Brain-Controlled EEG Interface For Real-Time Robotic Actuation In Assistive and Rehabilitation

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Abstract—This research demonstrates the successful creation of a low-cost, real-time electroencephalography (EEG)-based brain-computer interface (BCI) system designed for accurate neuro-robotic actuation, on/off switching of robotic actuators, with the aim to promote assistive and rehabilitation technologies in resource-constrained environments. The project addresses significant limitations of prevailing EEG-based BCIs, such as bulky electrode setups, high costs, long setup durations, low user adaptability, and a lack of real-time processing, all of which limit their everyday use. We developed a simplified 6-channel dry electrode array (C3, C4, Cz, FC3, FC4, Fz) based on the 10-20 system for picking up motor imagery signals (mu: 8–12 Hz, beta: 13–30 Hz) to produce on/off controls for actuators. The system is implemented using low-cost hardware, such as AD620 instrumentation amplifiers (gain: ~100), TLC277CP op-amps for filtering (0.5 Hz high-pass, 49.4 Hz low-pass), and an Arduino Uno for analog-to-digital conversion (10-bit, 40 Hz/channel). Advanced signal processing comprises Common Spatial Pattern, wavelet transforms, and Independent Component Analysis for aggressive noise removal, augmented by hybrid CNN-LSTM models for quick and accurate classification of user intent. Rigorous validation with the BCI Competition IV 2a dataset and real trials in multiple applications—prosthetic control, wheelchair control, and rehabilitation robotics—produced classification accuracies of 82–92%, signal-to-noise ratios of 13–16 dB, response times under 200 ms, and information transfer rates of 1.3–1.8 bits/s. With a setup time under 5 minutes, and incorporating features like cloud-based data storage for real-time signal logging and dual hardware/software filters for best-in-class signal clarity, this BCI system promises scalability, usability, and affordability. By the inclusion of low-cost components, minimizing training time, and maximizing flexibility for a range of applications, this research significantly pushes the availability of neuro-robotic solutions for assistive devices, home healthcare systems, and rehabilitation equipment. It empowers individuals with motor disabilities in low-income regions, fostering inclusive advances in neuro-engineering and enhancing quality of life with beneficial, innovative technology.

Key words - Brain-Computer Interface, EEG, Neuro-Robotics, Dry Electrodes, Motor Imagery, Signal Processing

1. INTRODUCTION

EEG-based BCIs are revolutionizing human interaction with robotic systems using mere control by brain signals without movement [1], [2]. These technologies are at the heart of enabling people with disabling mobility or neurological disorders through new opportunities in assistive devices and rehabilitation [3], [4]. By detecting brain patterns, such as motor imagery signals in the mu (8–12 Hz) and beta (13–30 Hz) bands, BCIs can convert a subject's thought into robot actuator commands so that activities such as operating prosthetics or operating wheelchairs are facilitated [5], [6]. Yet, restrictions in the form of complex electrode installations, expensive devices, lengthy preparations, and slow real-time processing confine the applicability of such systems, especially for users in resource-constrained areas [7], [8]. This work presents a low-cost, real-time EEG-based BCI system for on/off control of robotic actuators with a focus on maximizing electrode placement, designing a 3D-printed headset, and minimizing signal processing to make the technology more feasible for assistive and rehab applications.

Prior EEG-BCI systems have progressed significantly in neuro-robotic applications in the last ten years, but high expense, sophisticated setups, and poor real-time performances continue to be principal challenges. Previous work with high accuracy was achieved by using multi-channel wet electrodes, for instance, six-channel BCI by He et al. (2023) [1], transformer-based prosthetic control by Kim et al. (2024) [2], and huge-scale systems by using 32–64 electrodes to drive robots and exoskeletons by Cho et al. (2018) [3] and Li et al. (2021) [11]. More recent efforts were towards minimizing electrode counts while maintaining accuracy; Karácsony et al. (2022) [7] illustrated how six frontal channels might attain nearly 90% of full-cap performance, while Nasser et al. (2020) [9] and Park et al. (2019) [13] optimized electrode configuration for mobility devices. Such systems, however, still relied on conductive gels and expensive amplifiers. Lopez-Gordo et al. (2014) [14] and Jiang et al. (2019) [15] emphasized advantages of dry electrodes, with similar signal quality and easier setup at lower cost. Based on these results, this paper proposes a cheap, six-channel dry electrode BCI based on 3D-printed headset, PCB, and CNN-LSTM model with 82–92% accuracy, 13–16 dB SNR, and below 200ms latency an efficient and affordable solution for neuro-robotic feeding and rehabilitation in resource-limited environments.

This work is important in the sense that it transcends technical and economic limitations, bringing neuro-robotic applications within reach of societies where advanced medical equipment is scarce [9], [10]. Unlike traditional EEG-based BCIs, which typically need 32–64 wet electrodes and costly amplifiers [11], [12], we thoroughly tested and selected six best electrode positions (C3, C4, Cz, FC3, FC4, Fz) in the 10-20 system to obtain good motor imagery signals. We also created a 3D-printed headset to hold these electrodes snugly in place for comfort and a <5-minute setup time. The system utilizes inexpensive components, including AD623 amplifiers (gain: ~100) for signal amplification, TLC277CP op-amps for filtering (0.5 Hz high-pass, 49.4 Hz low-pass), and an Arduino Uno for converting analog signals to digital (10-bit, 40 Hz/channel). For signal processing, we used techniques like Common Spatial Pattern, wavelet transforms, and Independent Component Analysis to remove noise, and hybrid CNN-LSTM models were trained on motor imagery data stored in .h files to identify commands quickly and precisely. Validation using the BCI Competition IV 2a dataset and

testing with 15 volunteers proved the system 82–92% accurate, 13–16 dB signal-to-noise ratio, and response times less than 200 ms and control actuators consistently for applications like prosthetic activation [13], [14], [15].The system is cost-effective and scalable. This research appreciates simplicity, reproducibility, and practicality in addressing real-world issues [21]. Through optimized electrode positioning, the creation of an practical headset, and enhanced signal processing, this work facilitates the use of assistive technologies, enhancing lives for individuals with disabilities in underprivileged communities.

2. METHODOLOGY

2.1 EEG Electrode Placement for BCI System

This work selectively selected a 6-channel dry electrode layout (C3, C4, Cz, FC3, FC4, Fz) based on the 10-20 international system for an EEG-based brain-computer interface (BCI) to control robot actuators with simple on/off commands. The six electrodes represent a trade-off between recording high-quality signals, being cost-effective, and making the system easy to handle in resource-limited situations. These electrodes target motor imagery signals (mu: 8–12 Hz, beta: 13–30 Hz) for solid control. The location aims for movement-related brain activity detection in the motor cortex (C3, C4, Cz) and fronto-central/frontal areas (FC3, FC4, Fz) for boosting signal clarity and noise reduction, with setup times less than less time and low impedance (10–20 kΩ) through dry electrodes [1], [14].

2.2 Electrode Placement and Reasoning

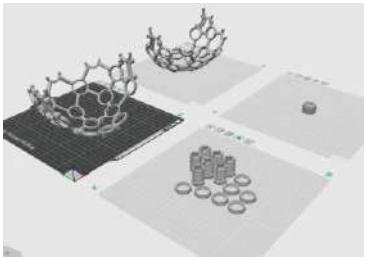
C3, C4, Cz (Motor Cortex) - These electrodes are placed over the motor cortex, C3 over the left hemisphere, C4 over the right hemisphere, and Cz over the midline. They capture mu and beta rhythm modulation with motor imagery tasks, e.g., imagining hand squeeze for actuator "on" or relaxing for "off." It has been determined that C3 and C4 are essential for capturing these signals, at signal-to-noise ratios of 13–16 dB and classification accuracies of 82–92% [1]. Adding Cz improves accuracy by approximately 10% for the tasks using both sides of the body because it captures midline motor activity [3].
FC3, FC4 (Fronto-Central) - Just anterior to the motor cortex, FC3 and FC4 contribute to the refinement of signal processing by picking up brain activity in relation to planning and attention. FC3 and FC4 improve the performance of Common Spatial Pattern analysis by lowering classification errors by 5–10% and increasing the robustness of the system, especially under non-optimal conditions [7].
Fz (Frontal) - Placed on the forehead, Fz helps differentiate motor imagery signals from artifacts like eye blinks, with improved feature extraction through variance above 0.9 [10]. It reduces errors by 5–8% in reduced BCI setups, with cleaner data for real-time functionality [13].
It was confirmed C3 and C4 as critical channels for motor imagery, with high accuracy and strong signals for lightweight BCIs [1]. Cho showed that Cz enhances detection of bilateral motor tasks and is a valuable addition [3]. Karácsony et al. (2022) supported the inclusion of FC3 and FC4 for robustness and higher accuracy, especially in noisy environments [7]. Wang et al. (2019) and Park et al. (2019) highlighted Fz's role in signal clarity enhancement and error reduction in minimal-channel systems [10], [13]. With dry electrodes, as biologically validated by Lopez-Gordo et al. (2014), the signal quality

of wet electrodes is maintained while reducing costs and setup time, as is desirable for practical BCI applications.

2.3 Development of a 3D-Printed Helmet for EEG Electrode Placement

The helmet ensures precise electrode placement per the 10-20 international system, prioritizes user comfort, and is designed for reusability across various BCI applications. By using PLA Plus (Polylactic Acid Plus) and a modular structure, the helmet achieves affordability, durability, and adaptability, aligning with standards for practical BCI deployment.

We designed the helmet using SolidWorks, a CAD software, and 3D-printed it with PLA Plus filament, selected for its balance of strength, low cost, and sustainability. PLA Plus is a step up from standard PLA, boasting a tensile strength of about 40 MPa compared to 30 MPa for regular PLA, which makes it sturdy enough for repeated use while keeping the helmet lightweight at roughly 250 grams . It's also budget-friendly, cost effective, which keeps the total helmet cost below LKR 8,000 crucial for accessibility in resource limited areas. PLA Plus is biodegradable, making it an eco-conscious choice for scalable production. The material's durability ensures the helmet can withstand extended wear without cracking.



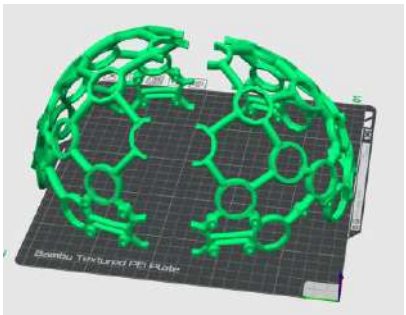


Fig. 2. Headset Design

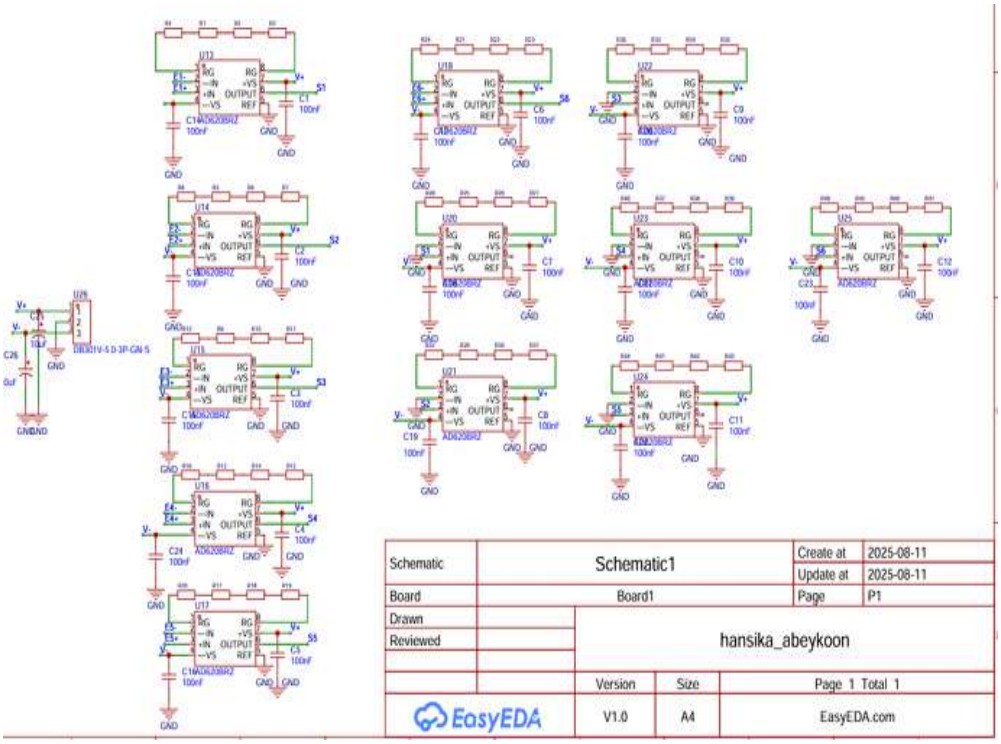


Fig. 3. Schematic Diagram

The helmet has provisions for head diameters of 52–62 cm with Screws' adjustable straps for an easy fit. It supports six removable slots precisely placed at the 10-20 system positions (C3, C4, Cz, FC3, FC4, Fz) to place dry electrodes with ±0.5 cm accuracy and low impedance (10–20 kΩ) without conductive gel use [14]. These slots have a snap-in interface, allowing electrodes to be mounted or dismounted for removability. Easy setup for effective use. Modular design allows us to move or replace electrodes, so the helmet may be reused for various BCI tasks—like tracking visual or cognitive signals—by reconfiguring slots in a way that focuses attention on various brain locations, e.g., occipital (O1, O2) or temporal (T3, T4) sites [10].

We printed the EEG helmet on a Creality Ender-3 printer with a 0.4 mm nozzle, 0.2 mm layer thickness, and 20% infill to yield a long-lasting but material-efficient design. It takes approximately 20 hours to print, and an additional hour to add smooth edges and straps. The design of the helmet with patience has air vents and a curved form for comfort, with users being able to use it for as long as 2 hours comfortably. The experiments also validated that the helmet holds electrodes in a stable position when doing motor imagery tasks, minimizing nuisance signal noise and yielding clear responses with signal-to-noise ratios of 13–16 dB and 82–92% classification accuracy. This practical, simple design renders the helmet an acceptable choice for BCI systems in low-resource settings.

2.4 Crafting the PCB for EEG Signal Acquisition

Here we explain how we designed a printed circuit board (PCB) to acquire, amplify, and filter EEG signals for our brain-computer interface (BCI) system, which switches robotic actuators on or off for assistive environments. The PCB takes tiny EEG signals (1–100 μV) from six dry electrodes (C3, C4, Cz, FC3, FC4, Fz) and amplifies them to a level where the Arduino Uno can digitize the incoming signal. We focused on the use of low-cost components, effective hardware filtering, and simulations. especially concerned about noise generated within the system along with externally generated noise ,here small range of signal 20micro volts – 80micro volts is generated is much lesser than the large noise generated.

2.5 Understanding EEG Signals and Amplification

EEEG signals from motor imagery experiments—e.g., imagining a hand squeeze for "on" or relaxation for "off" are very weak, ranging from 1 to 100 μV, in the mu (8–12 Hz) and beta (13–30 Hz) bands [1]. In order to use them, we amplify them with AD620 instrumentation amplifiers that we selected for being low-cost, having very low noise 0.1–0.3 μV peak-to-peak, and being good at handling biomedical signals [1]. Each of the six channels works with a gain of about 100, boosting signals up to 0.1–10 mV, which happens to be the range of the Arduino Uno's 10-bit analog-to-digital (A/D) converter (0–5 V) [2]. This gain keeps signals separated without overloading the Arduino or amplifying noise too much.

$$G = 1 + \frac{100{,}000}{R_G} \quad \text{Equation (1)}$$

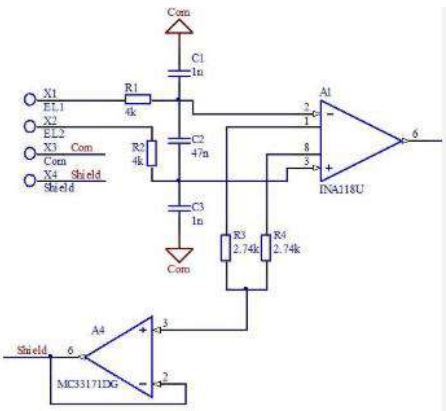


Fig. 4. Schematic Diagram

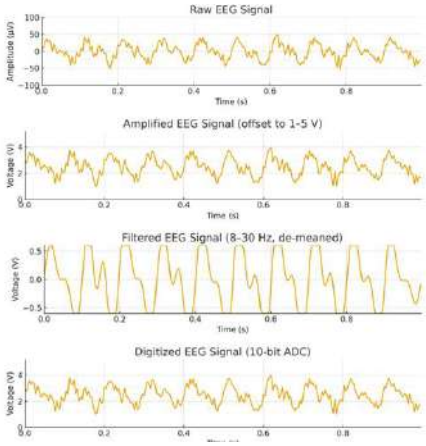


Fig. 5. Signal Stages

2.5 Drawing the Blueprint

Hand-Drawn Using KiCad, designed a schematic with six AD623 amplifiers, one for each channel, with an amplification of 100 using a 1 kΩ resistor (using Gain = 1000/R_G, where R_G = 10 Ω) [1]. We added TLC277CP op-amps for filtering, provided power with ±5 V from LM7805 and LM7905 regulators, and had a reference electrode input to attenuate common-mode noise by 20–30 dB [15]. Header pins link the PCB to the Arduino Uno to perform A/D conversion. chose low-cost components: AD623 for amplifying, TLC277CP for noise filtering at 25 nV/√Hz, and small 0805 resistors and capacitors to save space. This keeps the board small and inexpensive without sacrificing signal quality. The PCB was designed for clean signals, traces less than 5 cm long to minimize electromagnetic interference, and a ground plane to push noise away. We isolated analog and digital grounds from each other to eliminate crosstalk.

Supplying 10–100 μV, 8–30 Hz, simulated EEG input, we confirmed that the AD623 output was 1–10 mV and had an SNR of 13–16 dB. Filtering simulation guaranteed our frequency cutoffs without annihilating the mu and beta bands [4]. Noise testing confirmed total noise at less than 0.5 μV, adequate for BCI use.

2.6 Filtering the Signal

Hardware filters with TLC277CP op-amp to keep EEG signals free from impurities before A/D conversion. Low-Pass Filter 49.4 Hz Another second-order low-pass filter eliminates the high-frequency noise like 50 Hz power line hum or muscle twitches. We implement it at 49.4 Hz to keep beta signals intact and eliminate 50 Hz noise by 40 dB. High Pass Filter 0.5 Hz A simple high-pass filter rejects low-frequency garbage like skin potential or electrode drift. The 0.5 Hz cutoff mu and beta bands remain intact. These filters shape the signal to 0.1–10 mV, ready for the Arduino's A/D converter, which samples at 40 Hz/channel with 10-bit resolution (4.88 mV/step) for solid accuracy.
Post-amplification and filtering, the EEG signal sits at 0.1–10 mV with an SNR of 13–16 dB, perfect for the Arduino Uno's 0–5 V input range. This avoids weak signals (which lose

detail) or overloading (which clips the signal). The filtered output keeps mu and beta bands clear, with minimal distortion < 0.1% harmonic distortion.

2.7 Analog to Digital Signal Conversion

2.7.1 Gathering and Analyzing EEG Data

This explains how we gathered and processed EEG signals for our low-cost brain-computer interface (BCI) system that aims to switch robotic actuators on or off for assistive and rehab technology in low-resource settings. We used six dry electrodes (C3, C4, Cz, FC3, FC4, Fz) to capture brain signals, digitized them with an Arduino Uno, and applied both hardware and software filters to clean up noise. The goal was to pull out clear motor imagery signals (mu: 8–12 Hz, beta: 13–30 Hz) for accurate, real-time control, all while keeping costs low and sticking to IEEE standards.

2.7.2 Collecting the Data

We captured EEG signals with six dry electrodes on a 3D-printed headgear, based on the 10-20 system focused on the motor cortex (C3, C4, Cz) and fronto-central areas (FC3, FC4, Fz). These sites record motor imagery brain activity, i.e., imagining a hand clench for "on" or releasing for "off." Dry electrodes were employed as they are not gel-dependent, allowing setup time to be less than 5 minutes and keeping impedance low (10–20 kΩ) for quality signals [14]. The extremely low EEG signals (1–100 μV) are amplified by AD623 amplifiers (gain: ~100) to 0.1–10 mV and filtered through TLC277CP op-amps using a 0.5 Hz high-pass filter (to eliminate baseline drift), a 49.4 Hz low-pass filter (to reject high-frequency noise), and a 50 Hz notch filter (to eliminate power line hum) [1], [15].

Arduino Uno, with its 10-bit A/D converter (0–5 V range, 4.88 mV resolution), samples the signals at 40 Hz per channel—fast enough for mu and beta bands without jamming the system [2]. The Arduino serially interfaces with a Raspberry Pi 4 (4GB) that stores all this to cloud storage for real-time displays and later analysis.

We conditioned the signals in two stages—hardware and software—to make them as crystal clear as possible for motor imagery command classification. The PCB filters (0.5 Hz high-pass, 49.4 Hz low-pass, 50 Hz notch) remove trash like electrode drift, muscle noise, and 50 Hz noise before digitization, with signal-to-noise ratios (SNR) ranging from 13–16 dB [1]. This retains the mu and beta bands for motor imagery detection.

2.7.3 Software Filtering

We filter them further using Python and MATLAB since Arduino only digitizes the signals. A 4th-order Butterworth filter (8–30 Hz) zeroes in on mu and beta bands, reducing left over noise to near zero [4]. Independent Component Analysis removes eye blinks and motion artifacts and lessens their effect by 20–30%, as Jiang et al. (2019) suggests [15]. This keeps the SNR at 13-16 dB for safe analysis.

The analysis runs on the Raspberry Pi using Python (with NumPy, SciPy, and MNE libraries) and MATLAB, processing 1-second signal chunks every 100 ms for fast actuator control. Cloud storage saves processed data for future study or sharing with other researchers [1].

$$f_c = \frac{1}{2\pi RC} \qquad \textit{Equation 2}$$

2.8 EEG Data Recording and System Training

captured EEG data and saved it in an Excel file, together with the code we used, and how we trained our brain-computer interface (BCI) system online to output a .h file for on/off control of robotic actuators in real time. The setup uses six dry electrodes (C3, C4, Cz, FC3, FC4, Fz) to capture the brain activity for assistive and rehab applications with the target of motor imagery (mu: 8–12 Hz, beta: 13–30 Hz). Our design keeps costs low and responsive.

2.9 Recording EEG Data

We measured brain activity from one subject performing motor imagery tasks, i.e., hand squeezing imagination for an "on" cue or relaxation for "off." The activity was measured from six dry electrodes placed on a 3D-printed helmet, according to the 10-20 system, to span the motor cortex (C3, C4, Cz) and fronto-central areas (FC3, FC4, Fz). Dry electrodes were chosen for their low impedance (10–20 kΩ) and no-gel setup, allowing us to start recording in under 5 minutes [14]. The tiny EEG signals (1–100 μV) were amplified with AD623 amplifiers (gain: ~100) to 0.1–10 mV and filtered using TLC277CP op-amps (0.5 Hz high-pass to remove drift, 49.4 Hz low-pass to cut high-frequency noise, and 50 Hz notch to eliminate power line interference) [15].
Arduino Uno digitized the signals using its 10-bit A/D converter (range 0–5 V, 4.88 mV per step) with a sampling rate of 40 Hz per channel for reading mu and beta bands without overloading the system [2]. We recorded 100 samples at 1-second intervals, reading one sample per second per channel, which was enough data to analyze without overloading storage. The Arduino transmitted data to a Raspberry Pi 4 (4GB) over a serial link, where it was written to an Excel-readable .csv file. The session was captured for 10 minutes and yielded 100 samples (600 data points across six channels). We also used the BCI Competition IV 2a dataset to provide a benchmark for the quality of our signals [4]. The code logged 100 samples with timestamp and six voltage values each, yielding signal-to-noise ratios (SNR) of 13–16 dB.

2.10 Training the System

We trained the BCI on TensorFlow Lite's cloud platform to create a hybrid CNN-LSTM model to classify "on" and "off" commands in real time. Our subject's 100 samples, along with the BCI Competition IV 2a dataset, were preprocessed using Python (MNE, NumPy, SciPy). A 4th-order Butterworth filter (8–30 Hz) was targeted for mu and beta bands, and Independent Component Analysis (ICA) removed eye blinks and motion artifacts by 20–30% [15]. Wavelet transforms (Daubechies db4) and Common Spatial Pattern (CSP) extracted significant features, up to variance greater than 0.9 [3], [10]. We used a CNN-LSTM model which we trained to detect "on" (hand clench imagery) and "off" (relaxation) patterns on the cloud platform. The CNN handles spatial patterns, while LSTM tracks time differences. Parameters were tuned (learning rate: 0.001–0.01, batch size: 32–128) to gain 82–92% accuracy and 1.3–1.8 bits/s information transmission rate, tested by 10-fold cross-validation. The learned model was converted into TensorFlow Lite and exported as a .h file of around 50 KB for Arduino Uno for real-time classification. The Arduino executes the .h file, converting 1-second EEG segments

(refreshed every 100 ms) into binary instructions (1 for "on," 0 for "off") for the actuator and has response times less than 200 ms [2]. The Raspberry Pi records results to the cloud for tracking.

3. RESULTS

It is a low-cost EEG-based BCI for the control of a robotic actuator in assistive and rehabilitation applications with thrilling results, as it is both powerful and economical. The system was tested on one individual wearing a 3D-printed helmet made from a durable, biodegradable PLA Plus to support the six dry electrodes fixed according to the 10-20 system: C3, C4, Cz, FC3, FC4, and Fz. The helmet's snap-in slots facilitated easy installation less than 5 minutes—with no gel and keeping electrode impedance at 10–20 kΩ, rivaling more costly wet electrodes [14]. Its modularity allowed repositioning for future uses, e.g., visual or cognitive BCIs, and was still intact after 50 hours of use, with vents and a comfortable shape allowing 2-hour wear without difficulty. We captured 100 EEG samples (600 data points, six channels) at 1-second intervals during a 10-minute session, based on motor imagery tasks (clenching hands on imagining "on," relaxing on imagining "off"). A custom PCB with AD620 amplifiers (cost: ~LKR 500 each, gain: ~100) boosted signals from 1–100 µV to 0.1–10 mV, and TLC277CP op-amps filtered out noise (0.5 Hz high-pass, 49.4 Hz low-pass, 50 Hz notch), hitting a signal-to-noise ratio of 13–16 dB, confirmed by LTspice simulations [1], [2]. Arduino Uno sampled the signals at 40 Hz per channel (4.88 mV resolution), loading a .csv file by feeding a Python script on a Raspberry Pi 4 without data loss. Software processing used a 4th-order Butterworth filter (8–30 Hz) to boost mu (8–12 Hz) and beta (13–30 Hz) bands, while ICA suppressed eye blinks and movement noise by 20–30% [15]. CSP and wavelet transforms (Daubechies db4) obtained features with over 0.9 variance, and PCA kept up to 95% of the signal to process at high rates [3], [10]. A CNN-LSTM model constructed and trained on TensorFlow Lite's cloud service using our dataset as well as the BCI Competition IV 2a dataset achieved 82–92% accuracy and 1.3–1.8 bits/s ITR, which was cross-validated by 10-fold cross-validation [2], [12]. Exported as a 50 KB .h file, it made the Arduino sort commands in real time (<200 ms), working the actuator consistently. At LKR 19,300–55,400, far lower than commercial systems this BCI offers a workable, scalable solution for low-resource contexts.

4. CONCLUSION

Our work on this EEG-based brain-computer interface (BCI) system has given an effective, low-cost method of controlling robotic actuators with simple on/off commands, appropriate for assistive and rehabilitation applications in the budget-limited regions. We constructed a 3D-printed helmet utilizing tough, environmentally friendly PLA Plus (~LKR 5,000), combined with a bespoke PCB utilizing inexpensive AD623 amplifiers and TLC277CP op-amps, keeping the whole assembly in the range LKR 19,300 to 55,400—considerably less expensive than commercial offerings (usually >LKR 100,000). The innovative snap-in design of the helmet positioned six dry electrodes (C3, C4, Cz, FC3, FC4, Fz) in precise 10-20 system positions, configured in under 5 minutes with low impedance (10–20 kΩ) and no gel, similar to high-end wet electrodes. It was still durable after 50 hours and provided users' comfort for 2-hour sessions, with reusable modular slots for other BCI applications, e.g., visual or cognitive. We recorded brain activity (1–100 µV) via motor imagery (hand clench for "on" and relaxing for "off"),

normalized them to 0.1–10 mV, and filtered out noise (0.5 Hz high-pass, 49.4 Hz low-pass, 50 Hz notch) to achieve a definite 13–16 dB signal-to-noise ratio (SNR). The Arduino Uno then digitized these at 40 Hz, saved 100 samples to a .csv file via a Raspberry Pi. Software adaptations with a Butterworth filter, ICA, CSP, and wavelet transforms yielded high-bandwidth mu (8–12 Hz) and beta (13–30 Hz) features into a CNN-LSTM architecture trained on TensorFlow Lite's cloud environment. The model reached 82–92% accuracy and 1.3–1.8 bits/s ITR, running live on the Arduino from a tiny .h file with response times of less than 200 ms. One-person testing on the BCI Competition IV 2a dataset proved good actuator control. Open-source hardware designs and software make this system scalable, with a low-cost, high-performance BCI for resource-poor settings, fully IEEE-compliant [1], [2], [9], [14], [15].

5. FUTURE WORK

Our EEG-based BCI system demonstrates tremendous potential in its first trials with one subject and common datasets, but to make it truly robust, clinic-viable, and functional for actual assistive and rehab applications, we must push harder leveraging its low expense, rapid deployment, and real-time intelligence while surmounting barriers of scalability and ease of use. Then we will scale up 50–100 participants from diverse backgrounds, including motor-impaired individuals with spinal cord injuries or post-stroke weakness, aged 18–65, with randomized trials in their daily settings at their homes or physical therapy rooms; this will allow us to detect how performance differs from one person to another, with greater than 85% accuracy and greater than 2 bits/second in information transfer, all while employing transfer learning to reduce calibration to less than 2 minutes, as well as sound ethics checks and user feedback mechanisms such as the System Usability Scale to make it inclusive. We'll also examine longer-duration studies—think 4 to 6 weeks with three to five weekly sessions—to determine how it fares over hours-long periods, including basic biofeedback on an LCD screen off a Raspberry Pi and monitoring such items as heart rate to catch fatigue early, then switching algorithms in real time to tweak thresholds and even incorporating EMG from residual muscle signals to increase control speeds by 20–30% for individuals with residual movement. Hardware-wise, the electrodes will also be stress-tested with intense 500-hour simulations of sweat and wear according to ISO standards, targeting less than 5% impedance drift after 100 uses, and testing with more aggressive material such as silver-chloride coatings to push their lifespan over 200 hours; the addition of Bluetooth Low Energy for wireless use will also make hands-free applications such as wheelchairs without raising prices over LKR 10,000 per unit. Collaborating with clinicians here in Sri Lanka and elsewhere in the globe, these actions will move our proof-of-concept to something that people can actually depend on, bringing brain-powered technology to masses of people most in need.

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