B.TECH. PROJECT ON

IoT Enabled Brain Computer Interface

Submitted by

Monis Raza 2020UEI2818
Manya Bansal 2020UEI2829
Uditansh Bhandari 2020UEI2834
Tushar Bhushan 2020UEI2858

Under the guidance of

Prof. Dhananjay V. Gadre

Project-II in partial fulfillment of requirement for the award of B.Tech. in Electronics & Communication Engineering

Division of Electronics & Communication Engineering
NETAJI SUBHAS UNIVERSITY OF TECHNOLOGY
NEW DELHI-110078

May. 2024

CERTIFICATE

Certified that **Monis Raza (2020UEI2818)**, **Manya Bansal (2020UEI2829)**, **Uditansh Bhandari (2020UEI2834)**, and **Tushar Bhushan (2020UEI2858)** have carried out their project work presented in this project entitled **"IoT enabled Brain Computer Interface"** for the award of Bachelor of Technology, Department of Electronics and Communication, Netaji Subhas University of Technology, New Delhi, under my supervision. The project embodies results of original work, and studies are carried out by the students themselves and the contents of the project do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

Dhananjay V. Gadre
Associate Professor
Electronics and Communication Division
Founder, Texas Instruments Centre for Embedded Product Design
And, Centre for Electronic Design and Technology NSUT

Date:

ACKNOWLEDGEMENT

We wish to provide our sincere thanks to our mentor and supervisor **Prof. Dhananjay V. Gadre** for providing us all the necessary facilities and guidance required for the completion of the project and creating an environment of learning. He has also helped us immensely by discussing and analyzing the various intricacies involved in the project and provided us with innovative methods to deal with them.

We thank our families for believing in us and giving us strength to tackle all the problems that we face in our lives.

Monis Raza **Tushar Bhushan**

Manya Bansal **Uditansh Bhandari**

alextushar333@gmail.com.pdf

ORIGINALITY REPORT

9%	7%	5%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.acssonaicollege.com Internet Source	1%
2	Submitted to Netaji Subhas Institute of Technology Student Paper	1%
3	Submitted to Imperial College of Science, Technology and Medicine Student Paper	1%
4	Submitted to Technical University of Cluj-Napoca Student Paper	1%
5	Murali K. Rajendran, Priya Venugopal, Gajendranath Chowdary. "An Incremental Step Sensing MPPT Based SI-SIDO Energy Harvester With $>$99% Peak MPPT Efficiency for an Input Power Range of 30 μW to 33 mW", IEEE Journal of Solid-State Circuits, 2023 Publication	1%
6	www.springerprofessional.de Internet Source	1%

7	eprints.soton.ac.uk Internet Source	1 %
8	jsobject.info Internet Source	<1 %
9	scholarbank.nus.edu.sg Internet Source	<1 %
10	docplayer.com.br Internet Source	<1 %
11	www.biorxiv.org Internet Source	<1 %
12	Submitted to Nottingham Trent University Student Paper	<1 %
13	A. Jain, Insoo Kim, B. J. Gluckman. "Low cost electroencephalographic acquisition amplifier to serve as teaching and research tool", 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011 Publication	<1 %
14	Lin Zhu, Haifeng Chen, Xu Zhang, Kai Guo, Shujing Wang, Yu Wang, Weihua Pei, Hongda Chen. "Design of Portable Multi-Channel EEG Signal Acquisition System", 2009 2nd International Conference on Biomedical Engineering and Informatics, 2009 Publication	<1 %

15	Submitted to University of Surrey Student Paper	<1 %
16	www.science.gov Internet Source	<1 %
17	link.springer.com Internet Source	<1 %
18	iopscience.iop.org Internet Source	<1 %
19	es.slideshare.net Internet Source	<1 %
20	web.archive.org Internet Source	<1 %
21	Matteo Chiesi, Marco Guermandi, Silvio Placati, Eleonora Franchi Scarselli, Roberto Guerrieri. "Creamino: A Cost-Effective, Open-Source EEG-Based BCI System", IEEE Transactions on Biomedical Engineering, 2019 Publication	<1 %
22	Sunil Kumar Choudhary, Tushar Kanti Bera. "Designing of Battery-Based Low Noise Electroencephalography (EEG) Amplifier for Brain Signal Monitoring: A Simulation Study", 2022 IEEE 6th International Conference on Condition Assessment Techniques in Electrical Systems (CATCON), 2022 Publication	<1 %

23	core.ac.uk Internet Source	<1%
24	deepai.org Internet Source	<1%
25	minds.wisconsin.edu Internet Source	<1%
26	worldwidescience.org Internet Source	<1%
27	Tim Collins, Sandra I. Woolley, Nicholas C. Rawson, Luth Haroon. "Final-year projects using open source OpenEEG", Computer Applications in Engineering Education, 2016 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		

Contents

List of Figures

List of Tables

1 Introduction

The field of biotechnology has seen remarkable advancements in recent years, enabling us to delve deeper into understanding the complex physiological processes that underlie human health and disease. One of the pivotal aspects of this progress involves the study and analysis of biopotential signals. Biopotential signals are electrical signals generated within living organisms as a result of various physiological activities. These signals represent the electrical potentials produced by cells, tissues, and organs and are essential for the communication and coordination of biological processes. They serve as the foundation for creating interfaces for Human-Computer Interaction (HCI). At the frontier of HCI lies the transformative potential of Brain-Computer Interfaces (BCIs).

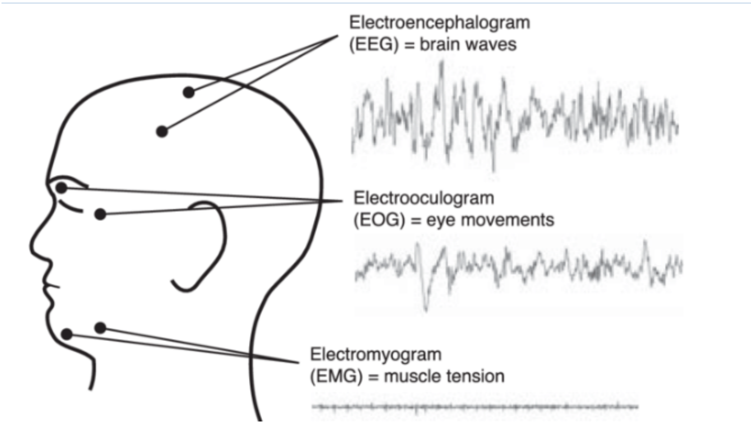


Figure 1: Biopotential Signals

1.1 Types of biopotentials

There are four distinct types of biopotentials used to serve as valuable indicators for monitoring human activities:

(A) **Electroencephalogram (EEG)**

The Electroencephalogram (EEG) serves as a pivotal instrument for investigating neural activity within the brain. It captures the electrical signals generated by neurons, providing valuable insights into cognitive states and cerebral functions. Researchers commonly employ EEG to scrutinize brain dynamics during cognitive tasks and sleep patterns. In clinical settings, EEG is an indispensable diagnostic tool for neurological conditions, particularly epilepsy, characterized by abnormal neuronal discharges. Additionally, EEG plays a crucial role in neurofeedback therapies, enabling cognitive enhancement through real-time feedback.

EEG signals are recorded using electrodes and typically have a low magnitude, ranging from 0.5 to 100 microvolts. Acquiring these faint EEG signals is challenging due to their vulnerability to noise.

(B) **Electrocardiogram (ECG)**

The Electrocardiogram (ECG) holds a vital position in the field of cardiology. It records and interprets the heart's electrical activity through distinct waveforms, facilitating the assessment of crucial cardiac parameters such as heart rate and rhythm. ECGs are instrumental in the early diagnosis and continuous monitoring of cardiovascular disorders.

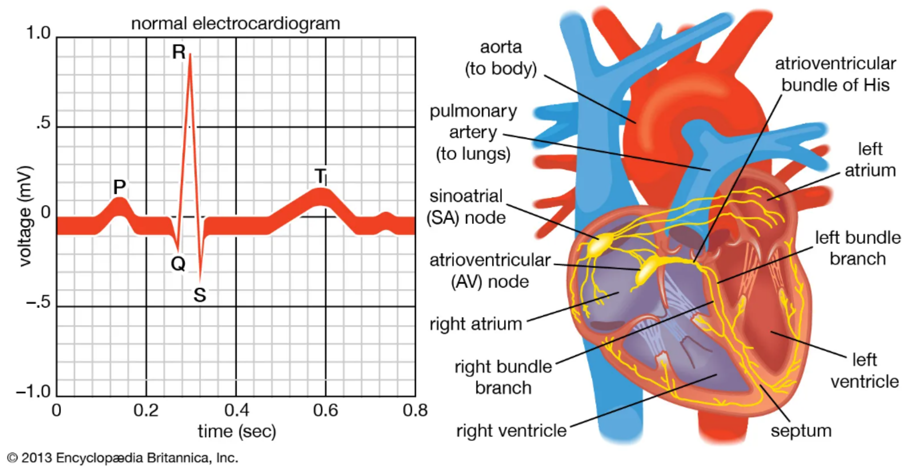


Figure 2: ECG graph and anatomy of a human heart

The effect of ECG on EEG is typically minimal due to differences in electrode placement and frequency ranges. While some minor interference is possible, advanced signal processing helps separate and remove any residual ECG artifacts from EEG recordings, preserving EEG data accuracy for neurological assessments and research.

(C) **Electromyogram (EMG)**

The Electromyogram (EMG) is an invaluable asset in sports medicine, rehabilitation, and neurology. It records the electrical activity of muscles during contractions and relaxations, allowing for a comprehensive examination of muscle function.

EMG measures muscle activity, and when muscles near EEG electrodes contract or move, they can introduce noise into EEG recordings. The biopotentials resulting from muscle movements tend to have shorter durations when compared to the brain-generated signals. This distinction makes it relatively straightforward to identify EMG signals based on their unique frequency patterns or firing rates.

(D) **Electrooculogram (EOG)**

The Electrooculogram (EOG) is crucial in sleep research and ophthalmology, assessing ocular muscle functionality and aiding in diagnosing eye issues.

EOG can affect EEG measurements due to artifacts from eye movements and blinks, particularly near-eye electrodes. These artifacts appear as high-frequency spikes in EEG data, obscuring brain activity. Bandpass filters narrow EEG signal frequencies, reducing EOG interference and enhancing data quality.

1.2 Motivation

The development of Brain-Computer Interfaces (BCIs) represents a paradigm shift in human-computer interaction, holding immense potential to transform the lives of individuals with disabilities and expand the horizons of human-machine collaboration. However, despite the promise of BCIs, their widespread adoption and integration into mainstream systems remain elusive. These sophisticated devices, essential for translating brain activity into actionable commands, have long been inaccessible to the broader public due to their high prices. Consequently, the transformative potential of BCIs has remained largely confined to research laboratories and specialized applications, leaving an untapped reservoir of innovative possibilities untouched. The implementation and enhancement of BCIs require a diverse skill set encompassing electronics, biopotential recordings, signal processing, and cognitive and human factors considerations. Often, the interdisciplinary nature of this work leads experts in one field to overlook the complexities of others, hindering progress. Therefore, the project also underscores the educational value of BCIs as a platform.

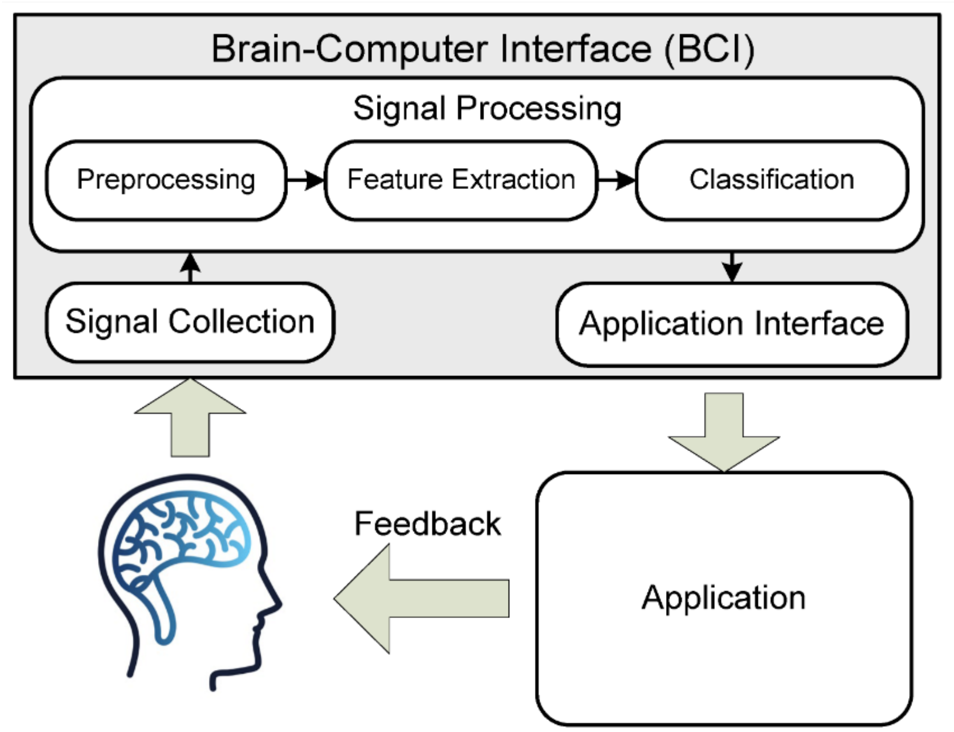


Figure 3: Block level representation of BCI system

The fundamental challenge we address in this project is the creation of a cost-effective BCI solution, with a specific focus on EEG-based systems. Our aim is to design a versatile BCI platform capable of performing data visualization and integration into various systems by end users. By making BCIs more accessible and affordable, we seek to bridge the gap between the advancements made in BCI research and their practical utility in everyday life. In doing so, we hope to unlock the potential of BCIs as a powerful tool not only for individuals with disabilities but also for a broader audience seeking innovative ways to interact with technology.

2 Internet of Things(IoT)

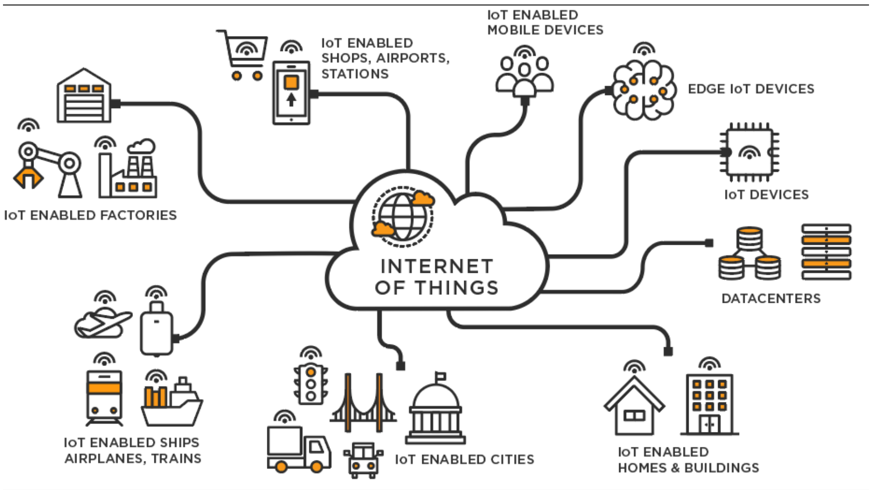


Figure 4: Internet of Things

The Internet of Things (IoT) represents a transformative technological shift that has ushered in a new era of connectivity and data exchange. At its core, IoT encompasses an extensive network of everyday objects and devices, from appliances and vehicles to wearable gadgets and sensors, all interconnected through the internet. IoT technology empowers us to establish seamless communication between the EEG system and external devices, enabling real-time data transmission, processing, and control. This fusion of neurotechnology and IoT opens up a realm of possibilities for enhancing the lives of individuals with neurological disorders.

The core function of IoT in the project lies in its ability to facilitate the acquisition and transmission of EEG data. The EEG system records electrical signals from the brain, which are then converted into digital format for analysis. IoT-enabled sensors and connectivity modules are integrated into the EEG apparatus, ensuring the efficient and secure transfer of these invaluable brain signals to a central processing unit. IoT not only enables the collection of EEG data but also empowers real-time processing. The collected brain signals are swiftly analyzed through advanced algorithms and machine learning models, extracting meaningful insights and patterns. This instantaneous analysis is critical for interpreting the user's intentions and issuing timely instructions to external devices. IoT further extends the reach of the project by enabling remote accessibility and monitoring. Caregivers, clinicians, and family members can securely access real-time EEG data and device control functions from remote locations. This feature not only enhances the user's independence but also facilitates remote healthcare monitoring and intervention when necessary. By merging neurotechnology with IoT, we are poised to enhance the quality of life for those who rely on this transformative technology.

3 EEG Signal Acquisition systems

An EEG (Electroencephalogram) signal acquisition system is a critical component in the field of neurophysiology and neuroscience, designed to capture and record the electrical activity of the brain. [1] It serves as a gateway to understanding the brain's intricate workings, providing valuable insights into cognitive processes, neurological disorders, and brain function. This sophisticated system involves a combination of specialized electrodes, amplifiers, and signal processing technology meticulously designed to detect and interpret the subtle electrical fluctuations within the brain. The EEG signal acquisition system plays a pivotal role in both clinical diagnostics and research, facilitating the study of brain disorders, sleep patterns, cognitive states, and various other aspects of neural activity. Its ability to capture and analyze the brain's electrical output makes it an indispensable tool in unraveling the mysteries of the human mind and advancing our knowledge of brain-related phenomena.

3.1 Montages and Technicalities

EEGs produce a comprehensive dataset covering the entire scalp by capturing individual electrical signals detected by electrodes. This process involves connecting all the electrodes in what is known as a montage [2]. Montages can be broadly categorized into two types: bipolar and referential.

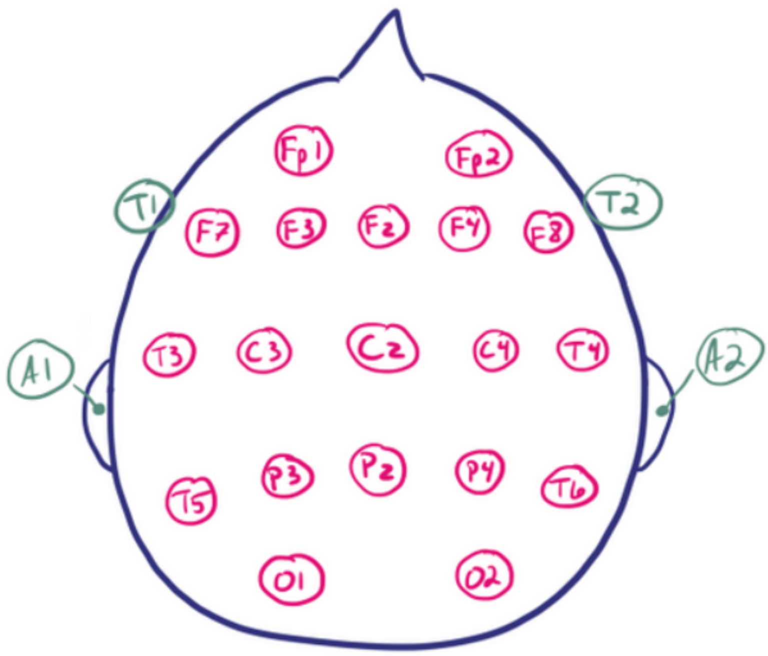


Figure 5: 10-20 System for placement of electrodes

10-20 International System: The first step in an EEG study involves electrode placement, typically using the internationally standardized 10-20 System. This system divides the skull into 10% or 20% increments for electrode positioning, ensuring consistency across individuals with varying head shapes and sizes.

Figure 6: Nomenclature of electrode placement for EEG acquisition

1. The letter indicates the brain region: F for frontal, T for temporal, P for parietal, and O for occipital (except for F7 and F8, which are over the anterior temporal region).
2. The number represents the side of the brain, with odd numbers on the left and even numbers on the right.
3. For midline/central electrodes, the letter is followed by ”z” instead of a number.

In setting up the 10-20 system, start by finding the spot where the nose bridge meets the forehead (nasion) and the small bump in the middle of the back of the head (inion). Afterward, divide the head into 10% and 20% sections to determine where to place the electrodes.

Types of Montages

There are two popular montage configurations used for EEG capture

- Bipolar Montage: To generate EEG tracings for this discharge, we simply link the electrodes in the double banana chain (temporal chain) and subtract each electrode's voltage from the one in front to obtain the voltage for that tracing pair. In EEG, positive values produce downward waves, while negative values create upward waves.

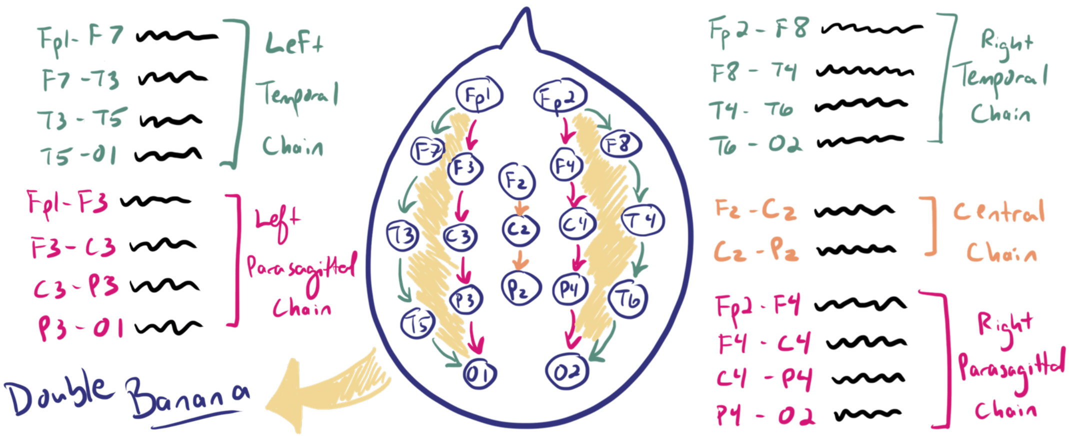


Figure 7: Bipolar montage configuration

- Referential Montage: While bipolar montages compare each electrode to another, referential montages assess all electrodes in relation to a single reference point. The reference point is typically the average voltage of all electrodes or the electrically neutral earlobe (auricle). On this website, average-type referential montages are commonly employed

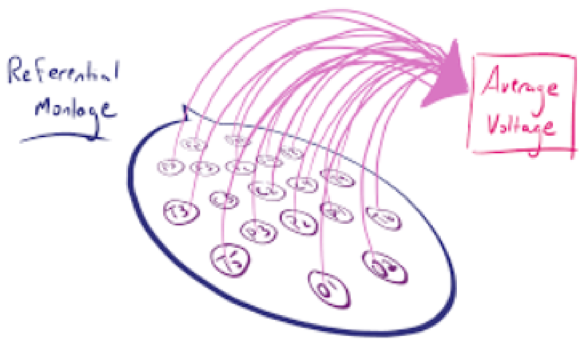


Figure 8: Referial montage configuration

3.2 Literature Review

Luigi Alosio Galvani's groundbreaking discovery of bioelectricity in 1780 marked the inception of a new era. Subsequently, bioelectric signals, particularly EEG signals, have witnessed a remarkable surge in research and exploration.

Several CMOS-based EEG amplifiers have been reported in the literature for the acquisition of EEG signals [3]-[4]. These are not suitable for clinical applications because of their high cost and non-ideal noise performance. L. Zhu et al.[5] give a foundational architecture for the pre-amplification and filtering circuitry of the EEG signals for reliable acquisition. It uses the internal A/D converter of MSP430 MCU for digitisation of the signals. However, it does not give provision for real-time acquisition and visualisation of the signals.

Jain et al.[6] developed a noninvasive Brain Computer Interface (BCI) for education and research. The acquisition amplifier is constructed using ADS1298 and a demonstration of visually evoked P300 signal is conducted. However, there are improved analogue front ends (AFEs) in the market which surpass the noise performance of ADS1298.

There are various open-source platforms pertaining to BCI systems. Collins et al.[7] promote the adoption of OpenEEG's open-source hardware and software resources to overcome the challenges associated with resourcing medical instrumentation projects.

There is reported literature on the development of multipurpose single-channel biosignal amplifiers for recording ECG/EEG/EMG for clinical applications by Sandesh R.S. and Venkatesan[8]. Another ECG acquisition system based on ADS1298 is reported [7], wherein the noise artefacts introduced due to the subject's instability are detected using an accelerometer.

4 BCI and its Pipeline

Brain-Computer Interfaces (BCIs) are pioneering systems that connect our brains to computers, offering unique ways to control devices and communicate. These interfaces are promising for helping people with disabilities and revolutionizing how we interact with technology. BCI pipelines are the key processes that turn brain signals into usable commands. They consist of several stages that decode and make sense of our brain's activity. In this overview, we'll explore BCIs, their applications, and the crucial pipelines that enable this incredible technology.

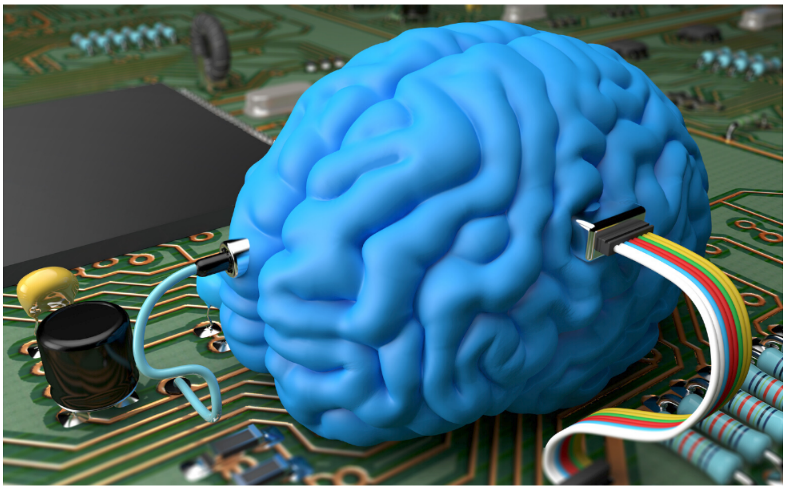


Figure 9: Human Machine Interface

The following are some of the application of BCI systems-

4.1 Emotion Recognition:

BCI technology can analyze brain signals to identify and classify emotional states. This has applications in mental health diagnostics, human-computer interaction, and market research, allowing for more emotionally responsive technology and enhanced user experiences.

4.2 Cognitive Load Assessment

BCIs evaluate cognitive load or mental workload in real-time, offering insights into users' mental states during complex tasks. This information aids in designing more user-friendly interfaces, optimizing educational settings, and enhancing task performance across various domains.

4.3 Driver State Monitoring:

Using EEG signals, BCIs monitor the cognitive state and alertness levels of drivers. By detecting signs of drowsiness or distraction in real-time, they contribute significantly to road safety, reducing the risk of accidents caused by impaired driving.

4.4 Meditation and Mindfulness:

BCIs support individuals in achieving deeper states of meditation and mindfulness by providing instant feedback on their mental states. This promotes self-awareness, relaxation, and mental well-being, fostering stress reduction and heightened concentration during meditation practices.

4.5 Speller Programs:

These systems empower the user by enabling them to interact with the outside world. The EEG signal acquisition system is attached to the individual and a keyboard of preferred language letters is displayed in front of the patient, the patient can choose the desired letter by just navigating through five commands- up, down, left, right and choose.

4.6 Prosthetic Control:

These advanced systems empower users by enabling them to seamlessly perform their daily routines, such as gripping objects or walking, through the attachment of a prosthetic arm or leg to their body. The active prosthetic is precisely controlled by capturing and interpreting EEG signals directly from the individual's brain, allowing for precise and intuitive control over the prosthetic limb's movements.

4.7 Stages of BCI

The following are the stages of a typical BCI system:

1. **Hardware Development:** In this initial stage, the focus is on designing and building the necessary hardware for data collection and processing. The hardware setup is tailored to the specific activity to be classified. Once established, it generates data that will be used in subsequent stages.

2. **Signal Processing and ML Training:** This stage involves automated signal processing using Python's MNE library. Simultaneously, a Machine Learning model is trained to recognize patterns in the processed data. The trained model is then uploaded to a processing unit like Google Coral or Jetson Nano for real-time processing of on-site data.

3. **Real-Time Data Collection and Processing:** The final stage involves the real-time collection of data and its input into the pretrained Neural Network model. The model performs real-time processing, predicts classification results, and subsequently triggers the desired task through the connected peripheral hardware. This comprehensive pipeline ensures the seamless operation of Brain-Computer Interface systems.

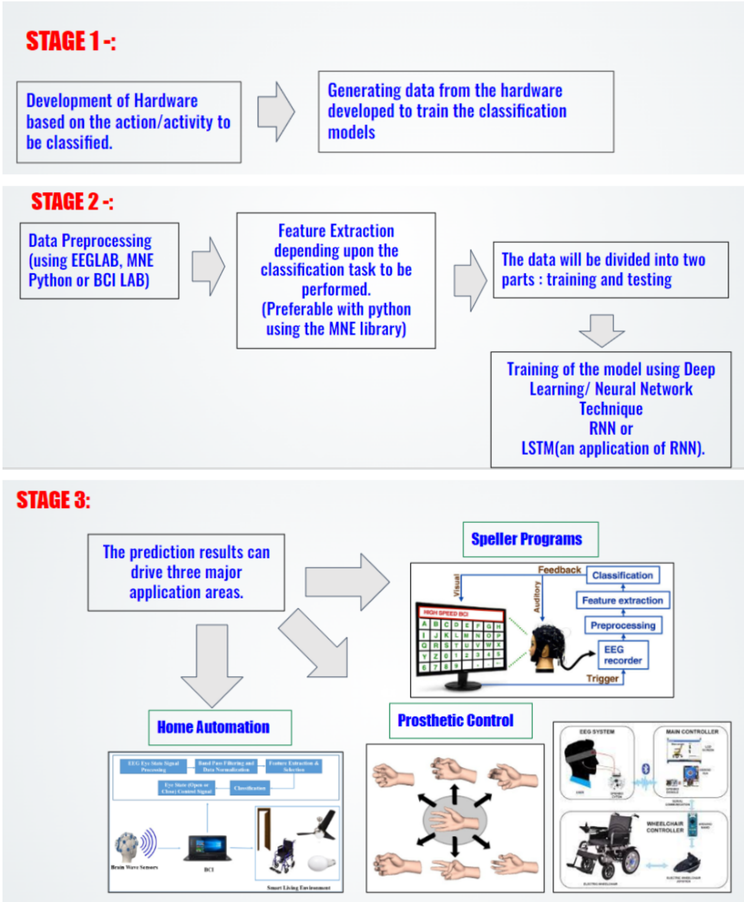


Figure 10: Various stages of BCI Pipeline.

5 Materials and Methods

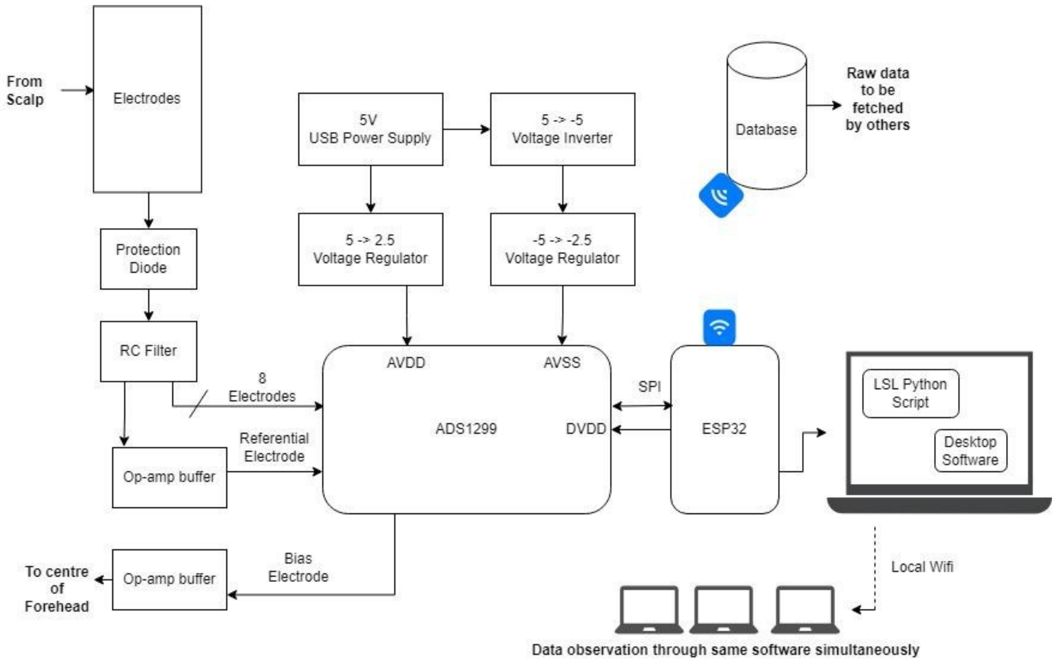


Figure 11: Block Diagram of the proposed system

We designed and in-house fabricated a printed circuit board (PCB) for our hardware setup using ECAD, ensuring it perfectly met the specific requirements of our EEG system. Our methods for data acquisition involve placing electrodes in accordance with the international 10-20 system to optimally capture EEG signals, which are processed and relayed through our hardware. To manage and analyse the processed EEG and other biometric data effectively, we utilized the LSL technology for real-time visualization and comprehensive analysis. Users are also given the provision to upload and save the processed data to a remote database for global real time access. The block diagram in Fig.11 presents the implementation of our system.

5.1 Electrodes Placement and Headset

Our EEG system is designed to capture biopotential signals, which originate from the density changes of charged ions in excitable cells such as those in muscles and nerves. These signals are detected using electrodes that transfer the data to our acquisition system. Specifically, EEG signals, which occur due to brain activity, range from 10 to 100 µV and consist of various frequency bands including delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–100 Hz) waves.

To ensure accurate EEG measurement, it's essential to minimize impedance, aiming for up to 40 k ohms in most cases, and as low as 5k ohms for sensitive applications like Brain-Computer Interfaces (BCIs). Our system uses dry electrodes primarily for their ease of use and quick setup. Although dry electrodes typically have higher impedance than wet electrodes, their convenience and faster preparation times make them preferable in real-time applications such as BCI. It eliminates the need for conductive gel in case of wet electrodes and allows for quicker, more comfortable placement on the scalp.

Electrode placement follows the 10-20 System, Fig.12 shows a standardized method that divides the skull into segments based on 10 and 20 increments to ensure consistent positioning across different head sizes. Each electrode placement site has a letter to identify the lobe, or area of the brain it is reading from: pre-frontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O), and central (C). Our EEG system adopts the referential montage approach, where all electrodes are measured relative to a single reference point, providing a stable baseline for signal comparison.

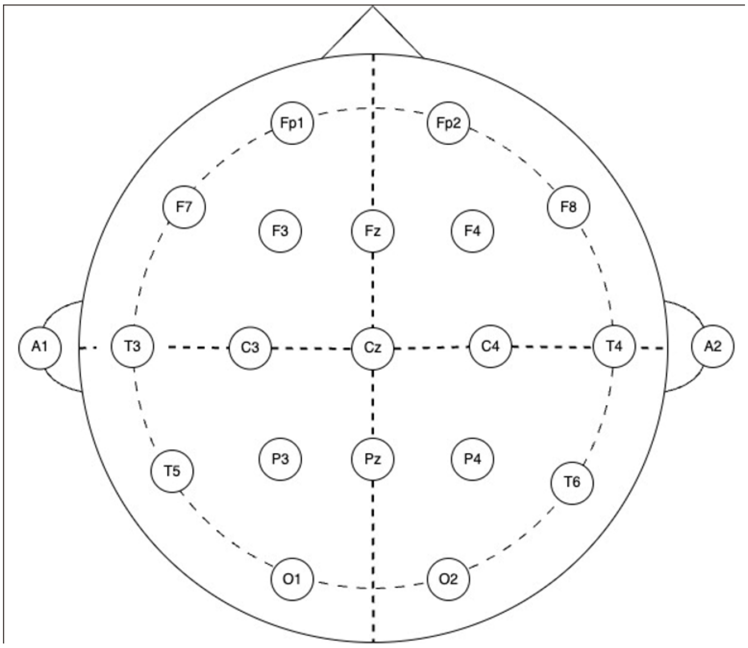


Figure 12: 10-20 System for placement of electrodes

We customized the OpenCV Mark IV headset as shown in Fig 13. to enhance its functionality; modifications included upgrading to 1.5mm DIN cables to reduce electromagnetic interference and employing 3D printing technology to develop a lightweight, adjustable frame suitable for various head sizes and electrode configurations.

Our system incorporates a total of 10 electrodes to monitor the brain's electrical signals—eight actives for detailed regional brain monitoring, one reference near the eye to minimize electrical noise, and one bias at the forehead's centre to stabilize the signal by signal grounding. The number of electrodes can be increased by daisy chaining multiple identical devices utilising the features provided by ADS1299. The number of devices that can be cascaded is limited by the required data rate as given by the following formula-

$$N_{DEVICES} = \frac{f_{SCLK}}{f_{DR}(N_{BITS})(N_{CHANNELS}) + 24}$$

Where:

$$N_{BITS} = \textit{device resolution (depending on data rate)}$$

$$N_{CHANNELS} = \textit{number of channels in the device}$$

These modifications ensure that our EEG system not only captures detailed and reliable brain activity data but also enhances user comfort and data integrity, making it ideal for both cognitive studies and sensitive applications like BCIs.

Figure 13: OpenBCI Headset

5.2 Hardware Description

5.2.1 ADC (ADS1299)

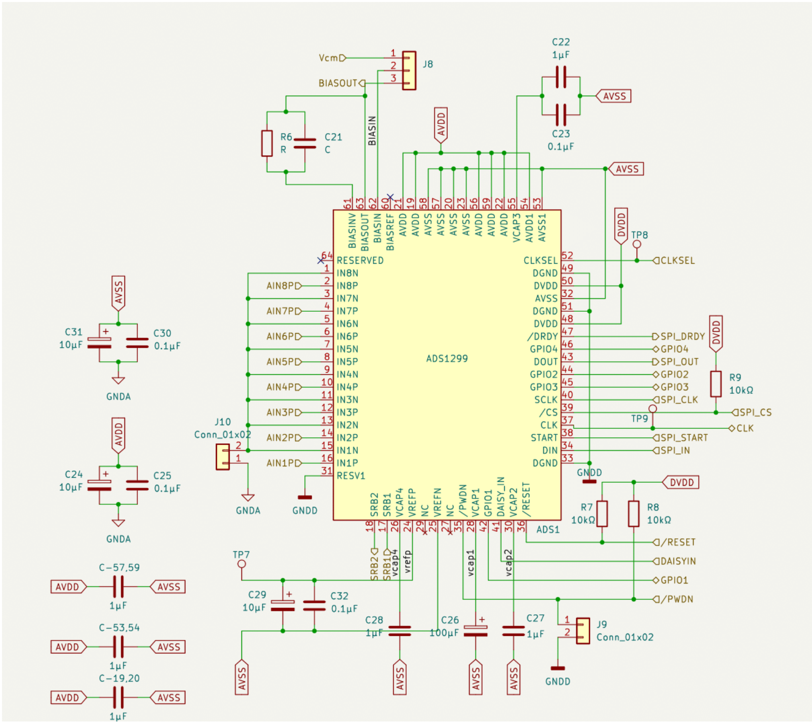


Figure 14: Schematic for the connections of ADS1299

EEG signal is analog in nature so it must be converted to digital before being computed, hence an ADC is used to convert the analog value to the digital value. ADC uses the concept of sampling followed by quantization. ADC samples the input voltage at a discrete time duration

Why ADS1299[9]?

- It has 24 bit resolution and can detect up to 0.26µV change in input signal.
- It has 8 sigma delta ADCs which enable simultaneous sampling from 8 analog channels.
- The IC is designed to have low input-referred noise, making it suitable for capturing weak bioelectric signals with minimal interference.
- The ADS1299 allows users to adjust the gain of each channel independently, allowing for the amplification or attenuation of signals as needed.
- Includes an integrated 4.5V voltage reference source to maintain accuracy in measurements.
- ADS1299 comes equipped with lead-off detection capabilities to monitor the connection quality of electrodes.
- Supports SPI to connect with microcontrollers providing a convenient means of data transfer and control.

- High common mode rejection ratio (CMRR) (110-120 dB) ensures accurate measurement of differential bioelectric signals.

- On-chip decimation filters remove high frequency noise and provide anti-aliasing filtering.

- Sampling rate is programmable (250 sps to 16 ksps)

5.2.2 Power Supply Block

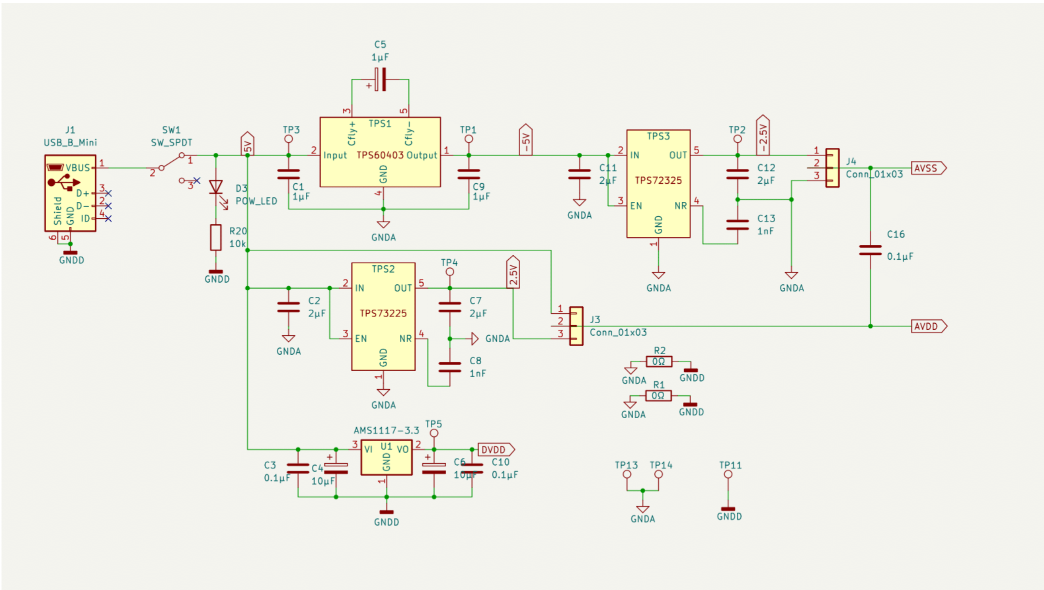


Figure 15: Schematic for the power supply

All electronic systems require a source of power for operation. This source can be a battery or USB Supply. Our system uses a 5V battery source, this source is fed to a low dropout regulator TPS73225 (2.5v)[10] and Voltage Inverter TPS60403 (-5v)[11]. The Voltage Inverter output is also fed to low dropout regulator TPS72325 (-2.5v)[12] A regulator is used to remove the ripples from the power source and to maintain the voltage at a particular level.

ADS1299 has the provision of being operated using both, monopolar and bipolar supplies. The proposed system operates using bipolar supply because bipolar power supplies provide a centered signal around ground, meaning that the signal can be both positive and negative with respect to a common reference point (usually ground). This is well-suited to EEG signals, which can be both positive and negative in nature. Bipolar setups can often provide a better SNR and signal integrity because they allow for the measurement of both positive and negative signal components, reducing the impact of noise and interference relative to a unipolar setup.

In mixed signal grounding it is important to separate "more noisy" digital return current from "less noisy" analog return current. This is done to prevent noise from ground currents.

5.2.3 Filteration and Protection circuitry

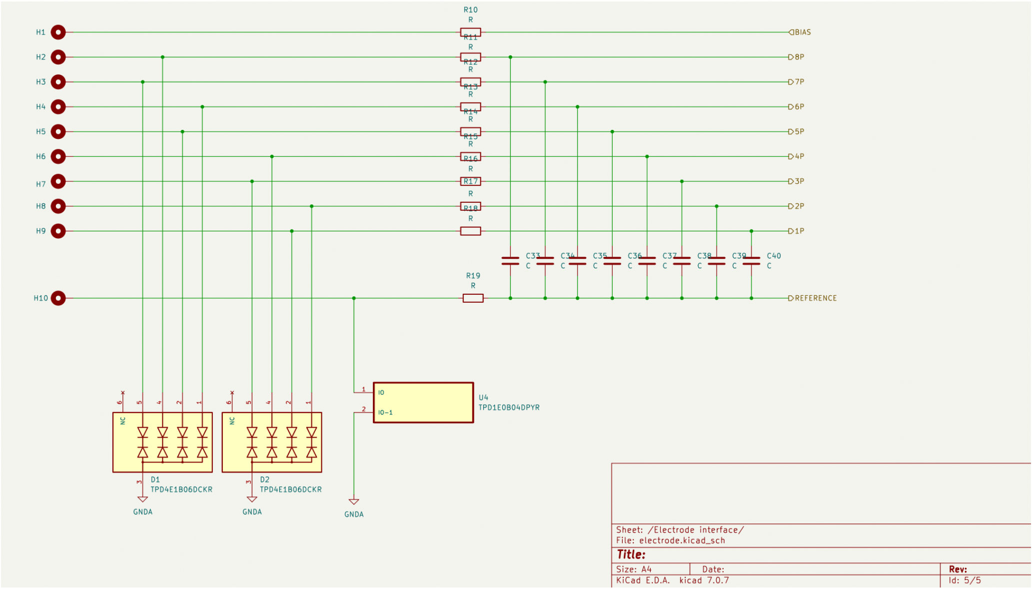


Figure 16: Schematic for Electrode interface

The inputs are taken in a differential fashion that results in the suppression of common mode noise. A reference signal is taken from the common electrode which is attached to the forehead. The input and the reference EEG signal are fed to a RC filter. The RFI filter removes the noise generated in the radio frequency range, these noises are usually generated by power and signal rails.

The BCI system continuously monitors the EEG signal using electrodes. The person should be protected from hazards, so a protection circuit should be deployed to prevent the person from any kind of electrical shock.

5.2.4 Op-amps as buffers

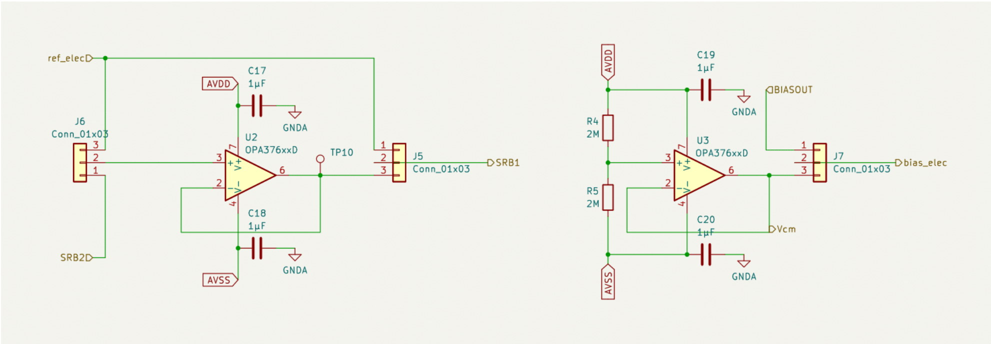
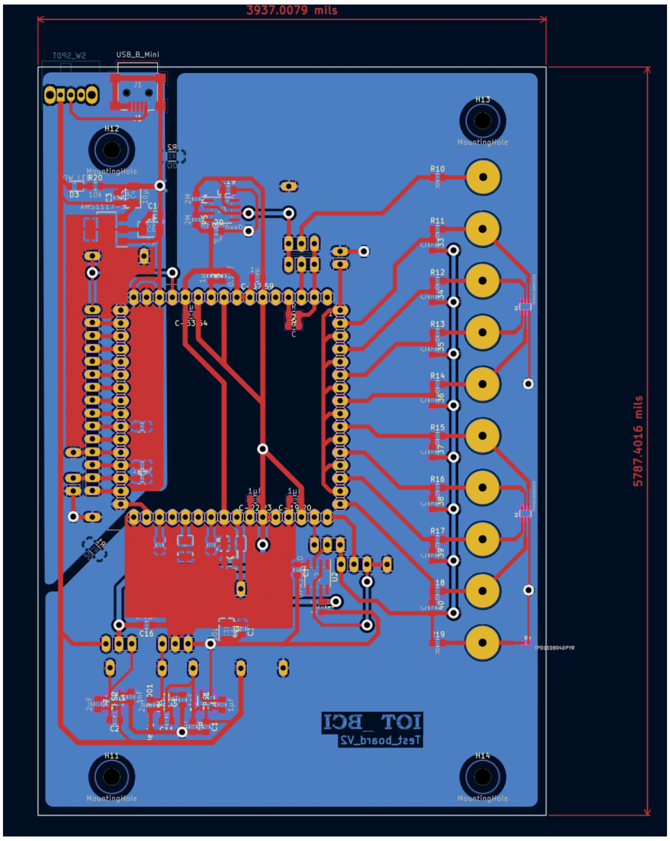


Figure 17: Schematic for Op-Amp buffer circuitry

OPA376 [13] op-Amp is used as the buffer amplifier at two instances.

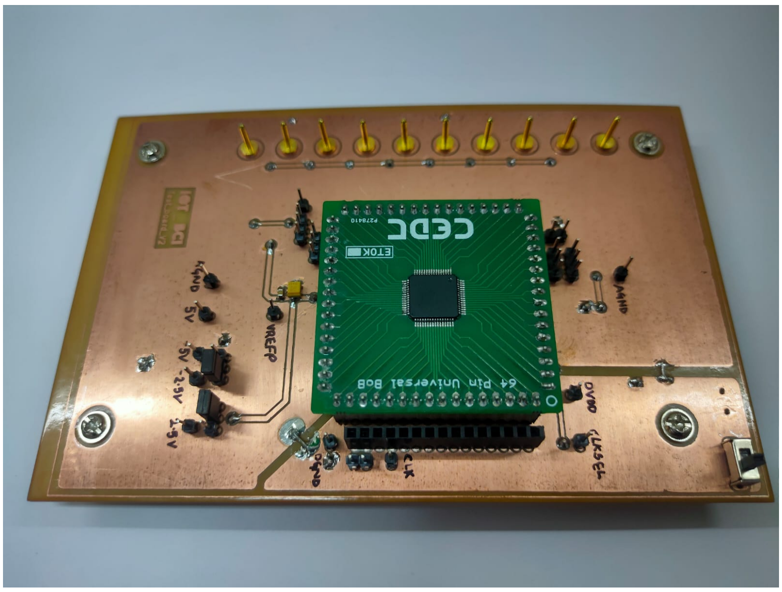
1. To increase the driving capability of the Reference electrode
2. To suppress common mode noise in Bias electrode

5.2.5 Test Board



(a)

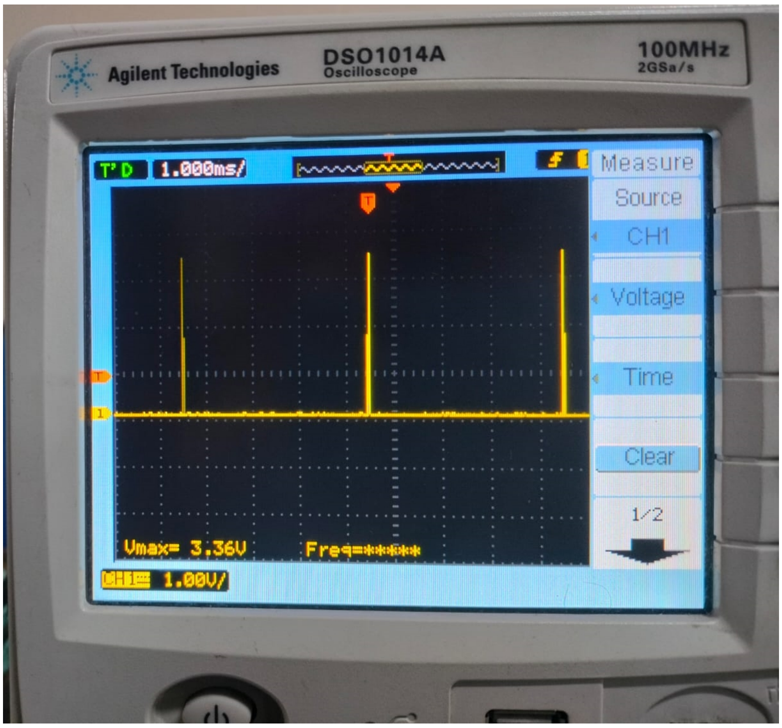
Figure 18: Top level schematic and board layout of Test Board



(a)

Figure 19: In-House Fabricated Board

5.2.6 Testing



(a)

Figure 20: DRDY pin output through an Oscilloscope

In the testing phase of our integration project involving the ADS1299 and ESP32, we focused on assessing the functionality of the Data Ready (DRDY) pin on the ADS1299. This pin plays a crucial role in indicating when data is available for extraction from the ADS1299. To initiate the testing process, we configured the ESP32 to send a high signal to the START pin of the ADS1299, prompting the device to begin its operation. Subsequently, we observed the DRDY pin's behavior, and it responded by generating pulses at a frequency of 250 Hz, effectively signaling that the ADS1299 was actively processing and acquiring data.

The DRDY pin serves as a pivotal indicator, notifying the ESP32 that the ADS1299 has completed its data acquisition process and is ready for the next step. Specifically, the DRDY pin sends a pulse when data is available for extraction, allowing our integrated system to synchronize and retrieve the acquired information in a timely manner. This successful testing of the DRDY pin reaffirms the proper communication and coordination between the ESP32 and the ADS1299, laying a solid foundation for the subsequent phases of our integration project.

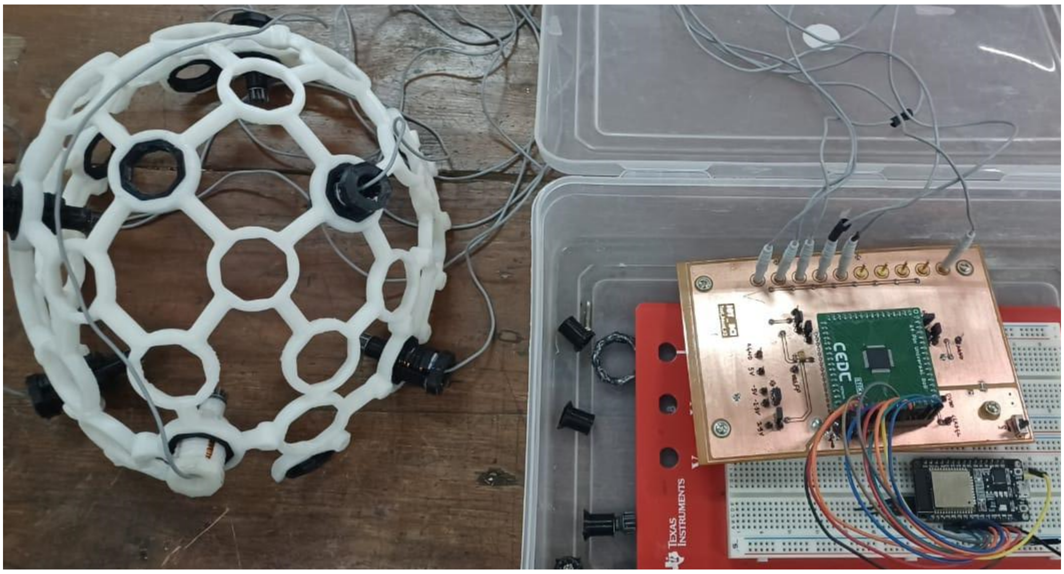


Figure 21: Testing Circuit

5.3 Software Description

5.3.1 Data Storage

Our EEG system utilizes the ESP32 microcontroller, equipped with dual-core processing capabilities, to manage the raw EEG data captured by the ADS1299 ADC efficiently. Operating under FreeRTOS for real-time performance, the system implements a ping pong buffer strategy to continuously and alternately store data. The cores of the ESP32 are optimally utilized to enhance system reliability: one core is exclusively dedicated to data acquisition, while the other manages data processing and uploads to Firebase Realtime Database upon completion. Such an arrangement ensures that the acquisition process is not interrupted by any network-related delays or processing overheads that occur during data upload. Uploading EEG data to the Firebase Realtime Database not only enhances data security and availability but also allows for real-time data access from anywhere in the world. This global accessibility is vital in collaborative medical environments and for scenarios requiring immediate expert analysis and decision-making from remote locations.

5.3.2 Data Visualization

For visualization, the data is formatted into a Lab Streaming Layer (LSL) stream using a Python script, ensuring easy access and visualization through the compatible BrainVision Viewer software. This software efficiently detects LSL streams and automatically identifies the number of channels transmitted, allowing for real-time plotting and immediate visualization of EEG data. The stream can be recognized and accessed on any device within the local network, enhancing its utility in multi-user or collaborative settings. The BrainVision Viewer further enhances the setup by offering robust visualization tools, including the ability to observe EEG signals and perform FFT analyses on up to four channels simultaneously. Additionally, we utilize the software's 50Hz notch filter to eliminate the power line noise, significantly improving the quality of the

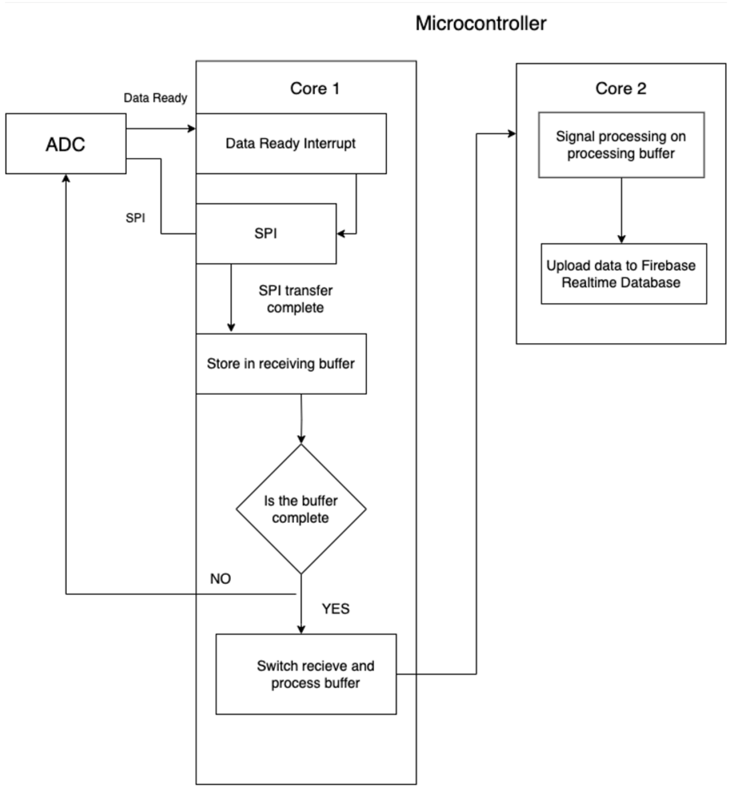


Figure 22: Software Block Diagram

EEG recordings. This streamlined approach allows us to avoid the complexities often associated with software setups for EEG data analysis, allowing us to focus more on the practical application and analysis of EEG data instead (Fig 23.) of becoming entangled in the intricacies of software development.

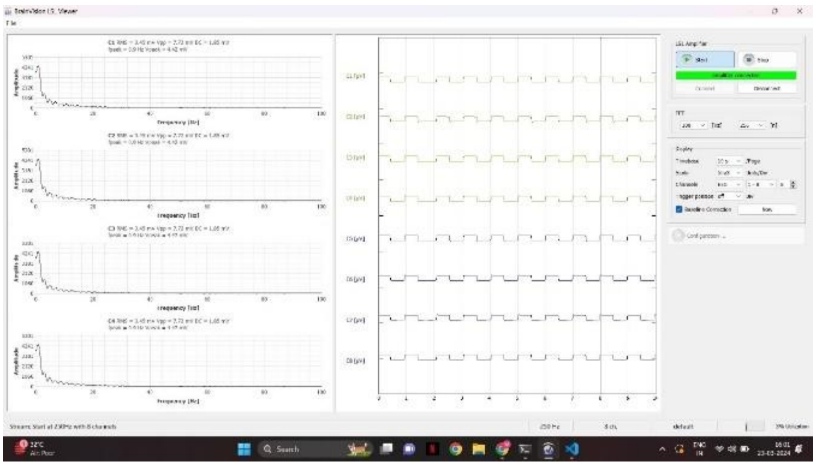


Figure 23: Test Signal generated by ADS1299, as seen on Brain Vision Viewer

5.3.3 ESP32 Code

The ESP32 code served as the bridge between the physical world and the digital realm, facilitating the acquisition and transmission of potentiometer data for our EEG brainwave monitoring system. In this critical component of our project, the ESP32 was programmed to read analog data from the potentiometer and establish a connection with the Google Firebase Realtime Database to transmit this data. The code implemented a continuous data acquisition loop, ensuring a steady stream of potentiometer readings for real-time monitoring.

The ESP32 code was instrumental in configuring the Firebase Realtime Database connection, establishing secure and efficient communication. Each potentiometer reading was timestamped and sent to the database, creating a chronological record of data points. This code also laid the foundation for the seamless integration with the React application, enabling the visualization of potentiometer data in real-time. Through effective serial communication and data formatting, the ESP32 code played a crucial role in the reliable and consistent transmission of potentiometer data to the cloud-based database, forming the backbone of our software system's data acquisition capabilities.

```
#include <SPI.h>
#include <FirebaseESP32.h>
#include <Firebase_ESP_Client.h>
#include "addons/TokenHelper.h"
#include "addons/RTDBHelper.h"

// Register Addresses
#define ID 0x00
#define CONFIG1 0x01
#define CONFIG2 0x02
#define CONFIG3 0x03
#define LOFF 0x04
#define CH1SET 0x05
#define CH2SET 0x06
#define CH3SET 0x07
#define CH4SET 0x08
#define CH5SET 0x09
#define CH6SET 0x0A
#define CH7SET 0x0B
#define CH8SET 0x0C
#define BIAS_SENSP 0x0D
#define BIAS_SENSN 0x0E
#define LOFF_SENSP 0x0F
#define LOFF_SENSN 0x10
#define LOFF_FLIP 0x11
#define LOFF_STATP 0x12
#define LOFF_STATN 0x13
#define GPIO 0x14
#define MISC1 0x15
#define MISC2 0x16
#define CONFIG4 0x17

// SPI Command Definition Byte Assignments (Datasheet, pg. 35)
#define _WAKEUP 0x02  // Wake-up from standby mode
#define _STANDBY 0x04 // Enter Standby mode
#define _RESET 0x06   // Reset the device
#define _START 0x08   // Start and restart (synchronize) conversions
```

```
#define _STOP 0x0A    // Stop conversion
#define _RDATAC 0x10  // Enable Read Data Continuous mode (default mode at power-up)
#define _SDATAC 0x11  // Stop Read Data Continuous mode
#define _RDATA 0x12   // Read data by command; supports multiple read back

#define _RREG 0x20 // (also = 00100000) is the first opcode that the address must be added to for RREG communication
#define _WREG 0x40 // 01000000 in binary (Datasheet, pg. 35)

#define HSPI_MISO 12
#define HSPI_MOSI 13
#define HSPI_SCLK 14
#define HSPI_SS 15

// Pin definitions
#define CLKSEL 32
#define DRDY 34
#define DAISY_IN 33
#define START 25
#define RESET 26
#define PWDN 27

int num_channels = 8;
float tCLK = 4.8828125e-7;          // 2.048 Mhz internal clk
static const int spiCLK = 2000000; // 2MHz
static const int SPI_BUFFER_SIZE = 28;
static const int PING_PONG_BUFFER_SIZE = 5400;
uint8_t pingPongBuf[2][PING_PONG_BUFFER_SIZE];
bool begin_tx = false;
unsigned long time_value;

int buf_idx = 0; /// selects the receiving buffer
int pingPong_idx = 0;

static TaskHandle_t rxData = NULL;
static TaskHandle_t proData = NULL;

//Firebase variables****
int FIREBASE_ARR_SIZE = 200;
FirebaseJsonArray firebaseArr;
FirebaseJsonArray temp;

// Insert your network credentials
#define WIFI_SSID "NSUT_WIFI"
#define WIFI_PASSWORD ""
#define API_KEY "AIzaSyCY56wk_UR5Z-HJHevj_3Mgl6pw65YaRQM"
#define DATABASE_URL "https://rtos-8a584-default-rtdb.asia-southeast1.firebasedatabase.app"

// Define Firebase Data object
FirebaseData fbdo;
FirebaseAuth auth;
FirebaseConfig config;
unsigned long sendDataPrevMillis = 0;
bool signupOK = false;
void ISR()
```

```
{
  xTaskResumeFromISR(rxData);
}

//***********************
//                             setup functions
//***********************
void SDATAC()
{
  SPI.beginTransaction(SPISettings(spiCLK, MSBFIRST, SPI_MODE1));

  digitalWrite(HSPI_SS, LOW);
  SPI.transfer(_SDATAC);
  delay(2); // 4tclk delay before making HSPI_SS HIGH again
  digitalWrite(HSPI_SS, HIGH);

  SPI.endTransaction();
}
void RDATAC()
{
  SPI.beginTransaction(SPISettings(spiCLK, MSBFIRST, SPI_MODE1));

  digitalWrite(HSPI_SS, LOW);
  SPI.transfer(_RDATAC);
  delay(2); // 4tclk delay before making HSPI_SS HIGH again
  digitalWrite(HSPI_SS, HIGH);
  SPI.endTransaction();
}

void WREG(byte _address, byte _value)
{

  SPI.beginTransaction(SPISettings(spiCLK, MSBFIRST, SPI_MODE1));

  digitalWrite(HSPI_SS, LOW); // Low to communicated

  SPI.transfer(_WREG | _address);

  SPI.transfer(0x00);
  SPI.transfer(_value);

  delay(2);                   // 4tclk delay before making HSPI_SS
    HIGH again
  digitalWrite(HSPI_SS, HIGH); // Low to communicated
  SPI.endTransaction();
}

//*********************
//                     2's complement
//*********************
long processNegative(long channelValue)
{
  if (channelValue >> 23)
  {
    channelValue |= 0xFF000000;
    channelValue = (~channelValue) + 1;
    channelValue = channelValue * (-1);
  }
```

```
  return channelValue;
}

//*********************
//                            ADC setup
//*********************
void setupADC()
{
  pinMode(RESET, OUTPUT);
  digitalWrite(RESET, HIGH);
  pinMode(PWDN, OUTPUT);
  digitalWrite(PWDN, HIGH);
  pinMode(START, OUTPUT);
  pinMode(DRDY, INPUT);
  pinMode(CLKSEL, OUTPUT);
  pinMode(DAISY_IN, OUTPUT);

  delay(128); // tPOR=2^18 tclk=0.128s

  digitalWrite(CLKSEL, HIGH);
  delayMicroseconds(20); // wake up time of internal oscillator

  // issuing reset pulse
  digitalWrite(RESET, LOW);
  delayMicroseconds(1);
  digitalWrite(RESET, HIGH);
  // wait for 18tCLK
  delayMicroseconds(9);

  SDATAC();
  WREG(CONFIG3, 0xEC);
  WREG(CONFIG2, 0xC0);
  WREG(CONFIG1, 0x96);
  WREG(CH1SET, 0x60);
  WREG(CH2SET, 0xF1);
  WREG(CH3SET, 0xF1);
  WREG(CH4SET, 0xF1);
  WREG(CH5SET, 0xF1);
  WREG(CH6SET, 0xF1);
  WREG(CH7SET, 0xF1);
  WREG(CH8SET, 0xF1);
  WREG(MISC1, 0x20);
  WREG(BIAS_SENSP, 0x01);
  WREG(BIAS_SENSN, 0x01);
//  WREG(CONFIG3, 0xE0);
//   WREG(CONFIG2, 0xD0);
//   WREG(CONFIG1, 0xB6);
//   WREG(CH1SET, 0x05);
//   WREG(CH2SET, 0x05);
//   WREG(CH3SET, 0x05);
//   WREG(CH4SET, 0x05);
//   WREG(CH5SET, 0x05);
//   WREG(CH6SET, 0x05);
//   WREG(CH7SET, 0x05);
//   WREG(CH8SET, 0x05);
//   WREG(BIAS_SENSP, 0x01);
//   WREG(BIAS_SENSN, 0x00);

```

```
  digitalWrite(START, HIGH);

  RDATAC();
}

//**********************
//                         Firebase Setup
//**********************

void setupFirebase()
{
  pinMode(LED_BUILTIN, OUTPUT);
  digitalWrite(LED_BUILTIN, 1);

  WiFi.begin(WIFI_SSID, WIFI_PASSWORD);
  Serial.print("Connecting to Wi-Fi");
  while (WiFi.status() != WL_CONNECTED)
  {
    Serial.print(".");
    delay(300);
  }
  Serial.println();
  Serial.print("Connected with IP: ");
  Serial.println(WiFi.localIP());
  Serial.println();

  config.api_key = API_KEY;
  config.database_url = DATABASE_URL;
  if (Firebase.signUp(&config, &auth, "", ""))
  {
    signupOK = true;
  }
  else
  {
    Serial.printf("%s\n", config.signer.signupError.message.c_str());
  }
  config.token_status_callback = tokenStatusCallback;

  Firebase.begin(&config, &auth);
  Firebase.reconnectWiFi(true);
}

//**********************
//                         Receive Data task
//**********************

void receiveData(void *parameter)
{
  while (1)
  {
    vTaskSuspend(NULL);

    SPI.beginTransaction(SPISettings(spiCLK, MSBFIRST, SPI_MODE1));
    digitalWrite(HSPI_SS, LOW);

    for (int i = 0; i < 27; i++)
    {
      byte dataByte = SPI.transfer(0x00);
```

```
      pingPongBuf[buf_idx][pingPong_idx++] = dataByte;
    }
    digitalWrite(HSPI_SS, HIGH);
    SPI.endTransaction();

    if (pingPong_idx == PING_PONG_BUFFER_SIZE)
    {
      buf_idx = 1 - buf_idx;
      pingPong_idx = 0;
      // time_value = millis();
      // Serial.print(" buffer full: ");
      // Serial.println(time_value);
      vTaskResume(proData);
    }
  }
}
//**********************
//                         Process Data Task
//**********************

void processData(void *parameter)
{

  int ARR_SIZE = 1800;
  long dataArr[ARR_SIZE];
  long dataPacket;

  while (1)
  {
    vTaskSuspend(NULL);

    // time_value = millis();
    // Serial.print("start: ");
    // Serial.print(time_value);

    int idx = 1 - buf_idx;

    ////////processing data/////////
    for (int i = 0; i < PING_PONG_BUFFER_SIZE; i++)
    {

      ////one data point corresponds to 3 bytes
      if (i % 3 == 0 && i != 0)
      {
        int j = (i / 3) - 1;
        dataArr[j] = processNegative(dataPacket);
        dataPacket = 0;

        if (j % 9 == 1)
        {
          firebaseArr.add(dataArr[j]);
        }
      }

      byte dataByte = pingPongBuf[idx][i];
      dataPacket = (dataPacket << 8) | dataByte;
    }
    dataArr[ARR_SIZE - 1] = processNegative(dataPacket);
```

```
    dataPacket = 0;
    //serial printing for debugging
    // for (int i = 0; i < 100; i++)
    // {
    //   // Serial.print("-6000");
    //   // Serial.print(" ");
    //   // for (int j = 1; j <= 8; j++)
    //   // {
    //   //   Serial.print(dataArr[9 * i + j]);
    //   //   Serial.print(" ");
    //   // }
    //    Serial.print((float)dataArr[9*i+1]*(0.536*pow(10,-6)));

    //    Serial.println(" ");
    //   // Serial.print("9000");
    //   // Serial.println(" ");
    // }


    if (Firebase.ready() && signupOK)
    {
      if (Firebase.pushArray(fbdo, "/measures", firebaseArr))
      {
        firebaseArr.clear();
      }
    }
  }
}

//********************
//                          VOID SETUP
//********************
void setup()
{
  Serial.begin(9600);
  Serial.flush();
  delay(10);
  setupFirebase();

  ////////////////////////////////////ADS1299 SETUP
   //////////////////////////////////
  delay(1000);
  while (!Serial)
    ;
  // define SPI pins
  pinMode(HSPI_SCLK, OUTPUT);
  pinMode(HSPI_MOSI, OUTPUT);
  pinMode(HSPI_MISO, INPUT);
  pinMode(HSPI_SS, OUTPUT);

  digitalWrite(HSPI_SCLK, LOW);
  digitalWrite(HSPI_MOSI, LOW);
  digitalWrite(HSPI_SS, HIGH);

  // configure SPI frequency, mode
  SPI.begin(HSPI_SCLK, HSPI_MISO, HSPI_MOSI, HSPI_SS);
  SPI.setFrequency(spiCLK);
  SPI.setDataMode(SPI_MODE1);
```

```

  setupADC();

  attachInterrupt(digitalPinToInterrupt(DRDY), ISR, FALLING);

  //tasks******
  xTaskCreatePinnedToCore(receiveData,
                          "Task 1",
                          1024,
                          NULL,
                          2,
                          &rxData,
                          0);

  xTaskCreatePinnedToCore(processData,
                          "Task 2",
                          20000,
                          NULL,
                          1,
                          &proData,
                          1);

  vTaskDelete(NULL);
}

void loop()
{
}
```

5.3.4 Google Firebase Realtime Database

In our project, the Google Firebase Realtime Database served as a crucial component for seamlessly storing and retrieving data from our ESP32 microcontroller. The ESP32, connected to a potentiometer for initial testing, continuously generated data that was then transmitted to the Google Firebase Realtime Database. This cloud-based database provides a scalable and responsive solution, storing the potentiometer values in a timestamped key-value format. The Firebase Realtime Database ensures real-time synchronization, allowing for immediate updates and retrieval of the latest data points. This asynchronous nature of the database facilitated the smooth flow of information between the ESP32 and the subsequent data processing components.

The use of Google Firebase Realtime Database also enabled easy integration with our React code. The React application, developed using Visual Studio Code, seamlessly fetched the potentiometer data from the Firebase Realtime Database. This dynamic interaction allowed for real-time visualization of the data on a web application, providing a user-friendly interface to monitor the potentiometer values over time. The integration of Google Firebase Realtime Database not only streamlined data communication but also laid the foundation for a scalable and responsive software architecture for our EEG brainwave project.

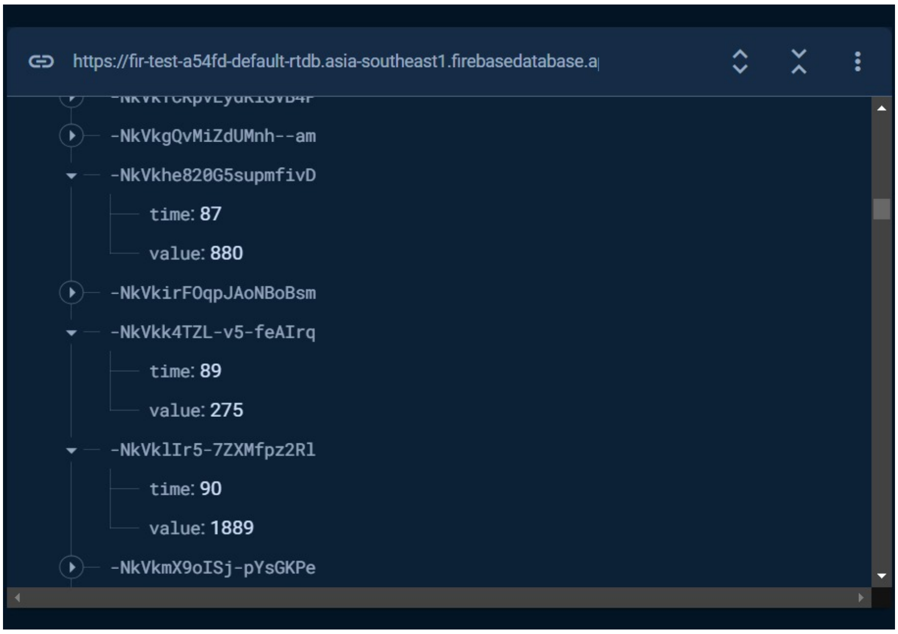


Figure 24: Real-Time Database

6 Demonstration

There are numerous engaging demonstrations that can be conducted with our biopotential monitoring system to educate undergraduate students about the properties and features of biopotential signals.

Figure 25: Demonstration Setup (a)

This section outlines some fundamental demonstrations we have recorded using the system, while also encouraging students to propose their innovative experiments based on their observations and

In a series of experiments, Fig. 25 and Fig. 26 we explored the electrical activities related to eye blinks and movements. Fig. 27 displays the signal variations from a normal single eye blink. This demonstration illustrates how the electric dipole moment at the eyeball changes with a blink, reflecting in the recorded biopotential.

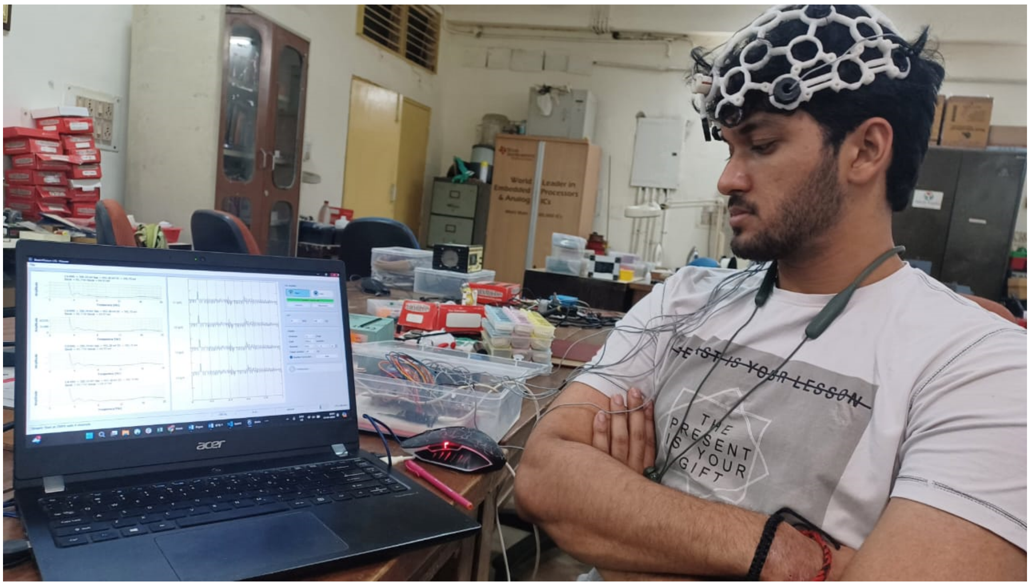


Figure 26: Demonstration Setup (b)

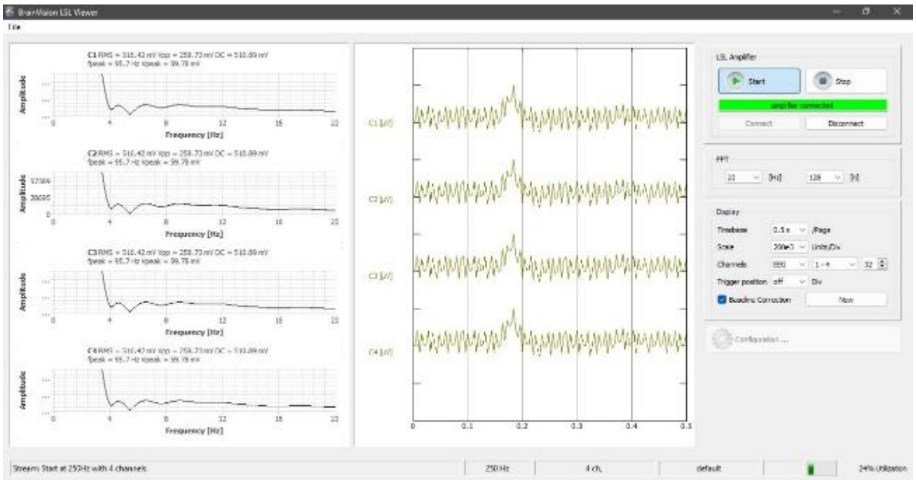


Figure 27

Additionally, we conducted experiments to record the biopotential changes associated with horizontal eye movements. Fig. 28 (a) and 29 (b) presents the signals obtained when the subject's eyes moved right and left. This experiment highlighted two major signal peaks corresponding to the right and left movements, with the second peak appearing as an inverse of the first, due to the reverse direction of the dipole moment.

The system was also used to demonstrate how different mental states affect brain activity, measured through EEG. We performed two distinct EEG recordings under different conditions: one with the subject's eyes open and another with the eyes closed in a relaxed state. The results, shown in Fig 30(a), reveal distinct variations in the EEG patterns between these conditions. Notably, alpha rhythms—indicative of relaxed mental states—were significantly amplified when the subject's eyes were closed. Fig 31(b) illustrates this through Fast Fourier Transform (FFT) analyses,which highlight a pronounced increase in alpha band amplitude (8-12 Hz) during closed-eye relaxation. This change emphasizes the typical increase in alpha activity, offering valuable insights into the subject's neurophysiological state.

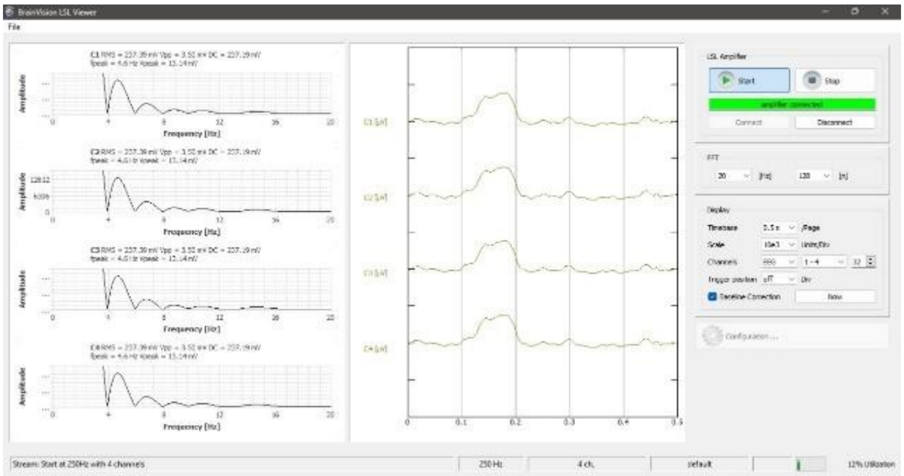


Figure 28: (a)

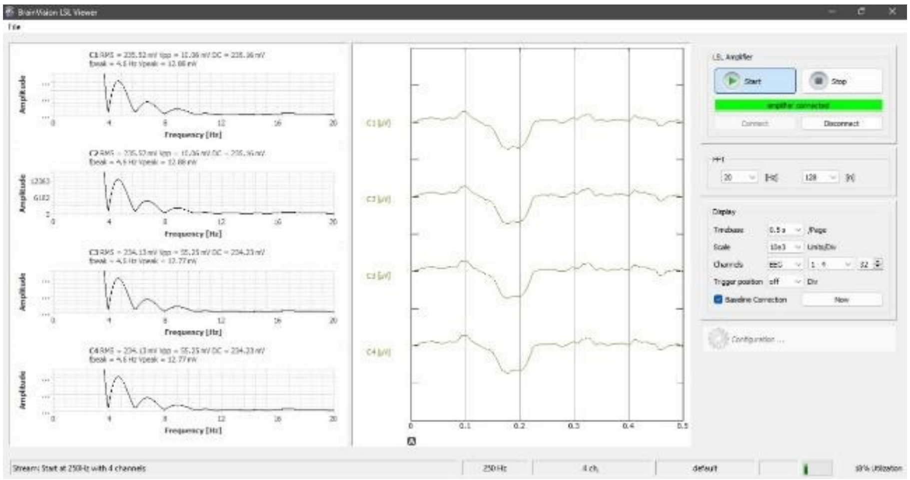


Figure 29: (b)

The Fourier transforms of these recordings provide a clear visualization of the frequency components associated with each state. These patterns are particularly useful for students to understand the physiological changes that occur in the brain during different sensory and cognitive activities.

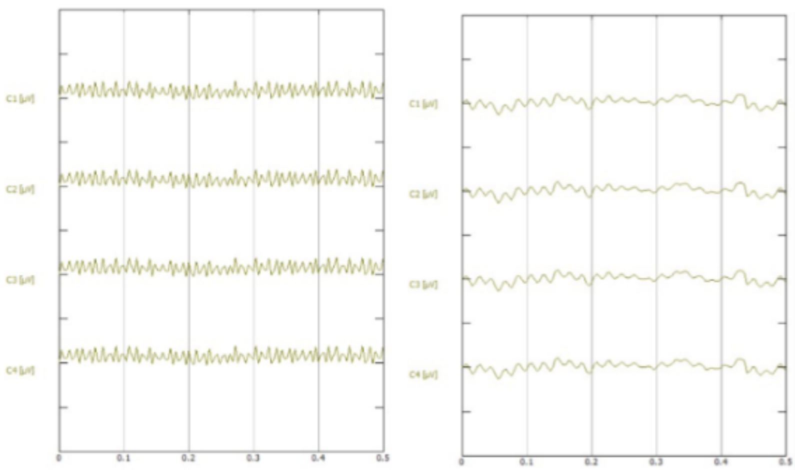


Figure 30: (a) EEG waveforms with eyes open (left) vs eyes closed (right)

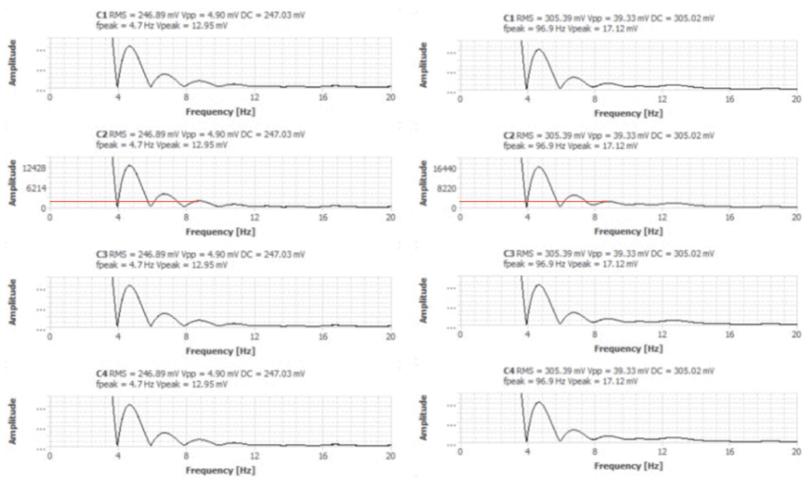


Figure 31: (b) FFT analysis of EEG data comparing the frequency spectrum with eyes open (left) to eyes closed (right)

7 Conclusion

Our project has successfully demonstrated the feasibility and educational value of a cost-effective Brain-Computer Interface (BCI) system designed specifically for academic environments. Through the integration of an 8-channel EEG headset and an in-house fabricated board with advanced signal processing capabilities, we have shown that high-quality biopotential monitoring can be made accessible to students and researchers without the need for expensive, commercial setups.

The use of the Lab Streaming Layer (LSL) for real-time data streaming and the seamless integration with our visualization application have significantly simplified the user experience. This setup not only reduces the learning curve associated with EEG data analysis but also enhances the interactive learning component by allowing immediate, hands-on experience with neurotechnology. Our demonstrations of eye blinks, eye movements, and different mental states through EEG recordings have provided concrete examples of the system's capabilities in capturing and analysing complex neural activities. By focusing on cost-efficiency and user-friendliness, this project enables institutions with limited resources to incorporate advanced biotechnological tools into their curricula, thereby fostering a more inclusive educational environment. Furthermore, this initiative prepares students for future challenges and innovations in neuroscience and engineering, equipping them with the knowledge and skills to drive forward the field of bioengineering. As we look to the future, the potential applications of this BCI system extend beyond the classroom. The modular design and scalability of the system suggest its applicability in a range of research settings, from cognitive science studies to advanced computational neuroscience projects. Continuing to refine and expand the capabilities of this system will undoubtedly unlock new possibilities for exploration and discovery in the vast field of brain-computer interfacing.

A BOM

S.no	Name	Type	Cost (in Rs)
1	ADS1299 IPAGE	ADC	5,254
2	TPS60403 QDB RQ1	Voltage Regulator	104
3	TPS72325 QDB RQ1	Voltage Regulator	289
4	TPS73225QDBVRQ1	Voltage Regulator	64
5	OPA376AID	Op-Amp	184
6	TPD4E1B06DCKR	Protection Diode	50
7	TPD1E0B04DPYR	Protection Diode	34

Table 1: Bill of Materials

References

[1] "Fundamentals of eeg signal." https://www.youtube.com/watch?v=YTH-CXphdXw&t=1932s, April 2019.

[2] "Montages and technicalities." https://www.learningeeg.com/montages-and-technical-components.

[3] R. R. Harrison and C. Charles, "A low-power low-noise cmos amplifier for neural recording applications," *IEEE Journal of solid-state circuits*, vol. 38, no. 6, pp. 958–965, 2003.

[4] E. Bottino, S. Martinoia, and M. Valle, "Integrated low noise low power interface for neural bio-potentials recording and conditioning," in *Bioengineered and Bioinspired Systems II*, vol. 5839, pp. 193–203, SPIE, 2005.

[5] L. Zhu, H. Chen, X. Zhang, K. Guo, S. Wang, Y. Wang, W. Pei, and H. Chen, "Design of portable multi-channel eeg signal acquisition system," in *2009 2nd International Conference on Biomedical Engineering and Informatics*, pp. 1–4, IEEE, 2009.

[6] A. Jain, I. Kim, and B. J. Gluckman, "Low cost electroencephalographic acquisition amplifier to serve as teaching and research tool," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1888–1891, IEEE, 2011.

[7] T. Collins, S. I. Woolley, N. C. Rawson, and L. Haroon, "Final-year projects using open source openeeg," *Computer Applications in Engineering Education*, vol. 24, no. 1, pp. 156–164, 2016.

[8] T. Uktveris and V. Jusas, "Development of a modular board for eeg signal acquisition," *Sensors*, vol. 18, no. 7, p. 2140, 2018.

[9] "Ads1299 datasheet." https://www.ti.com/product/ADS1299.

[10] "Datasheet for tps7322." https://www.digikey.in/en/products/detail/texas-instruments/TPS73225QDBVRQ1/1672899.

[11] "Datasheets power supply." https://www.digikey.in/en/products/detail/texasinstruments/TPS60403QDBVRQ1/770875.

[12] "Datasheet for tps72325." https://www.digikey.in/en/products/detail/texas-instruments/TPS72325QDBVRQ1/2589811.

[13] "Opa376aid." https://www.digikey.in/en/products/detail/texas-instruments/OPA376AID/1666348.