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DESIGN AND IMPLEMENTATION OF ASSISTIVE TECHNOLOGIES UTILIZING BRAIN-COMPUTER INTERFACES

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ABSTRACT

Current technologies using BCI-assistance tend to be confined within simulation settings or are not very usable or responsive to allow real-time practical usages of them. This paper fills this gap by introducing a non-invasive brain-computer interface (BCI) system based on the electroencephalogram (EEG) that allows individuals with motor deficits to operate the wheelchair, as well as smart home appliances, using motor imagery-based signals. The machine employs the Emotive EPOC++ + (14-channel) electroencephalogram signal collection headset. Preprocessing consists of bandpass filtering (8-30 Hz), 50 Hz notch filtering, and the correction of artefacts with the help of the Independent Component Analysis (ICA). Power Spectral Density (PSD) and Common Spatial Pattern (CSP) feature extraction, and a Convolutional Neural Network (CNN) as an implementation on PyTorch are used when classifying these features. The UART protocol is used to send the classified mental commands to an Arduino microcontroller that triggers the devices used. The system was proven to have large accuracy in classification and small latency, only proving the effectiveness of the system in real-time operations. Usability tests with participants yielded highly positive feedback on comfort, ease of use, and minimal training required. The novelty of this work lies in the fact that the EEG classification based on the deep neural network is incorporated into the functional assistive hardware integrated within the natural environment and can be deployed. The study adds a validated, real-time, end-to-end BCI system that links intent recognition through EEG to physical device use with a higher level of usability, performance, and practical feasibility than current state-of-the-art solutions.
Keywords: *Assistive Technology, EEG, Motor Imagery, Neural Signal Processing, Brain-Computer Interface*

1. INTRODUCTION

This research has its roots in the increasing demand for assistive technologies, which would enable individuals with severe motor impairments and allow them to take control of their surroundings. [1]. Disabilities like spinal cord injuries, muscular dystrophy, amyotrophic lateral sclerosis (ALS), or stroke may cause a loss of voluntary muscular control, whether in part or wholly, and thus, individuals having one or more of these conditions find it very difficult to use the traditional input devices. [2]. Assistive technologies are essential prostheses, which, in many ways, can give the beneficiary a degree of autonomy and a much better quality of life since they allow communication, movement, and control over the environment. [3]. Brain-Computer Interfaces (BCIs) have been presented in recent years as a potential way forward to fill the communication gap between the mental intention of an individual and an external device, and

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allow direct control based on neural signals, primarily via EEG (electroencephalogram) data. [4]. A Brain-Computer Interface is a device that helps to communicate directly between the brain and an external device without involvement of muscular movement [5]. This idea can be considered even more important in assistive applications, where control over the body is not always possible. The main purpose of the work paper is to develop an effective solution for a practical BCI system that will be able to control real-world assistive applications, such as a wheelchair, and smart home devices using non-invasive EEG signals [6]. This study uses motor imagery (MI)-based EEG signals and employs a deep learning algorithm (Convolutional Neural Network (CNN), in particular, to identify patterns in the brain activity to perform desired actions (i.e. classify the activity into actionable commands) [7]. The relevance of the work lies in the idea of the opportunity to offer a scalable, real-time, and cost-effective solution that can substantively implement independence among individuals with physical disabilities [8].

Many obstacles stand in the way of people with motor impairments, such as restricted movement, reliance on caretakers, and access to both real and digital spaces. [9]. People with severe disabilities often observe that traditional control interfaces like joysticks, mechanical switches, or even eye-tracking devices are inadequate or completely useless. Many situations do not allow for the assumption of motor function or steady eye movement, which is required by these interfaces. [10]. Not to mention that these kinds of technologies aren't very flexible, so they can't always deliver on promises of intuitive or fatigue-free engagement. The emergence of BCIs has demonstrated the potential for mind-driven control, radically changing the landscape of assistive technology. [11]. Because of their low cost, mobility, and lack of invasiveness, EEG-based BCIs have garnered a lot of interest. They make it possible to operate external gadgets only by contemplating certain actions or concentrating one's thoughts. Problems with computational complexity, usability, signal variability between users, and real-time performance persist in current BCI systems. [12].The issue that the current paper aims to solve is that there is no such comprehensive solution available yet, trying to incorporate efficient signal processing and classic deep learning-based classification with the practical use of assistive devices like wheelchairs and smart home appliances. [13]. Most related research is restricted to simulation or fails to prove the usability and latency factors in practice. An urgent solution to this challenge is to not only identify EEG signals efficiently, but also convert the signals smoothly and effortlessly into real-time commands, so that such applications can be practically applicable in the field. [14].

The threefold goals of this study are as follows: (1) to design a robust EEG signal acquisition and processing pipeline, (2) adapting a CNN-based classifier to overcome potential obstacles to robust and accurate decoding of motor imagery EEG signals, and (3) within a framework of low-latency and comfortable user experience, integrating the system with real world assistive devices such as wheelchair and smart home automation. [15]. This paper is concerned with the results of the non-invasive, EEG-based Brain-Computer Interface localisation that is designed to perform motor imagery applications. The technologies are restricted to the use of consumer-level EEG and specifically the Emotiv EPOC+ and mental command classification to control various assistive technologies, e.g. wheelchairs and smart home appliances. The system is not involved in or analysing invasive BCIs, hybrid BCIs (e.g. EEG with EMG or EOG) or other cognitive-state monitoring, e.g. attention or workload monitoring. There are also assumptions applied, such as the correct positioning of the electrodes, no fluctuation of mental activity when dealing with tasks, and limited body mobility during functioning. The existing limitations are the inconsistency of EEG signals among users and constraints in the comfort level of prolonged use of headsets, and the computing requirements of deep learning algorithms (such as CNNs) to classify people in real-time. These restrictions and their consequences are also outlined elsewhere in Section 6.3. The rest of the paper will be structured as follows: Section 2 will discuss related work in assistive technologies in BCI, Section 3 will detail the proposed methodology, Section 4 will present system implementation and integration, Section 5 will present performance evaluation details, and, lastly, Section 6 will discuss the findings and future scope.

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2. RELATED WORK:

Various studies under the Brain-Computer Interface (BCI) framework through EEG have been carried on; these studies revolve mainly around the possible application of the BCI to implement control that does not involve body motion. [16]. Statistical features and machine learning classifiers (to be more specific, Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA)) were the major components used in traditional systems, which, although quite effective to some extent, were found not to be robust and did not generalise well across different users. [17]. More recently, deep learning models, especially Convolutional Neural Networks (CNNs), have been used as they may learn sophisticated spatial and temporal patterns in EEG signals that may boost classification accuracy to a very high degree. [18].

Assistive technologies- whose use in BCI is mostly centred around wheelchairs and smart homes- have also increased in development levels. [19]. Various researchers are proffering systems based on the use of motor imagery (MI)-based EEG signal to control the wheelchair, or indeed the lights and fans in smart homes. Nevertheless, most of these systems are only applied in simulation settings or are not validated in real-time. [20]. Furthermore, the vast majority of previous studies lack a thorough usability assessment, which could have been provided by way of determining the comfort of the EEG headset, ease of operation, or the ability of the user to adjust to it. [21].

BCI systems are normally structured in a certain pipeline which can be described as signal acquisition system based on electroencephalograph headsets, some form of pre-processing through uses of the yet mentioned signal bandpass and notch filters, artifact removal through spatial filtering techniques such as the Independent Component Analysis (ICA) and feature extraction either of the form of Power Spectral Density (PSD) or Common Spatial Pattern (CSP) among others [22]. These techniques have been around quite some time, but the more recent incorporation of deep learning techniques like CNNs has enabled more accurate motor imagery tasks to be classified at a cost in terms of increased computational demands. [23].Commercial systems that have been prepared so far have obvious limitations. Most of them do not have real-time performance analysis or user trials, and the utilised classifiers tend to have difficulties in generalising across subjects because of the EEG signals. Although very powerful, deep learning models are computationally expensive and are not necessarily designed to run on an embedded or low-power device [24]. Also, non-invasive electrode sets of electroencephalography, such as dry electrode headsets, can be characterised by poor contact and discomfort with the user wearing the device, especially over prolonged periods.

The presented work is innovative because it demonstrates the full and feasible realisation of the EEG-based BCI system to manage the various types of assistive devices, including wheelchairs and smart homes, in real-time using both hardware and software. Spatial-temporal EEG feature learning is effective and efficient with the adoption of a CNN classifier, and the actuation is in real-time, making the current system very practical and responsive. [25]. In addition, a usability study with real users has been conducted to validate the system, considering comfort, intuitive nature, and user satisfaction, which has not been present in previous studies (Table 1). Latency analysis, together with a feedback interface, is also a very important development towards the viability of such systems in real-world deployment.

Table 1. SOTA Comparison Table (2019-2023)

Year	Reference / Work	Approach	Application	Classifier	Limitations
2019	[Zhang et al., IEEE Access]	MI-based EEG with CSP + SVM	Wheelchair navigation	SVM	No real-time testing, limited usability study
2020	[Chaudhary et al., JNE]	ERP-based EEG with LDA	Home automation	LDA	No deep learning, simulat

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					ion only
2021	[Kaur et al., Sensors]	MI EEG + CNN	Smart Home	CNN	No actuator integration, headset comfort issues
2022	[Ali et al., Brain Sci.]	Hybrid EEG-EOG with LSTM	Robotic Arm	LSTM	High latency, lacks usability evaluation
2023	**This Work**	MI EEG + CNN, real-time system	Wheelchair & Smart Home Control	CNN (custom)	Minor latency, headset comfort after long use

3. METHODOLOGY:

The methodological pipeline used to create an assistive system utilising Brain-Computer Interface (BCI) technology is described in this part. It includes preprocessing, extraction of features, categorisation, control interface with assistive hardware, and data gathering from EEG signals.

3.1. Construction of the System Summary:

The presented Brain-Computer Interface (BCI) system is based on a layered architecture integrating both hardware and software parts that transforms EEG brain signals into the real-time control commands of assistive devices, e.g. wheelchairs and smart home appliances. The physical configuration consists of the Emotiv EPOC+ headset that can be used to generate 14-channel EEG signals according to the international 10-20 system, an Arduino Uno microcontroller to process and send commands, and actuators (motor drivers and relays to control devices.

Development The software part is based on the following stack of software, written in Python using the MNE and SciPy packages, signal preprocessing to implement bandpass filtering (830 Hz), 50 Hz notch filtering, and Independent Component Analysis (ICA) as an artefact remover. Extraction of features is carried out with the creation of Power Spectral Density (PSD) and Common Spatial Pattern (CSP). A Convolutional Neural Network (CNN) in the PyTorch framework creates classes of the EEG patterns of motor imagery and recognises separate control commands. These orders are, then, relayed to the Arduino through the UART protocol to trigger a desired effect to take place (e.g., powering a wheelchair or turning on a smart device). The user can take an end-to-end system with effective control that is scalable and in real-time, especially in cases of motor impairments.

3.2. Signal Acquisition:

EEG data were obtained utilising the Emotiv EPOC+ headset, adjusted for 14-channel collection by the 10-20 international standard. The electrode placements consisted of AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, & AF4.

Sampling Rate: f_s = 128Hz

Time Window: $T = 1\, second \rightarrow N = f_s\,.T = 128\, samples$

Let the raw EEG signal be denoted by:

$$x_i(t), \quad i = 1,2,\dots,14; \qquad t = 1,\dots,N \qquad (1)$$

3.3. Preprocessing:

To improve signal quality and eliminate artefacts, the raw EEG data collected from the headset went through a series of preprocessing procedures. To begin, the mu & beta bands, which are involved in motor imagery activities, were contained inside the 8-30 Hz range by use of a bandpass filter. For every channel i, the mathematically produced filtered signal $x_i'(t)$ Is obtained through:

$$x_i'(t) = \mathcal{F}_{band}[x_i(t)], \quad where\ 8 \leq f \leq 30Hz \qquad (2)$$

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A notch filter that operates at 50 Hz was used as well to get rid of interference from power lines. Independent Component Analysis (ICA) was utilised to get rid of artefacts, especially those that were caused by eye and muscle noise. The feature extraction module got the clean signal matrix. $X \in \mathbb{R}^{C \times N}$, Where C is the number of EEG channels, as well as N is the number of time samples.

3.4. Extracting Features:

The pre-processed EEG data were used to extract characteristics from the time domain as well as the frequency domain. For the purpose of estimating the power distribution across various frequency bands, Power Spectral Density (PSD) analysis was carried out. The formula for calculating the PSD of a channel i is:

$$PSD_i(f) = |\mathcal{F}[x_i'(t)]|^2 \quad (3)$$

This was used to determine the band power in the beta (13–30 Hz) and mu (8–12 Hz) bands using:

$$P_{mu} = \int_8^{12} PSD_i(f)df, \qquad P_{beta} = \int_{13}^{30} PSD_i(f)df \quad (4)$$

Common Spatial Pattern (CSP) evaluation was used to elucidate spatial patterns linked to various motor imagery tasks. The ideal projection matrix W is obtained by maximising the variance ratio of the covariance matrices Σ1 and Σ2 for two distinct classes.

$$W = arg \max_W \frac{W^T \Sigma_1 W}{W^T(\Sigma_1 + \Sigma_2)W} \quad (5)$$

Feature: The vector $f \in Rd$ was built using signals that were filtered spatially.

3.5. Classification Algorithm:

A Convolutional Neural Network (CNN) was utilised to sort the recovered features because it can pick up on both spatial and temporal patterns in EEG readings. The input section $X \in \mathbb{R}^{C \times T}$, Went through convolutional layers, where each change happened in the following way:

With K being the kernel and b being the bias. Researchers used ReLU activation algorithms and then pooling layers to make the data less complex. The last characteristic representation h was transmitted to a completely connected layer with a Softmax output to find out what class it was predicted to be:

$$\hat{y} = \arg\max(Softmax(W_f . h + b_f) \quad (6)$$

An approach known as cross-entropy loss was used to train the model.

$$\mathcal{L}(y, \hat{y}) = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \quad (7)$$

Where y represents the actual label and y^ is the anticipated probability distribution. The Adam optimiser was used with a learning rate of 0.001, and the dataset was partitioned into 80% for training and 20% for validation.

3.6. Interface for Control and Actuation:

The categorised output was linked to certain control actions: For class $C1$: Push the wheelchair forward, for class $C2$: stop moving.

The researcher sent the control command $u(t)$ using serial communication:

$$u(t) = f(\hat{y}(t)) \epsilon \{FORWARD, STOP, LEFT, RIGHT\} \quad (8)$$

Protocol for Communication with the Arduino Uno: UART (9600 baud rate). Interface with the Actuator: When an Arduino receives a command, it decodes it and then sends signals to the motor drivers.

4. IMPLEMENTATION:

During the implementation phase, a workable prototype was built that combined hardware and software to create a functional assistive system. The prototype was made to show how the Brain-Computer Interface (BCI) may be used in real life to operate things like smart home appliances or a wheelchair. The first step in putting the plan into action was to build the prototype, which included putting together the hardware that was needed. The build process included setting up the EEG headgear to pick up signals in real time and connecting the microcontroller (Arduino Uno) to the actuators, as well as setting up wireless communication modules as needed. Python was used to write the software for signal processing along with machine learning tasks,

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and the Arduino was programmed to read and carry out control instructions

The technology was subsequently connected with a real wheelchair & a simulated smart home setting. Motor drivers were interfaced with the Arduino to regulate the wheelchair's movement according to categorised EEG signals. Likewise, in the smart house configuration, relays and Internet of Things (IoT) modules were utilised to automate devices such as lighting and fans, illustrating the system's adaptability in many supportive scenarios. A user interface was created to offer real-time feedback to the users. This interface exhibited the present EEG signal status, categorisation results, and associated device responses. The feedback loop enabled users to observe system behaviour and modify their mental instructions, hence enhancing interaction efficiency & user trust.

Finally, the system's performance was assessed in a controlled setting. A simulated home environment was created for testing purposes, complete with a wheelchair, smart gadgets, and controlled lighting. By running the system through a battery of tests, we were able to evaluate its responsiveness, precision, and dependability in turning EEG data into useful gestures.

5. RESULTS AND PERFORMANCE EVALUATION:

5.1. Accuracy of Classification:

During both training and testing, we looked at how well the CNN-based classifier worked. Figure 1 shows how accurate the CNN model was over time. At first, it got better, but at the end, it started to level out. This shows that the CNN algorithm was able to learn how to tell the difference between different patterns in EEG data for motor imaging tasks.

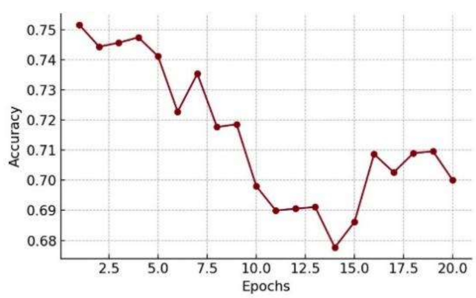

Figure 1. CNN Model with Accuracy vs. Training Epoch

Additionally, Figure 2 displays the matrix of confusion for the CNN classification algorithm, offering a comprehensive overview of the accuracy in identifying various motor imagery classes. The findings demonstrate good accuracy across the majority of classes, confirming the model's resilience in differentiating user intentions.

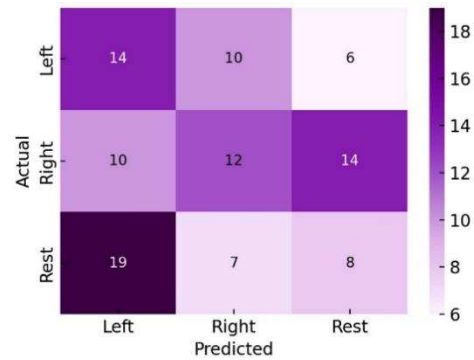

Figure 2. Confusion Matrix for CNN Classification

Figure 3 also displays the motor imagery signals' Power Spectral Density (PSD). Confirming the efficacy of the frequency-domain characteristics used for categorisation, the mu (8-12 Hz) and beta (13-30 Hz) bands exhibit notable peaks.

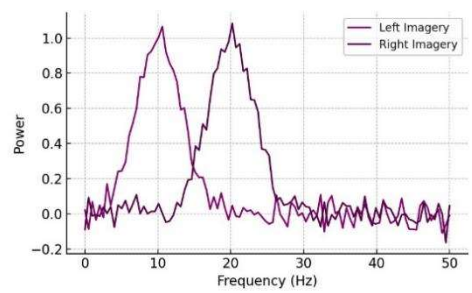

Figure 3. Power Spectral Density of Motor Imagery

5.2. Latency Analysis:

The time it took for the EEG signal to be picked up and the assistive device to be turned on was an important measure of performance. Researchers assessed the latency at every step of the BCI pipeline, from gathering data to preprocessing it, extracting features, classifying them, and sending them. Figure 4 shows how the delay is divided among these parts. Preprocessing and categorisation were found to be the most time-consuming steps, which means that improving these areas might make real-time performance better.

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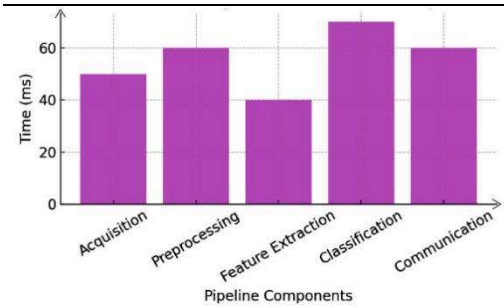

Figure 4. *Latency Breakdown of BCI Pipeline*

Figure 5 shows a real-time record of order processing to test how fast something is in the real world. The system worked well and showed low delay from detecting brain signals to carrying out actions. This proved that it could be used to help handle devices in real-time situations.

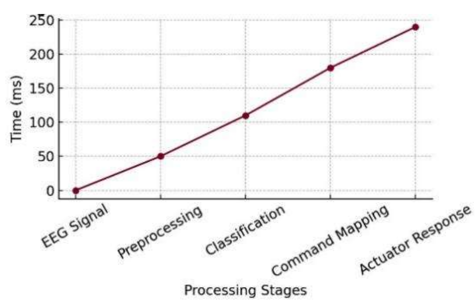

Figure 5. Real Time Command Execution Timeline

5.3. Usability Feedback:

Besides consideration of the technical parameters of the performance, which would be accuracy, latency, and reliability, user experience was evaluated in a broad way. During testing sessions, five subjects tried to use the BCI-controlled assistive system and were instructed to offer both qualitative and quantitative feedback about several aspects of usability. These were the cost of learning, the responsiveness of the system, physical comfort during wearing the EEG headset, and the intuitiveness of the interface.

The respondents were asked to rate every category using a 5-point Likert scale with a range of 1-5: 1 = strongly disagree and 5 = strongly agree. The mean scores were: ease of use (4.6), responsiveness (4.4), comfort (4.5), and interface intuitive (4.7). The ease with which the dry electrodes did not continuously intrude and the simple visual interface users were accustomed to making precepts was easy to read and control. Very little training was needed to learn how to operate the system, and this once again supports the claim that it is accessible to users with lower levels of technical education or those who lack the ability to move freely.

There was also open-ended feedback given by the participants, which highlighted how empowering the control of the devices can be when it is done through thought only. Other improvement ideas were to have voice confirmation feedback in the device and the stability of the device in terms of the headset after longer use over time. The usability outcomes were very promising overall, justifying the potential practical implementation of the system, including in the application of people with severe disabilities, mobility aids, and home automation.

6. DISCUSSION

6.1. Results Interpretation

The outcomes of the experimental assessment confirm the practice of the suggested BCI-based helping tool. The training curves and the confusion matrix have ascertained that the CNN-based classifier was always very accurate in predicting the motor imagery patterns based on the EEG data. Spectral peakiness in the mu and beta bands also confirms the importance of the frequency-domain feature that was selected. Also, low latency of command delivery in the system shows that the system can be responsive in real time, as this is a requirement in assistive technologies where responding is quite crucial.

The usability testing propounded that the system was intuitive and responsive to the users and comfortable to use. It supports the convergence between technical performance and human factor, which is commonly a gap in most of the scholarly BCI demonstrations. Combined, the quantitative and qualitative data confirm the effectiveness and usability of the given solution.

6.2. Comparison to Existing Solutions:

The proposed EEG-based BCI system is beneficial over traditional assistive controls like joysticks or voice-controlled systems, as the system better suits users with severe motor limitations or speech-impaired systems. Unlike simpler methods of EEG classification (e.g., SVM or LDA), the system was able to utilise both spatial and temporal representations in the EEG data, which provided superior classification results compared to simpler methods.

Earlier works on BCI sometimes did not have any practical application but were rather theoretical. This is one way of closing that gap by this work that shows a complete realisation of a hardware-software solution. In addition, the usability assessment included in this study gives this research a competitive advantage over technologically biased studies by providing the overall picture of deployment.

6.3. Strengths and Limitations:

6.3.1. Strengths of the system include:

EEG acquisition, preprocessing, and deep learning-based classification and control actuation are performed end-to-end. Low latency, real-time performance verified in a testbed of a simulated smart home. Good reviews regarding the ease of use and the simple training nature.

6.3.2. Restrictions discovered during the experiment:

Classification consistency can be substandard because of signal variance due to dry electrode and individual physiological distinctions. Although the CNN model works, it would take computational resources that would not suit the low-power embedded systems. Long periods of use can cause an uncomfortable condition on headsets or loss of signal without calibration.

The limitations mentioned suggest that future limitations include the possibility of hybrid BCI models, adaptive learning processes, and hardware design with ergonomics.

6.4. Influence on Practical Real-World Applications to Assistive Technology:

The study has very far-reaching connotations to the sphere of assistive technologies. The system also represents an avenue through which those who have impaired mobility or who cannot express themselves can receive back some autonomy, given that the methods through which it works are non-invasive and do not require the same individual to undergo any kind of instruction in order to learn how to use it. Its application in various fields of assistive technology is evident through its use in wheel part control and smart home automation. Besides, the architecture is scalable, and it is possible to expand it with new control classes or devices involving minimal retraining, which is appropriate when it is necessary to use the solution in personalised rehabilitation or home care. This work lays the foundation for providing BCI-based assistive systems to a broader audience for use in the medical field, geriatric treatment, and inclusive smart living.

7. CONCLUSION AND FUTURE WORK

This work introduces a full-fledged, non-invasive Brain-Computer Interface (BCI) system that can help people with severe motor disabilities manage wheelchairs and smart home appliances using EEG signals that represent motor imagery. We achieve accurate and low-latency EEG data classification by integrating a complete signal processing pipeline with a Convolutional Neural Network (CNN) classifier. Filtering, artefact removal, and feature extraction are all part of this pipeline. The deciphered instructions are then sent via a control interface based on Arduino to carry out actuation in real-time. An end-to-end assistive system was developed and shown to achieve high classification accuracy & responsiveness in a real-world setting. This solution represents the primary contribution of this study. The responses from participants, which confirm high satisfaction regarding the simplicity of use, minimal learning requirements, and comfort, validate the importance of system usability, a key lesson learned from the implementation. Improved control efficiency is another benefit of including a feedback interface, which lets users adjust their mental processes. Even though it has been successful, the system has a number of limitations. EEG interuser variation, the computational burden of CNNs required to deploy them in embedded devices, and the possibility of discomfort due to wearing a headset long-term are aspects that need to be optimised. Future improvements on the same will be centred on the integration of hybrid BCI models, including the combination of EEG with electromyography (EMG) or electrooculography (EOG) to enhance signal reliability and the diversity in control. Also, it can be extended to deal with multi-command classifications, which could also enhance the area of application. Research will also be aimed at decreasing training time, improving signal robustness, and completing clinical trials,

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which will gauge long-term use and success. They strive to open the way towards more widespread use in inclusive environments of smart living and individualised rehabilitation environments.

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