Results

A total of ten participants were invited to evaluate the Neurowarn system. These were individuals aged 18-25 who were willing to spend time to train and test the Neurowarn system. Each test session lasted three hours per participant. Participants were first asked to train the mental commands which took 1.5 hours and train the RNN model which took another hour.

A 6x3 meter area was then converted into an obstacle course to allow participants to test the wheelchair. A predetermined path was set within this space, with four obstacles strategically placed along the path. The obstacle was a 32 cm x 22 cm x 24 cm box, large enough for the wheelchair sensor to detect. Figure 42 illustrates the obstacle course design.

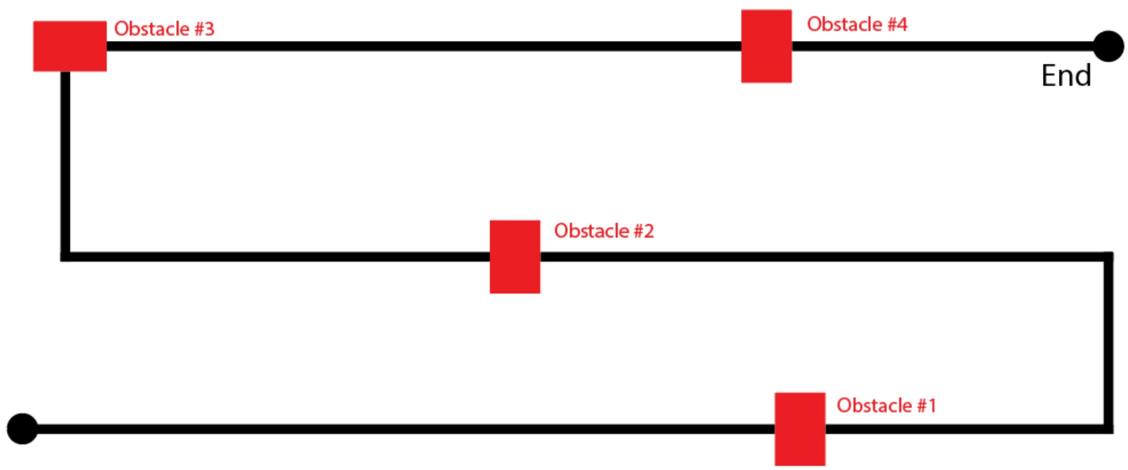

Figure 42. The course design

Participants were then given 15 minutes to complete the obstacle. They were instructed to simply follow the predetermined path and avoid the obstacles.

ISO 9241-11

The NeuroWarn BCI was then evaluated using the ISO 9241-11 standards. It was selected for its focus on usability in Human-Computer Interaction (HCI) systems. This standard was particularly relevant for assessing safety-critical systems such as EEG-based wheelchair control where usability is essential to ensure safe and effective operation [59].

According to the ISO 9241-11 standards, usability is defined as the range in which a product can be used by specific users to achieve certain specified goals with effectiveness, efficiency, and satisfaction in a specified context of use [60].

A 30-item questionnaire, comprising 10 questions for each aspect of usability—effectiveness, efficiency, and satisfaction—was written for the evaluation. These questions were based on the specific standards outlined in ISO 9241-11 [60]. Participants were asked to rate each question on a 5-point Likert scale, where 1 represents "Strongly Disagree" and 5 represents "Strongly Agree." The purpose of this assessment was to gather participants' perspectives on the overall usability of the NeurowarnBCI system.

Participant	Effectiveness	Efficiency	Satisfaction	Total Usability Score
Participant 1	4.1	4.3	4.5	4.3
Participant 2	4.0	4.2	4.3	4.2
Participant 3	4.2	4.4	4.4	4.3
Participant 4	4.3	4.1	4.5	4.3
Participant 5	4.0	4.3	4.4	4.2
Participant 6	4.1	4.2	4.3	4.2
Participant 7	4.2	4.4	4.5	4.4
Participant 8	4.1	4.3	4.3	4.2
Participant 9	4.2	4.3	4.4	4.3
Participant 10	4.1	4.2	4.4	4.2
Overall Average	**4.13**	**4.27**	**4.40**	**4.27**

Table 2. Results Table

Scales of Mean	Description
5 - 4.1	Very Good
4 - 3.1	Good
3 - 2.1	Fair
2 - 1.1	Poor
1	Very Poor

Table 3. Evaluation Legend

Table 2 presents the average Likert scale ratings for Effectiveness, Efficiency, and Satisfaction across 10 participants, using the evaluation legend from Table 3. It also includes the Total Usability Score for each participant. The highest possible score was 5, and the lowest was 1. The following is the interpretation of each usability aspect;

Effectiveness

Effectiveness, as defined by ISO 9241-11, refers to the accuracy and completeness with which users achieve specified tasks using the system. NeuroWarn received an average effectiveness score of 4.13, indicating that users generally perceived the system to accurately interpret and respond to their commands. Most participants felt that NeuroWarn could reliably predict intended directions and effectively detect and avoid obstacles in the environment. This score reflects a solid performance in interpreting user inputs and providing an accurate response that aligns with user expectations for a navigation assistive device.

Efficiency

Efficiency measures the resources expended, such as time and mental effort, to achieve a goal while using the system. NeuroWarn achieved an average efficiency score of 4.27, reflecting a high level of perceived efficiency. Participants reported that they could focus more on navigating the course rather than on managing NeuroWarn’s controls, allowing for faster and smoother task completion. The system’s responsiveness and interface clarity contributed to this high-efficiency rating, enabling users to maintain a steady pace with minimal interruptions.

Satisfaction

Satisfaction reflects the overall comfort and positive experience users have with the system. NeuroWarn scored an impressive 4.40 in satisfaction, the highest average across the three categories. This high score indicates that users were generally very pleased with the system's usability, performance, and intuitive interface. Participants expressed confidence in using NeuroWarn and appreciated its clear feedback, smooth interface, and visually appealing design.

Overall Usability Score

The combined average usability score for NeuroWarn was 4.27. This robust rating signifies that NeuroWarn is a well-rounded system with strengths across effectiveness, efficiency, and satisfaction as outlined in the ISO 9241-11 standards [60]. Participants felt that it met their expectations for performance, ease of use, and navigational support, with minimal mental effort required to achieve tasks.

CHAPTER 5 SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary of the Proposed Study Design and Implementation

A smart wheelchair system was developed that integrates a 5-channel Emotiv Insight EEG headset for brainwave acquisition and LiDAR sensors for obstacle detection. A Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) architecture was employed to predict the user's intended direction, enhancing the system's autonomous navigation capabilities. To facilitate user interaction and provide real-time feedback, a web application was designed to simplify complex system inputs, such as EEG signals, LiDAR data, and RNN-LSTM predictions, into intuitive visual prompts. Auditory alerts were also implemented to provide additional warning signals.

Summary of Findings

NeuroWarn BCI’s smart wheelchair system demonstrated effective obstacle detection capabilities, with LiDAR sensors providing a 1.5-meter range for front obstacles and 1-meter range for rear obstacles. The system's predictive algorithm, based on an RNN-LSTM architecture, achieved an accuracy of 86.05% in predicting user intent, as measured by the xtest dataset.

To assess the system's usability and effectiveness, an evaluation was conducted using the ISO 9241-11 standard. The results indicated a high level of user satisfaction and system performance, with an overall average rating of 4.27 out of 5 across the dimensions of effectiveness, efficiency, and satisfaction.

Conclusions

This study successfully developed and evaluated a smart wheelchair system that leverages advanced technologies to enhance user autonomy and safety. By integrating a 5-channel EEG headset, LiDAR sensors, and an RNN-LSTM-based predictive model, the system accurately interprets user intent and detects obstacles in real-time. A user-friendly web interface and auditory alerts further improve usability and effectiveness.

The system's performance, as evaluated using the ISO 9241-11 standard, demonstrated high user satisfaction and effectiveness. The results indicate that the system effectively meets the needs of users, particularly in terms of ease of use, efficiency, and overall satisfaction.

Recommendations

To further enhance the accuracy of brainwave data acquisition, the use of a higher channel EEG system is recommended. While resource constraints limited the scope of this study, future research could explore the potential benefits of such a system.

Additionally, optimizing hyperparameter tuning can significantly impact the model's performance. Experimenting with different LSTM layer sizes, dropout rates, and regularization strengths may improve the balance between accuracy and recall. Moreover, varying the sequence length can enhance the model's ability to identify pertinent patterns in the data, which could increase sensitivity and precision.

Also, in terms of data augmentation, providing the model with more instances to train from, and supplementing data for classes with fewer samples may assist increase recall and the F1-score. Exploring alternative model architectures like transformer-based networks or GRUs could also lead to more effective capture of EEG patterns.

Future research in BCI should also explore different testing frameworks for evaluating BCI models. By directly analyzing raw EEG data to predict usability metrics, such frameworks can provide more objective and quantitative assessments, moving beyond traditional subjective questionnaires.

Finally, to enhance and prove its efficiency, it is recommended that the system be tested on actual quadriplegic patients. If proven effective, its implementation would represent a significant advancement in the biomedical field.

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