Design Of Wearable EEG Headset For Emotion Monitoring

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Dedication

This study is dedicated with deep gratitude to our respected families, whose constant support, inspiration, and contributions have been a strong base of endurance throughout our academic journey. Their resilience, affection, and trust in us have motivated us to persevere and succeed. This project also devote to our esteemed and honored supervisor and co-supervisor, whose outstanding guidance, knowledge, and mentorship have been invaluable. Their perceptive ideas, helpful response, and unwavering support have greatly influenced the direction and quality of this work. Finally, the contribution and dedication to all those who the motivate and encourage young researchers to strive for knowledge, innovation, and excellence in the field of science and technology. .

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Abstract

This research provides the design and development of a portable, low-cost Electroencephalography (EEG) based real-time emotion recognition system. Emotion recognition is crucial for comprehending human behavior, psychological monitoring, and Human-Computer interaction (HCI). Compared to traditional emotion recognition methods such as questionnaire and manual observation, EEG provides a convenient and objective technique that directly measures brain activity. In this study, a Convolutional Neural Network (CNN) model is applied to differentiate emotional states among positive, neutral, and negative classes by learning spatio-temporal features automatically from the EEG signals.

A hardware system was built by combining a 24-channel EEG headset with a microcontroller of ESP32 and an ADC of ADS1256. Signal acquisition and transmission can then be effectively realized. In order to obtain better signal quality, the signals are first pre-processed with band-pass filtering (0.5-50 Hz), artifact rejection and normalization, followed by feature learning and classification of the CNN model. The experimental results show that the developed system achieves stable and reliable accuracy in real-time and quickly response. The system can effectively recognize emotion states like happiness and sadness and can function outside a lab environment.

Generally, this developed technique represents a practical and low-cost solution for real world applications such as mental status supervision, stress detector, and wearable Human-Computer Interface system.

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Chapter 1

Introduction

1.1 Project Background

Emotion plays a vital role in human behavior, make decisions and social interaction [3]. The study involved the use of EEG which is a non-invasive technique to measure the electrical activity within the brain using a set of scalp electrodes. Human emotion also affects the interaction among human beings. The conventional methods of emotion detection such as questionnaire and observation were less accurate due to subjective responses and self reporting and real time measurement was also not possible. The objective and real time brain wave can be monitored using EEG which makes it suitable for the emotion recognition. [3, 4]. EEG lets us see what is going on in the brain at that moment. It can detect how people are feeling. It does this in real time. Electroencephalography is a tool, for understanding emotions and emotional states. It looks at brain rhythms like delta, theta, alpha, beta and gamma to figure out how humans are feeling. This means it can detect emotions like happiness, sadness and stress [4]. Portable devices for human emotion recognition are now commonly available as technology is advancing. In order to automatically recognize human emotions, the combination of electroencephalography(EEG) and machine learning algorithms is used. High-density arrays of electrodes are used to collect accurate EEG signals from the brain for reliable classification of emotional states like happiness, sadness and stress. EEG for emotion recognition have diverse applications such as health monitoring, Human-Computer Interface and affective computing. [17]. Information space with multi-electrode systems is more extensive, and the classification precision of emotion recognition is improving. A wearable headset which is designed for the younger generation to detect their emotion, which is used for tracking and analyzing human's activities and emotions by this medical device and sends a signal to computer is applied. Brain-Computer interface and human machine interface are employed in this design which are useful in healthcare, education, adaptive system, and emotion identification. [9]. For the physiological signals, EEG is regarded as one of the most potential approaches for the emotion recognition task. As a direct measure to neuronal activity, EEG possesses good temporal resolution and thus it's feasible to observe and analyze neural dynamics in real-time. Since emotion processing is a complicated cognitive activity accompanied by activity of central nervous system, EEG contains significant information for perception and control of emotions and hence shows greater accuracy and reliability than peripheral physiological signals. [3]. Based on these recent progresses, EEG-based emotion detection has been actively researched over the past few decades especially on signal processing methods, machine learning approaches and BCI technology. The EEG signals can be decomposed into several frequency bands-delta (0.5-3Hz), theta (3-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-200Hz)-which have a lot of significant information in different physiological and psychological aspects of human emotion. Each of these frequency bands are closely related with emotional, cognitive and attention states. [23]. Emotional statuses like happy, sad, stress or relaxed can be identified correctly if these features of EEG frequency bands are analyzed. Moreover, the detection of emotions from EEG signals is least affected by social masking or emotional suppression that can affect emotion detection techniques such as facial or speech based approaches. This allows EEG signals to capture the true emotion by their correlation to direct neural activation patterns and it is less influenced by deliberate masking of emotions by human behavior. [19]. EEG based emotion recognition has gained attention in recent years as a most suitable solution for real-time emotion detection systems. This method facilitates consistent, unobtrusive monitoring of the emotional state of humans and offers promising future in affective computing.

Earlier research mainly uses machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (KNN) for classification of EEG signals. Normally these methods use the features extracted manually such as power spectral density, statistical values of the EEG signals. However, these methods depend on the knowledge of the expert and generalization ability of the methods is relatively low in various subjects and datasets.

According to the recent studies, it can be shown that the CNNs achieve better performance for EEG based emotion recognition as it can extract spatial-temporal features from the EEG signals automatically, resist noise well and can achieve a better generalization in different subjects. Therefore, the CNN models can be regarded as an efficient solution for wearable real-time emotion recognition systems. EEG signals are measured using the electrodes put on the head and they are usually represented in frequencies of delta, theta, alpha, beta, and gamma waves.

Table 1.1: EEG frequency bands and their corresponding brain functions

S. No.	**Frequency Band**	**Frequency Range (Hz)**	**Associated Functions**
1	Delta	0.5–4 Hz	Deep sleep, unconscious states
2	Theta	4–8 Hz	Memory, learning, emotional processing
3	Alpha	8–13 Hz	Relaxation, calmness, meditative state
4	Beta	13–30 Hz	Attention, active thinking, cognitive engagement
5	Gamma	30–50 Hz	Higher cognitive functions, information processing

Recent advances in wearable EEG systems have enabled 24-channel dry electrode headsets, which follow the 10–20 system for precise spatial coverage, portable real-time monitoring, and comfort during extended use [19].

1.2 Problem Description

The problem addressed in this project is the development of a low-cost, reliable EEG-headset capable of acquiring brain signals and extracting features corresponding to emotions like happy, sad, and stressful emotional states in real time. These systems are costly, bulky, and impractical for daily use. Conversely, consumer-grade EEG devices with multiple electrodes are con venient to prioritize due to limited spatial information. This project aims to address these challenges by developing a 24-electrode portable EEG headset to optimize user-friendliness with high-quality data acquisition. This system will show hardware design, signal acquisition, preprocessing, feature extraction, and real-time emotion classification.

1.3 Project Objectives

The main objective of this project is to acquire emotional signals through the electrodes from the brain. It is the brain-computer interface and human interaction interface. Firstly, place the 24 electrodes on the scalp and build the EEG headset to give us the activity of the brain performed by the human, as well as mental disorders, stress, and psychological issues are also checked through the signals that come from the brain. This device is user friendly and easy to wear for everyone. This is a real-time field-testing medical device. Secondly, the preprocessing is done in the EEG signals for the removal of noise in the signal. The EEG signals are in microvolts within the range of 5 µV to 100 µV, so it's difficult to measure [16]. There is the noise that comes across the signal, so by applying filters like notch, bandpass, etc., these filters are used to remove the noise and such artifacts as eye blinks. Thirdly, extracting the features for emotions in time, frequency, and spatial domains. Fourthly, by using machine learning and to classify the emotional states such as happiness, sadness, and stress accurately. Train it by using models (CNN) Convolutional Neural Network is a type of deep learning architecture that people use a lot for feature learning and classification. This is especially true for things like image and signal processing for example when we want to recognize emotions from EEG signals.

A Convolutional Neural Network has a few parts, including convolutional layers. These layers look at the data and find the important features. Then there are pooling layers that make the features smaller. They still keep the good stuff.

After that we have connected layers that take these features and figure out what they mean.

The Convolutional Neural Network is really good at its job because it can find features on its own without anyone having to do it. This makes it very powerful and efficient for recognizing patterns.

The Convolutional Neural Network is very useful for recognizing emotions from EEG signals because it can learn about the patterns in brain signals that happen over time and space. This is really helpful for classifying emotions and for tasks that involve biomedical signals.

The Convolutional Neural Network is a tool, for these kinds of tasks. Furthermore, Test the system in real-time on youth and compare the real-time data with existing methods using the available datasets.

1.4 Project Scope

The project encompasses the full pipeline for EEG-based emotion detection using a 24-electrode wearable headset. Such as:

1.4.1 Hardware Design

The hardware aspect involves low-cost components such as the 24 dry comb electrode, ADS1256 analog-to-digital converter, INA129 amplifier, dry EEG electrodes, and ESP32 microcontroller.

1.4.2 Software Design

Real-time acquisition, preprocessing, feature extraction, optional visualization on PC/mobile. It includes multi-channel EEG-acquisition that is integrated with a microcontroller and wireless communication.

1.4.3 Signal Acquisition

The EEG is recorded from the regions like frontal, central, occipital, and temporal lobes in the brain.

1.4.4 Signal Processing

The filtration of noise, removal of artifacts, and analysis of the signals are segmented.

1.4.5 Feature Extraction

Calculating the time-domain (e.g., variance, mean amplitude), frequency domain (alpha, beta, gamma, theta, etc.), and spatial features (e.g., con nectivity measures).

1.4.6 Emotion Classification

The application of machine learning including (CNN), and classify accuracy, this is the high density EEG setups that provide the spatial information, which is important for effective feature extraction, and accurate emotion recognition.

1.5 Project Motivation

The young population is highly susceptible to emotional stress due to academic competition, social expectations, and uncertainty regarding future careers. Youth are suffering from undetected emotional stress that can negatively impact learning outcomes, decision-making abilities, and overall mental health. Continuous emotional monitoring and early stress detection are inadequate to replace traditional evaluation methods. An EEG based emotion recognition framework enables the potential for real-time, objective emotional assessment, enabling timely identification of emotional distress. These systems can support and facilitate early treatment and strategies in educational institutions, mental healthcare, and personalized well-being applications. The motivation of this project is to contribute and invest towards developing an efficient, reliable, and youth-focused EEG based emotion recognition framework.

Chapter 2

Literature Review

2.1 EEG Technology Overview

Emotional recognition is a major field of study within affective computing that concentrates on detecting human emotional states through observable cues. Many researchers have proposed for years that several emotion recognition approaches depend on facial expressions, speech signals, and physiological responses. While speech-based emotion recognition uses acoustic features including pitch, tone, energy, and speech rate, facial expression analysis typically depends on visual features such as facial landmarks, muscle movements, and action units. In contrast psychological signal based emotions such as happy, sad, angry, relax, focused, etc. are recognized for objective reliable and efficient approach for capturing the response that are harder to manipulate into intentionally. EEG signal reflect real-time brain activity and offers external behavioral observations in the persons emotional states on deeper insights. Psychological signals are less affected by personal bias or control of deliberate except the traditional techniques that depend on facial expression or self-reported data. In real-world applications, it makes particularly useful for exact precise emotion detection where the reliability and consistency are important. These signals are analyzed for subtle emotional changes which are not be visible through environment. As a result, psychological signals plays an essential role for developing the advanced technologies for the applications such as in mental health monitoring, stress analysis, and human computer interaction. The activity of the neural system reflects signals in electroencephalography (EEG), electrocardiography (ECG), galvanic skin response (GSR), and electromyography (EMG) during emotional experience [24]. EEG signals contain rich information spread over multiple frequency bands, usually grouped as delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (greater than 30Hz). Every frequency band has been linked with distinct emotional, cognitive, and attentional processes [22]. For instance, increased beta and gamma activity has been correlated with increased arousal (activation) and stress level. So, alpha asymmetry between the left and right frontal lobes has been widely connected to emotional valence. Several studies have demonstrated that analyzing EEG spectral features, temporal dynamics, and hemispheric asymmetric patterns can effectively differentiate between several emotional states, such as happiness, sadness, fear, and relaxation. EEG provides a more direct representation of emotional functioning in brain, making it less susceptible to external disturbance. These characteristics have developed EEG as a prominent signal modality for emotion recognition research and BCI-based affective systems [38]. Recent enhancements in Artificial Intelligence (AI), particularly deep learning, have significantly revolutionized EEG-based emotion recognition and brain-computer interface (BCI) systems. Deep learning models such as Convolutional neural net works (CNN), Long short-term memory (LSTM) networks, and hybrid architectures have demonstrated the best performance as compared to traditional machine learning approaches. These models are more capable of automatically learning discriminative and multi-level pattern features directly from raw or minimally processed EEG signals, reducing the need for individual feature engineering. Particularly, the effective CNN model is mainly for capturing spatial and spectral patterns in EEG data, while LSTM networks are well-suited for the modeling of temporal dependencies and emotional changing-patterns. In real-time by integrating deep learning models within a BCI framework, for decoding of brain signal, more adaptive techniques are used in emotion recognition systems, and they translate them into a more meaningful emotional output. This combination allows intelligent human-machine interactions, individual-based emotion tracking, and adaptive mental health support systems. Moreover, BCI systems, AI driven, are more robust to noise, improve generalization across subjects, and have scalability for real-world deployment. For making deep learning based BCI and human machine interface, there are more advantages, and approaches are highly suitable for applications such as stress detection, mental health assessment, neurofeedback, and affect-aware wearable systems. Consequently, the combination of a more powerful paradigm, EEG, AI, and BCI for future-oriented emotion recognition techniques [22].

2.2 Wearable EEG Headsets

The development of a real-time monitoring wearable EEG system, outside the laboratory, has been greatly accelerated by the combination of dry-comb electrodes with an embedded processing platform (ESP32). Traditionally, EEG is implemented within laboratory/clinical settings, as conventional systems utilize heavy apparatus, are wired and require wet (gel) electrodes, leading to the introduction of skin-to-electrode impedance for enhancing the signal and creating electrical conductivity between the electrode and the scalp. In contrast, wearable EEG systems employ miniature, low-power embedded platforms, and acquisition modules to allow real-time, remote and portable monitoring of brain activity. ESP32 is an economical microcontroller choice for wearable EEG acquisition systems, because it possesses dual cores and lower power consumption [35].

For convenience and to support portable and long-term monitoring of EEG signals, the use of dry-comb electrodes over wet electrodes is favored. This type of electrode requires the application of conductive gel to decrease the electrode-skin impedance. However, the application of conductive gel takes more time and the gel can eventually dry out, which decreases the signal to noise ratio, and irritates the skin. Moreover, gel systems require careful cleaning after each session and it is not convenient for repetitive or daily monitoring. On the other hand, dry electrodes do not require the application of gel; therefore, setup is quicker and the maintenance is minimized. These properties allow dry electrodes to be particularly attractive in wearable EEG devices, healthcare and consumer-oriented neurotechnology applications [1].

An important challenge during EEG signal acquisition is to provide consistent and low electrode-skin impedance, especially over hair-covered regions. To tackle this issue, the dry-comb electrodes possess a structural design based on multiple projecting pins, which easily penetrate the hair and maintain direct contact with the scalp. The multiple pins, combined with the comb-like shape, help achieve and maintain the electrical contact of the electrode with the skin by the enhanced mechanical coupling of the electrodes. Multipin dry electrodes are shown to possess suitable impedances and remain relatively stable even during motion. The quality of signal from these electrodes has been demonstrated to be comparable to wet electrodes under optimal conditions, hence suitable for real time monitoring in the context of wearable devices [5]. Advancements in materials science (conductive polymers, flexible substrates, nanomaterials) have greatly improved conductivity and biocompatibility, as well as the durability and flexibility of the dry electrodes.

With respect to the signal quality of dry electrodes, several studies show that even modern dry electrodes can perform nearly as well as the wet ones if they are well optimized. High electrode impedances can usually be decreased to acceptable levels for EEG by using active electrodes with built-in amplifiers. The active dry electrodes thus are able to increase the

SNR and make the acquisition more resilient to electrical noise, which is frequently encountered in real-world environment. Studies prove that using the dry electrodes we can detect well known features of EEG signals such as ERPs, alpha rhythm and SSVEPs, which make them suitable for various applications such as brain-computer interfaces and emotion detection. However, the impedance of dry electrodes may still increase under less favorable conditions, leading to noise in the recorded signal and the deterioration of the SNR. This issue can also be reduced to an acceptable level by sophisticated analog and digital signal processing [7].

Another benefit of using dry-comb electrodes is that they are reusable and very comfortable to the user. As opposed to the disposable wet electrodes, the dry electrodes maintain good signal acquisition quality for many applications throughout repeated usage, thus diminishing the running cost and impact on environment. Moreover, their ergonomic structure allows wearers to maintain comfortable long-term use and also makes wearable EEG headsets based on dry electrodes usable in a broad range of applications including neurofeedback, gaming and brain-computer interfaces [5].

The use of an embedded processing platform significantly enhances the wearable EEG system. The ESP32 microcontroller can provide on-chip processing capacity and allow data acquisition and effective handling of EEG signals. Combined with the ESP32 microcontroller, it allows remote access for the processing of brain signals in conjunction with another processing platform such as mobile phones or personal computer for visualizing brain activity in real-time, leading to applications such as telemedicine, remote diagnostics and neurofeedback [9].

The design proposed of 24 channels, with electrodes distributed on the frontal, parietal, temporal and occipital regions, can capture and represent the spatial distribution of brain signals accurately. The use of multi-channel

EEG system provides detailed spatial information required for efficient signal interpretation and covers most brain areas of interest for the analysis. A balance between resolution and portability has been struck by employing a 24 channel setup. EEG is a modality with excellent temporal resolution which can accurately capture neural activity in real time making it suitable for cognitive workload detection [13].

Further advancement with multi-channel wearable EEG system enables sophisticated processing algorithms for EEG signal processing such as source localization, artifact removal or feature extraction to be performed. Such advanced techniques will increase the accuracy and robustness of interpretation in real-world environment. EEG system with the aid of machine learning, is capable of classify brain state for application such as emotion detection, stress monitoring or diagnose neurological disorders. Combination of smart software with wearable hardware can improve current technology to adaptive personalized neurotechnology systems [10].

At last, a novel 24-channel wearable EEG system based on ESP32 microcontroller and dry-comb electrodes has been presented. In contrast to the conventional wet electrodes system which requires external heavy apparatus and is confined within laboratory/clinical settings, the design of this wearable system ensures portability, user-friendliness and real-time monitoring of the brain signals in real-world environments. The dry electrodes, combined with sophisticated electrode-skin coupling mechanism, permit ease of application while maintaining good signal acquisition quality. With the utilization of low-power and dual core ESP32 microcontroller, the device supports efficient on-chip signal acquisition and handling, and can seamlessly transmit the acquired brain signals to another platform such as a mobile device or desktop computer for on-site visualization and further analysis, bringing advanced neurotechnology to mainstream application.

2.3 Emotion Recognition Using EEG Signals

Emotions generate distinct variations in brain activity that shows in EEG patterns. Features widely adopted methods include Time-domain: mean, variance, RMS amplitude Frequency-domain: alpha/beta power, spectral density Frontal asymmetry for positive/negative emotion detection EEG based emotion recognition enables quantitative emotion assessment independent of self-reported feedback [8]. based emotion recognition enables quantitative emotion assessment independent of self-reported feedback [5].

2.4 Signal Processing and Feature Extraction

EEG signal is largely used to classify and recognize human emotion through extraction of meaningful patterns from the signal for further analysis and classification of emotions. These signals are useful in detecting the features like frequency components, variation of amplitude and temporal dynamics that are relevant to varying human emotional states. Preprocessing of raw EEG signal is necessary to ensure data quality and accuracy, which is characterized by filtering of brain waves that are significant for the range from 0.5 Hz to 50 Hz and are separated from the noisy signals like muscles, eyes, electricity etc. In addition preprocessing involves removing artifacts, from the EEG signals. These artifacts can be caused by eye blinking or muscle activity. Independent Component Analysis (ICA) or a threshold-based correction can be used to minimize these problems. EEG signals are used for emotion recognition. Preprocessing helps to get features. Features are used for classification. Effective preprocessing significantly improves the quality of EEG signals and increases the quality and stability of the emotion classification system [26]. Once EEG signals are preprocessed, features are extracted to describe the signals. Mean, standard deviation and peak-to-peak amplitude are statistical properties of the EEG signals, whereas spectral power, alpha/beta ratio, and asymmetry represent the distribution of brain activity across frequency ranges and are used to classify emotions.

These features provide measured metrics of emotional states and are delivered into real-time classification modules [11]. Firstly, the benchmarking is done, and the model is trained in the available dataset, and then we have to compare its accuracy when testing in a real-time dataset. After preprocessing, the raw 24-channel EEG signals, sampled at 128 Hz, were supplied to a 1D Convolutional Neural Network (CNN) for automated feature extraction. The CNN was implemented to ability to seek spatial-temporal characteristic patterns across multiple channels. This method obviates manual feature engineering while extracting complex EEG dynamics important for emotion recognition [38].

Chapter 3

Requirement Specifications

3.1 System Overview

The suggested framework of the emotion recognition system is structured under a Brain-Computer Interface (BCI) framework that enables direct communication between the human brain and an intelligent computational system. The overall architecture contains four main stages: EEG signal acquisition, signal processing, AI-based emotion classification, and emotion output generation. Initially, the participants have wearable EEG headset to record raw EEG signals by using wearable EEG headset during which, participants are exposed to controlled emotional stimuli. These signals are then passed through a preprocessing stage to remove noise and artifacts that may reduce the data accuracy. Subsequently, the preprocessed EEG data are converted into appropriate formats for deep learning. A Convolutional Neural Network (CNN) is employed to automatically extract meaningful characteristics and classify emotional states. Finally, the predicted emotional output is generated instantly in real-time, enabling objective and continuous emotion monitoring. Currently, the online dataset is used, the institutional approval was sent, and it is waiting for approval. So, that's why benchmarking is done in this research. The results here are approximately true when the implementation is in real-time. This flexible structure ensures scalability, usability, robustness, and suitability for real-world emotion recognition applications, specifically in youth-focused mental health monitoring systems.

3.2 Existing System

Most emotion recognition systems that use EEG signals need equipment with wet electrodes. This equipment is really expensive and big so it usually stays in labs. The electrodes need a gel to work properly. Setting up this equipment is not easy. Requires people who know what they are doing to confirm the results of the electrodes are correct and the signals are more accurate. The data from these systems is usually looked at later not away which means they are not exact for checking emotions in real life as it happens. This is why the usual EEG systems are not accurate for detecting emotions when you are moving around or need something that does not cost a lot, outside of research labs. EEG systems like these are just not portable or cheap enough for use, which is what makes them unsuitable for emotion detection outside of labs that do research, like the ones mentioned in [30].

3.3 Proposed System

To get around the problems with systems we have a special headset that people can wear. This wearable 24-channel electrode EEG headset is for watching emotions in real time. The headset does not need gels so it is easier to set up and people feel more comfortable wearing it. We get the EEGsignals. Do the first steps of processing them right away. Then we find the parts of these signals and sort them into emotions like happiness and sadness. The wearable 24-channel electrode EEG headset uses an ESP32 microcontroller to send the data to computers or mobile devices without using any wires. This lets us see and study the data away. This design is easy to carry does not cost a lot and's simple for people to use. So it is a solution, for real life including watching mental health managing stress and interacting with computers. So, the system EEG-based emotion detection is done using dry electrode which is portable, that is, much more reliable and efficient to use. Also it is done in real-time data acquiring.

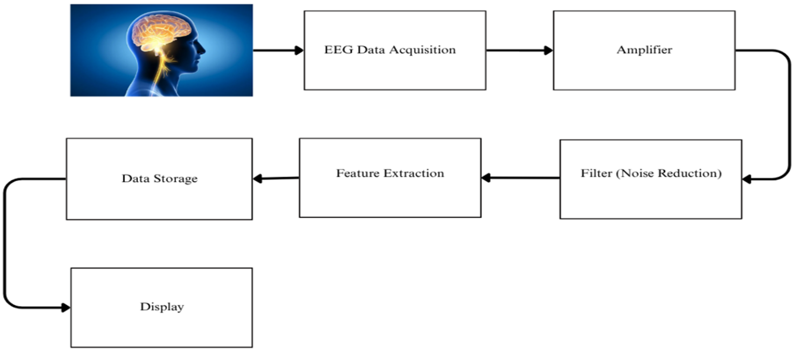


Figure 3.1: Block Diagram of the Proposed EEG-Based System

Figure 3.1 illustrates the overall block diagram of the proposed EEG-based emotion recognition system. The process begins with EEG data acquisition, where brain signals are captured from the human scalp using electrodes. These signals are then passed through an amplifier to strengthen the weak electrical signals.

After the amplification, the filtering stage is applied for the signals to process and remove the noise and unwanted artifact. The feature extraction includes bandpass filtering retained frequency component while ignoring low frequency drift and high frequency noise. These features modules are done to clean the signals that are essential characteristic for further analysis are extracted. These extracted features are saved in the data storage unit simultaneously with the use of real time classification and visualization. In this process, the trained model in which features are predicted for the corresponding emotional state at present results in the visualization tool and understandable format. Finally, this process data is shown to the user through graphical interface that provide real-time emotion prediction along with confidence level. It enables consistently detecting these emotional states.

3.4 Hardware Implementation

3.4.1 Hardware Components

This system portable , cheap and easy to use. It is designed mainly for EEG acquisition. It is designed by using cost effective and also easy to capture unwanted emotions that is difficult to manipulate. This health monitoring system can give the signal. Also it for youth to measure their stress level. This was the hardware made for 24-channel EEG-headset for emotion detection.

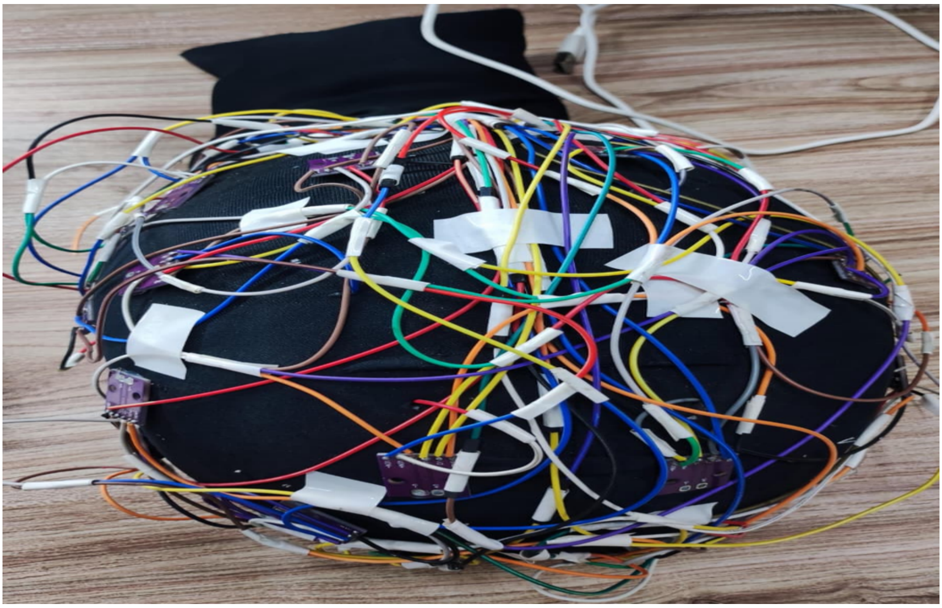


Figure 3.2: EEG-Headset with 24-Channel

The hardware components used in this project are listed below:

- ADS1256 ADC Module
- Screws
- INA129 Instrumentation Amplifier

- ESP32 Microcontroller Module
- Dry-Comb EEG Electrode

3.4.2 Dry-Comb EEG Electrodes

The dry-comb electrode does not require any gel to record EEG signals. The dry-comb electrodes are used to detect brain activity without direct contact with the scalp gel. This makes the system easy to use and reduces the preparation time required for participants. As a result, users can quickly begin experiments with the Brain-Computer Interface (BCI) without any lengthy setup process.

3.4.3 Electrode Placement

24-channel electrode configuration to capture the neural activity from the important brain regions. This is done while keeping the equipment portable. The electrodes are positioned according to the international 10-20 EEG system [18]. The main focus of the 24-channel electrode configuration is on the frontal, occipital, and temporal regions of the brain [22]. These brain regions are strongly linked with processing. The 24-channel electrode configuration is important for this purpose.

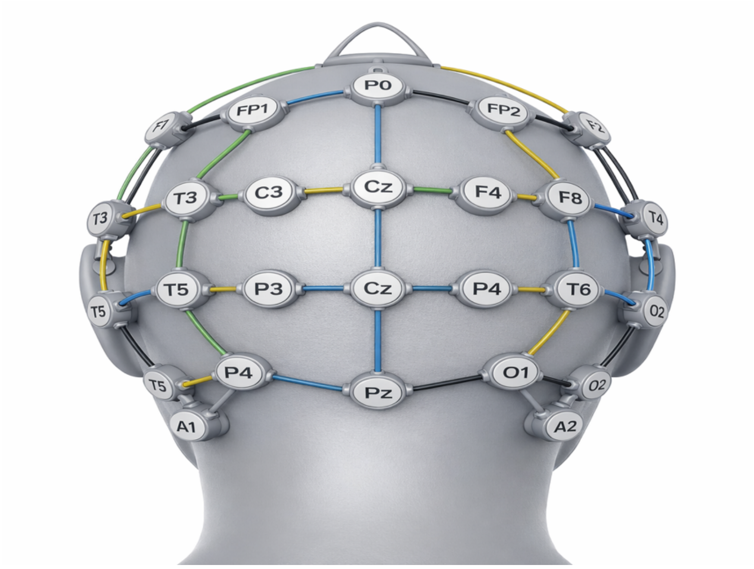


Figure 3.3: Electrode placement Design

Table 3.1: EEG Electrode Placement and Associated Brain Functions

Brain Region / Electrode	**Channels**	**Functions**
Frontal Lobe	Fp1, Fp2, F3, F4, F7, F8	Emotional processing, decision-making, attention
Central Region	C3, C4, Cz, FCz	Motor control, sensory-motor integration
Parietal Lobe	P3, P4, P7, P8	Sensory perception, spatial awareness, attention
Temporal Lobe	T3, T4, T5, T6	Memory, auditory processing, emotional processing
Occipital Lobe	O1, O2	Visual processing, visual attention
Reference Electrodes	A1, A2	Baseline electrical activity reference
Ground Electrode	Fpz	Noise reduction, signal stabilization
Midline Electrode	Pz	Midline brain activity recording, central reference

Data Acquisition Parameters

- Sampling rate: 256 Hz
- Duration per stimulus: 30–60 seconds
- Total channels: 24 (as defined above)
- Real-time streaming to the classification system

3.4.4 EEG Signal Feature

1. **Time-Domain Features:** Time-domain features are used to analyze EEG signals over time. The mean represents the average signal value, while the variance measures how much the signal fluctuates.

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} x_i(t) \tag{3.1}$$

$$\sigma_i^2 = \frac{1}{T}\sum_{t=1}^{T}(x_i(t) - \mu_i)^2 \tag{3.2}$$

2. **Frequency-Domain Features:** Frequency-domain analysis is performed using the Fast Fourier Transform (FFT). The Power Spectral Density (PSD) shows how signal power is distributed across different frequencies.

$$PSD_i(f) = \frac{1}{T}\left|\sum_{t=1}^{T} x_i(t)\, e^{-j2\pi ft/T}\right|^2 \tag{3.3}$$

3. **CNN Input Representation:** The preprocessed EEG signals are arranged as a matrix and provided as input to the CNN model. Here, T represents time samples and N represents the number of channels.

$$X_{CNN} \in \mathbb{R}^{T \times N} \tag{3.4}$$

In this project, we acquire EEG signals from electrodes on the scalp. These are very low amplitude signals, so they are first amplified (using an INA129 instrumentation amplifier) to increase the amplitude of the signals and remove some of the noise, thereby improving the quality of the data. After the signals are recorded, it is preprocessed to enhance their quality. Then, the analysis is done in two ways: time domain and frequency domain. In time domain, the mean and variance values are extracted to get an idea about the temporal changes in brain activity. These provide a basic understanding of the amplitude and variability of the signal. Furthermore, it extract the frequency domain of EEG signal via FFT to check the energy of each frequency which is known as power spectral density (PSD). With the PSD analysis can detect the brain wave activity which correlates with human emotion, for example the alpha and beta wave. Besides the manual detection, the preprocessed EEG signals is fed into the CNN, it learns the relationships within data without explicit feature design and able to recognize the emotion state (happiness, sadness) which can apply to real-time emotion monitoring system.

3.4.5 Instrumentation Amplifier (INA129)

EEG signals obtained from scalp electrodes are highly faint, that is measured in microvolts and are very responsive to external electrical interference. An instrumentation amplifier (INA129) is significant front-end component in the designed framework. It is used for reducing noise in the signal. It has low-amplitude EEG signals to level t for further processing of shared electrical disturbances [35]. The amplitude output is expressed as

$$V_{out} = G(V^{+} - V^{-}) \tag{3.5}$$

where G indicates the amplifier and are the electrode input. Hence, the INA129 plays a crucial role in upgrading EEG signal quality before digi talization.

Table 3.2: EEG Feature Domains and Emotional Relevance

Feature Domain and Feature	**Purpose / Emotional Relevance**
Time-Domain: Mean, Variance	Track overall signal power and arousal level [41]
Time-Domain: Hjorth Parameters (Activity, Mobility, Complexity)	Describe temporal structure and signal dynamics [1]
Frequency-Domain: Alpha Band (8–13 Hz)	Correlated with relaxation and idle mental states [6]
Frequency-Domain: Beta Band (13–30 Hz)	Related to stress, focus, and high arousal [8]
Spatial-Domain: Frontal Alpha Asymmetry (FAA)	Indicates emotional valence (positive vs. negative emotions) [6, 8]

3.4.6 Analog-to-Digital Converter Module (ADS1256)

EEG signals remain in analog form, and they are converted into digital signals for computational analysis [20]. The ADS1256 analog-to-digital converter (ADC) module is employed in the proposed system. It is a 24-bit ADC, which is the high resolution, exact digitalization of low-amplitude analog EEG waveforms into digital samples.

3.4.7 Microcontroller Unit (ESP32)

The central processing unit of wearable emotion recognition system is ESP32 microcontroller [18]. It digitized EEG data from the ADS1256 module and performed pre-processing operations before transmitting the data for classification. The filters are applied 50 Hz notch filter low pass filter for reducing the noise in the signal. Dc blocker is used for removing the drift baseline [24]. The DC blocker function filters out the D.C. Offset and very slow baseline drift that corrupts the EEG signals, producing a more stable signal with minimal loss of useful information. It is expressed as:

$$Y(t) = \text{Filter}(X(t)) \tag{3.6}$$

It enables wireless communication through Wi-Fi, and Bluetooth, allowing EEG signals to stream to a computer or mobile interface for further deep learning-based emotion classification. In real-world applications, ESP32 provides an efficient for portable, EEG detecting and support the practical deployment of the system.

3.5 Operational Requirements

3.5.1 Functional Requirements

The functional requirements of the proposed EEG-based emotion monitor ing system are:

Table 3.3: System Workflow for EEG-Based Emotion Recognition

Step	**Process Description**
1	Acquire 24-channel EEG signals from the wearable EEG headset.
2	Preprocess EEG signals using band-pass filtering, notch filtering, and artifact removal techniques to remove noise and unwanted interference.
3	Extract both time-domain features (mean, variance, etc.) and frequency-domain features (PSD, alpha/beta bands) from the EEG data.
4	Detect emotional states such as happiness and sadness in real time using processed EEG features and machine learning/CNN model.
5	Display EEG signals and emotion-related results on a PC or mobile interface for real-time monitoring.
6	Store and log EEG data for offline analysis, model improvement, and future evaluation.

3.5.2 Non-functional requirements

Operational requirements are the underlying requirements for the system to perform correctly under desired conditions. They influence architectural decisions and development process of the system as they place the constraints in areas like performance (response time, processing speed), quality (accuracy, reliability), design constraints (hardware limitations, power efficiency and compatibility). For the scope of this project the operational requirements ensure the real time, consistent quality and accuracy of the EEG based emotion recognition system under usage scenarios. Also operational requirements are the driving factors for the whole system design concerning the choice of hardware component, signal processing and machine learning model.

Table 3.4: System Requirements for EEG-Based Emotion Monitoring

Category	**Description**
Performance	$< 250\,\text{ms}$ latency for real-time emotion detection
Reliability	Stable signal quality across multiple sessions
Usability	Comfortable wearable design for 2–3 hours usage
Portability	Lightweight system ($< 500\,\text{g}$) with wireless operation
Security	Encrypted wireless data transmission
Scalability	Support for additional electrodes and cloud integration

3.5.3 Use Cases

The application cases of the 24-channel EEG system present the whole procedure of the designed real-time emotion recognition framework. Starting from receiving the EEG signal collected from the wearable headset; the brain signal is acquired at real-time and wirelessly transmitted to a mobile phone. The received signal is preprocessed on the mobile side, such as filtering and artifact removing, to improve the signal quality. After processing, some important features of the EEG signal, represent the brain state in time and frequency domain, are extracted and fed to the classifier to recognize emotions like happy and sad at real time. The recognized emotion will be directly demonstrated on the mobile phone so that users get an immediate feedback of their emotional states. It is developed to be a real-time application system and it does not use a pre-stored dataset but rather acquire real-time EEG signal from the headset. Moreover, the wireless transmission enables a continuously stream of data; also the system stores the data in the mobile phone for later investigation.

Table 3.5: Use Cases of the 24-Channel EEG System

Use Case	**Description**
EEG Signal Acquisition	Acquire EEG signals from the wearable headset in real time.
Signal Preprocessing	Filter EEG signals and remove noise/artifacts for clean analysis.
Feature Extraction	Extract time-domain and frequency-domain features from EEG signals.
Real-Time Emotion Classification	Detect emotional states such as happiness and sadness.
Visualization and Feedback	Display EEG graphs and emotion results on PC/mobile interface.
Wireless Data Transmission	Stream EEG data wirelessly to external devices.
Offline Data Logging	Store EEG signals for future analysis and model training.
Calibration and Setup	Adjust headset for accurate and stable signal recording.

Chapter 4

System Design

4.1 System Architecture

The suggested framework is designed to acquire, process, and examine cognitive electrical activities for the objective of detecting human affective states. It functions by collecting EEG signals from the scalp using dry-comb electrodes that are positioned according to the standard electrode placement system. These intensely low-amplitude neural signals are then strengthened, converted into digital form, analyzed, and ultimately sent to a graphical user interface for visualization and classification. The system design consists of various connected modules which include EEG signal acquisition, signal processing, feature extraction, data storage, and result visualization. The EEG signal acquisition module focuses on protecting the brain waves using electrode positioned in various locations in this scalp. The weak signals are amplified using low noise amplifier and converted into digital form through ADS1256 analog-to-digital converter for more processing. This system architecture focuses on cost affordability, compactness on the signal which maintains its fidelity for efficient emotion recognition. In this system design interconnected modules work together to form EEG-based emotion recognition these modules form a complete processing pipeline from input to output. After the amplification, the filtering stage is applied for the signals to process and remove the noise and unwanted artifact. The feature extraction includes bandpass filtering retained frequency component while ignoring low frequency drift and high frequency noise. These features modules are done to clean the signals that are essential characteristic for further analysis are extracted. These extracted features are saved in the data storage unit simultaneously with the use of real time classification and visualization. In this process, the trained model in which features are predicted for the corresponding emotional state at present results in the visualization tool and understandable format. Finally, this process data is shown to the user through graphical interface that provide real-time emotion prediction along with confidence level. It enables consistently detecting these emotional states. The analyzed signals is ultimately used for categorization using a Convolutional Neural Network (CNN), which acquires deep patterns from EEG brain signal features to identify various emotional states such as happiness, sadness, or stress. The functional process initiates when EEG electrodes capture brain activity from various regions of the neural system. These raw signals are first made stronger by an amplifier called the INA129. This helps the signals get better. After that, the signals are changed into form using the ADS1256 converter. The ESP32 microcontroller gets the data from this conversion. The ESP32 microcontroller does some work on the data, like cleaning it up and making it clearer to get rid of the unwanted noise in the signals. The ESP32 microcontroller does this by using some steps to process the digital data from the signals. The cleaned signals are subsequently used for feature extraction and classification. Finally the results after processing are stored and visually represented through a graphic interface, for a deeper analysis. Following amplification the EEG signal is higher in amplitude, however the desired brain activity is more clearly present, as well as the unwanted noise in the recording. Then it goes through some filters. The EEG signal is amplified to get higher amplitude but will also contain a lot of noise of different types (drift, muscle artifact, 50Hz). Filtering is applied during the signal processing within the ESP32. The filter chosen is a band-pass filter from 0.5-50Hz. The low-pass filter has a threshold of 50Hz so the signals do not be too high frequency (which could be noise) but also that there is no very low frequency drift (like baselines). The filter between 0.5 and 50Hz means that the filter is chosen so that brain signals can stay and the very low frequency drift is removed as well as the high frequency noises (like power line interference, but more importantly high frequency stuff from muscle activity and similar). A 50Hz notch filter is used to remove line interference as it is one of the most prominent and common noise components in EEG recording, particularily indoors. Reducing this specific frequency drastically reduced electrical contamination and helped create more stable data. Additional smoothing or low-pass filtering was used to smooth any spikes from motion or bad electrodes that make the waveform fluctuate in amplitude, in turn creating a more stable, continuous wave. Finally, a band pass filter was used which retains useful EEG frequencies while cutting out the low-frequency drift and high frequency noise from environmental (and some physiological) sources like eye blink and muscle artifact. The band-pass filter can be mathematically represented in frequency domain as:

$$H(f) = \begin{cases} 1, & 0.5 \leq f \leq 50 \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

This means only frequencies within the defined range are allowed to pass.

In addition to this a notch filter is applied to get rid of power line interference, which usually happens at 50 Hz or 60 Hz it depends on where you're

The notch filter is made to stop a small range of frequencies, around this value.

Mathematically the notch filter can be expressed in equation 4.2:

$$H(f) = 1 - \delta(f - f_0) \tag{4.2}$$

where f-0 is the interference frequency, 50 Hz. This ensures that electrical noise from power sources does not distort the EEG signal. The other aspect is the removal of artifact from EEG signal, which refers to some unwanted fluctuations in EEG signal recordings. As artifacts are mainly caused by eye blinking,jaw movements, facial expression and muscles activities, which heavily deteriorate the EEG data's quality and accuracy. As artifacts have no relations to the brain activity, and thus have a severe effect in the extracted features and classification stages of emotion recognition. As a result artifact removal is considered a necessary preprocessing stage in order to make EEG signal clear and clean and just contain neural information. These signals are actually not the brain's activities and we should suppress them to the lowest value before further analysis. In an EEG signal processing system, the common methods of removing those unwanted artifact are adaptive filtering and statistical thresholding. A basic method of artifact removal could be explained using thresholding based on the mean and the variance, when the signal's value goes far from the statistical mean they are removed in order to reduce artifact from the signal.

$$x_{\text{clean}}(t) = \begin{cases} x(t), & |x(t) - \mu| < k\sigma \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

where the mean signal value is represented by **μ**, the standard deviation is represented by **σ**, and K is a predefined constant threshold used to identify and remove unwanted signal variations.

After cleaning the EEG signal, it is passed to the feature extraction stage, where the raw signal is converted into meaningful numerical representations that describe brain activity. These features are extracted from three main domains: time, frequency, and spatial domains. In the frequency domain, EEG signals are analyzed by decomposing them into standard brainwave bands such as delta, theta, alpha, beta, and gamma. These frequency components provide important information about different mental states and are widely used in emotion recognition systems.

Table 4.1: EEG Frequency Bands and Their Ranges

EEG Band	**Frequency Range (Hz)**
Delta Waves	0.5 – 4
Theta Waves	4 – 8
Alpha Waves	8 – 13
Beta Waves	13 – 30
Gamma Waves	Above 30

Each of the EEG frequency band can relate to certain cognitive or emotional state. For instance, alpha wave is usually related to a restful or relaxed state, such as lying down, without the intention of analyzing the surrounding information. Another example is beta wave which may relate to an alert or attentive, or even agitated or stressful state; when a person is having concentrated mental tasks, or experiencing some stressful environment; in certain state, it can relate to certain emotion state of the person. The method to analyzing these frequency components is by applying Fourier Transform on the EEG signal. It can transform the signals in the time domain to the frequency domain. Through the calculation, we can analyze the amount of power of each wave band.

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi f t}\, dt \tag{4.4}$$

This allows the system to analyze how the energy of the EEG signal is distributed across different frequency components. After identifying these relevant signal patterns, the data is passed to the classification stage, where a Convolutional Neural Network (CNN) is used to interpret the extracted features. CNN is particularly effective for this task because it can automatically learn meaningful patterns from structured data without manual feature engineering. In the case of EEG signals, the CNN learns spatial relationships between different electrode channels as well as temporal variations in brain activity over time. This makes it highly suitable for emotion recognition tasks, where subtle changes in brain signals must be detected and classified accurately. Mathematically, the operation of a Convolutional Neural Network can be expressed as follows:

$$y(t) = (x * w)(t) = \sum_{i} x(i)\, w(t-i) \tag{4.5}$$

The input signal is what we call x. The convolution filter is what we call w.

A typical CNN system has a few parts: it has convolution layers that help find important things in the input signal pooling layers that make the data smaller and fully connected layers that help make the final decision.

The output layer then gives us probability scores, for each category and it does this using a thing called a softmax function.

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{4.6}$$

where z_i' is the input to the output neuron and $P(y_i)$ represents the probability of each emotion.

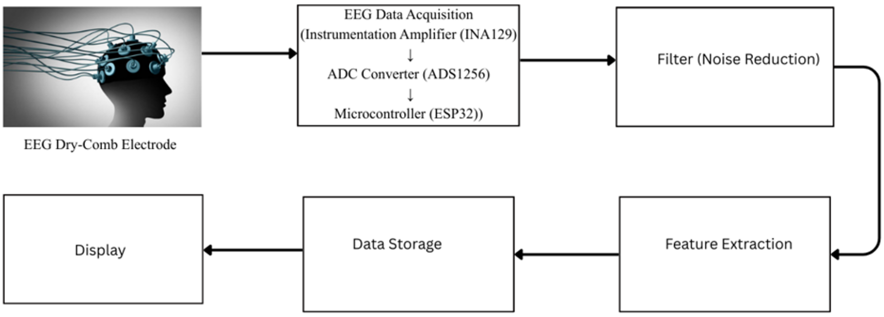


Figure 4.1: Block diagram of the proposed EEG-based emotion recognition system

Figure 4.1 illustrates block diagram presents the entire workflow in an EEG system. EEG dry-comb electrodes are attached to the head in order to acquire minute electrical signals from brain waves without conductive gels. These signals are forwarded to the Data acquisition part, which consist of a Instrumentation Amplifier (INA129) used to increase amplitude of the very small brain waves, while removing unwanted signals, an ADC converter (ADS1256) to change analog to digital values, and a microcontroller (ESP32) that manage flow of data and communication between components. These digital values are forwarded to filtering part in which undesired noise such as power line interface, and muscle interference, are remove from signals so that we obtain a clear EEG signal. Features extraction, from which relevant data such as frequency bands, specific characteristics associated with brain state or emotion, were collected from EEG signal. The EEG data are recorded or transmitted for later process and the obtained result are displayed to the user as graphs or interpret data.

4.2 Design Constraints

The architecture is affected by several technologies, hardware, and environmental constraints. One of the significant technical challenges is the extremely low amplitude of EEG signals, which are usually in the microvolt range and highly vulnerable to noise and interference from external sources such as power lines and muscle movements. Additionally, real-time processing constrains the computational capabilities of the ESP32 microcontroller, which requires efficient algorithms for efficient operation, especially when merging AI-based classification, such as a deep learning model (CNN). From a hardware aspect, the system is developed to be cost-effective, which constrains the use of high-performance EEG acquisition devices. A trade-off between performance and cost is achieved by using parts like the ADS1256 ADC and INA129 instrumentation amplifier. Power consumption is another crucial factor because the technology is worn and portable. Environmental elements such improper electrode placement, body movement, and electromagnetic signal interference can introduce noise or artifacts into the EEG data in addition to influencing signal quality and accuracy. It is considered that electrodes are correctly aligned according to the standard system, the user remains relatively stable during data acquisition, and wireless transmission of data between components remains stable during operation. The cost comparison between the proposed DIY EEG headset and commercial EEG systems is presented in Table 4.2.

Table 4.2: Cost Comparison Between Proposed DIY EEG Headset and Commercial EEG Systems

Category	**Item / Headset**	**Price (PKR)**	**Description**
Hardware (Proposed EEG Headset)			
	ADS1256 (ADC)	15,000	Analog-to-digital conversion of EEG signals
	INA129 (Instrumentation Amplifier)	18,000	Amplifies weak EEG signals and reduces noise
	ESP32 Module	1,100	Microcontroller for data acquisition and transmission
	Jumper Wires (M-M, F-F, F-M)	1,400	Electrical connections between components
	Dry-Comb EEG Electrodes	25,000	Main signal acquisition electrodes (39% cost)
	Total DIY Headset	**60,500**	Low-cost, portable, and customizable system
Commercial EEG Headsets [34]			
	EMOTIV Insight (5-channel)	217,000	Mid-range commercial EEG system for research
	Emotiv EPOC X	200,000 – 250,000	High-end EEG headset with advanced features
	OpenBCI (8–16 channels)	150,000 – 200,000	Research-grade EEG acquisition system

4.3 Design Methodology

The framework design applies a component-based and organized method to provide growth capabilities and ease of maintenance. Each functional unit is designed independently and then combined into the entire system. The development process includes requirement evaluation, system modeling, module decomposition, implementation, and testing. The system also follows a machine learning intelligent system-based workflow where EEG signals are collected, preprocessed, and transformed into significant features. These features are used to train a Convolutional Neural Network (CNN), which is used for emotion classification. The trained network learns intricate spatial and temporal patterns from EEG data to enhance classification accuracy. The final system consists of hardware components with software processing modules to achieve real-time emotion recognition and visualization.

4.4 High Level Design

In the high level design of this proposed system, it is divided into five key components signal acquisition, preprocessing, feature extraction, classification, and visualization.

1. Conceptual or Logical a specific function is done to execute in each module. To ensure a continuous stream it communicates with adjacent module. In this module, signal acquisition is done which captures the raw EEG data from the user. After it preprocessing is done to remove interference and artifact improve the strength of the signal enhance the quality of the EEG signal. The feature extraction module can identify important patterns from the EEG signal. The CNN convolution neural network also the classification module determines the emotional state that is depend on extracted features. In the visualization module, it suggests the result to the user in an understandable form. All modules are connected and then consistently exchange data and adjust a smooth processing flow.

2. Process during execution time, EEG signals are initially collected from the scalp using dry-comb electrode. These signals are then filtered to remove interference, artifact removal preprocess for more further analysis. These techniques boost the signal quality. This cleaned signal is then passed to the feature extraction stage; related characteristics are identified. Then classification CNN convolution neural network process the features to identify emotional state for example, happy, sad, stress, and focused. These predicted outputs are transmitted wirelessly through the ESP32 microcontroller. Finally, the output comes on the graphical user interface (disscussed later) for

real-time monitoring.

3. In this physical form, the system contains the EEG headset which is connected to an ESP32 microcontroller that controls data acquisition and wireless communication. The overall design is compact, lightweight, portable, and suitable for real-world usage in the outside laboratory environment.
4. The system is also divided into software modules, including firmware, signal processing, machine learning, and user interface components, each responsible for a specific task.
5. Secure communication is maintained using wireless protocols to ensure safe data transmission.

4.5 Low Level Design

At the low-level design stage, each module is further divided into smaller functional units. The EEG acquisition module consists of interface in electrode and analog front-end circulatory circuit to detect filtering algorithms for example bandpass 0.5 to 50 Hz and notch filter 50 to 60 Hz to reduce noise, interference, and artifact removal, unwanted noise, and power lines noise. Basic artifact removal methods applied to overcome disturbances caused by eye blink, muscle movement, and external unwanted noise. A voltage divider circuit is used to generate a mid-rail reference voltage, which provides a stable biasing point for accurate EEG signal acquisition. A mid-rail reference voltage is produced using a voltage divider circuit to provide a stable biasing point for EEG signal acquisition and processing. The program's feature extraction segment analyzes the EEG signals. Discovers various statistical details and characteristics associated with the occurrence of the signals.The features extraction section takes EEG signals as input and extracts a number of statistical attributes that represent characteristics of activity. These attributes are then used as input of the CNN where the automatically learned features and classification is executed. The CNN effectively learns the features from the input and removes the manually selected feature which is good in EEG-based emotion recognition. The Convolutional Neural Network consists of layers such as convolution, pooling, and dense processing layers, concluding with a layer that provides a probability output to determine an individual's emotional state.

The software is structured so that each component is distinct, allowing for work on one section without impacting others, which also simplifies locating and resolving issues. This structure also allows optimized integration of machine learning components with hardware-based signal acquisition.

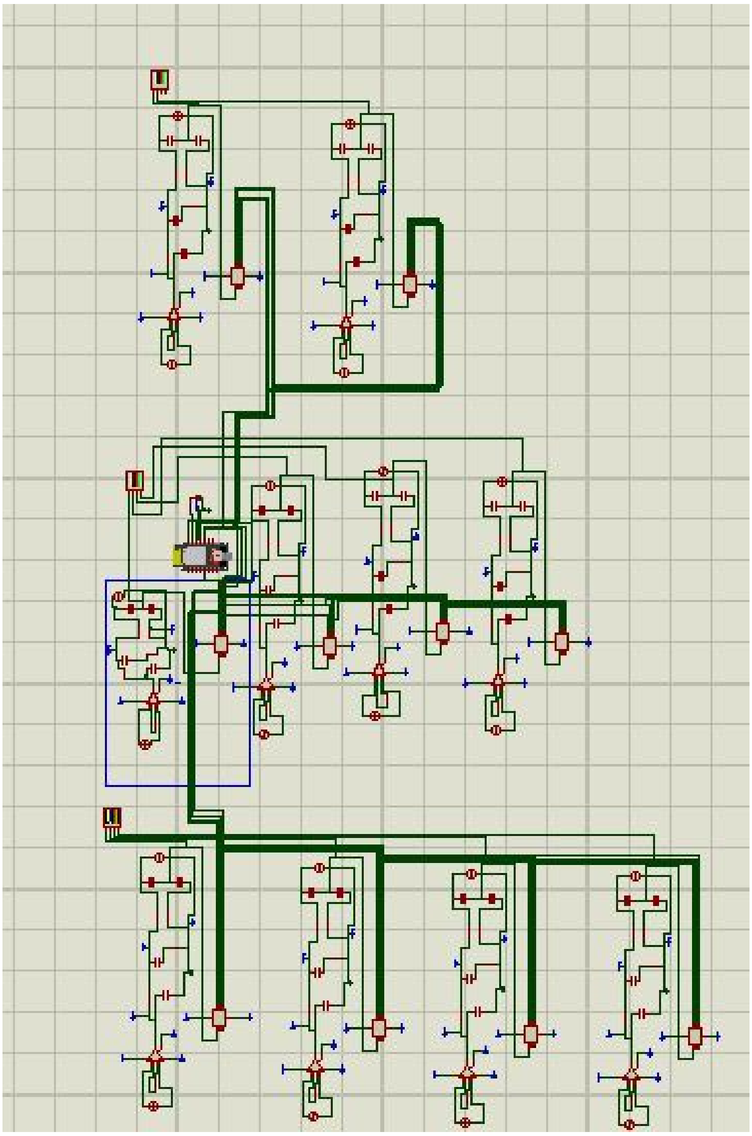


Figure 4.2: Simulation of the proposed EEG-based emotion recognition system

Figure 4.2 illustrates a 24-channel EEG signal acquisition system designed in Proteus. In this system, the same signal conditioning circuit is repeated for each electrode channel. Every electrode on the scalp collects the very low-amplitude signals generated from the brain and picked up by the scalp. The amplitude of these signals is in the microvolt order. Since the signals are very weak, a stage of amplification is present in each channel to amplify the signals. After amplification, filtering circuits with resistor and capacitor are introduced to filter out noisy and unnecessary signals such as the power line interference.

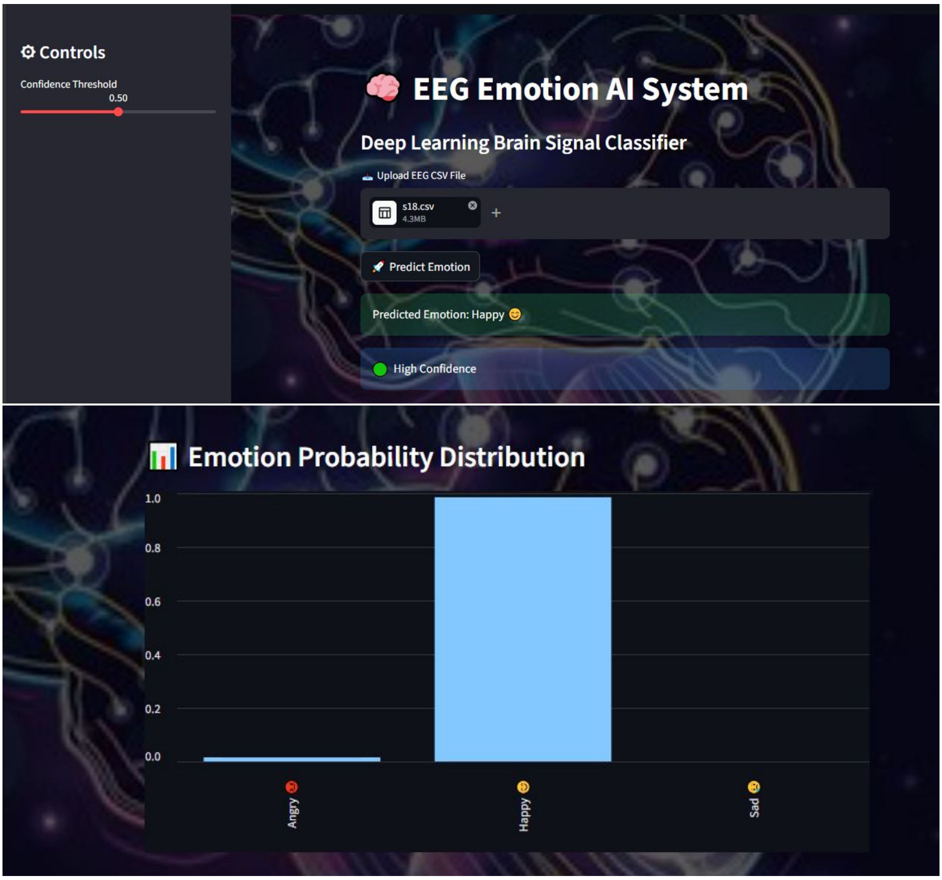
The ADS1256 analog-to-digital converter is then used to interface the conditioned signals from all 24 channels and transform them into digital form. The ESP32 microcontroller plays a vital role in processing digital data for analysis and generating output. The finished signal is an EEG signal in which filters are applied making it appropriate to use like emotion detection and monitoring brain.

4.6 Database Design

This system incorporates a structured feature extraction and classification for the output to support further improved analysis for evaluation. The data storage system consists of structure tables for raw EEG data analyze features and categorize emotions these recording predict information including time record, signal amplitude, extracted parameter values, and to detect emotional states. Additionally the system stores results from the Convolutional Neural Network(CNN) which are used to evaluate how the model accuracy is performed over time. The database allows tasks like basic operations such as data entry, extraction, and modification of records. This helps handle data, for both current and past analysis. The CNN results are used to check model accuracy performance across time.

4.7 Graphical User Interface Design

The graphical user interface is made to show EEG readings and anticipated emotional states in real time. It enables users to observe brain activity in an interactive and user-friendly way by displaying live signal plots, emotional state displays, and system control options. The interface updates the display in real time by wirelessly gathering data from the ESP32 microcontroller. In addition to the anticipated emotion labels produced by the Convolutional Neural Network (CNN), it displays both raw and filtered inputs. In order to ensure that users can efficiently assess brain activity without technical complexity, the design places a strong emphasis on simplicity, quick reaction, and usability.



Confidence Threshold 0.50

s18.csv 4.3MB

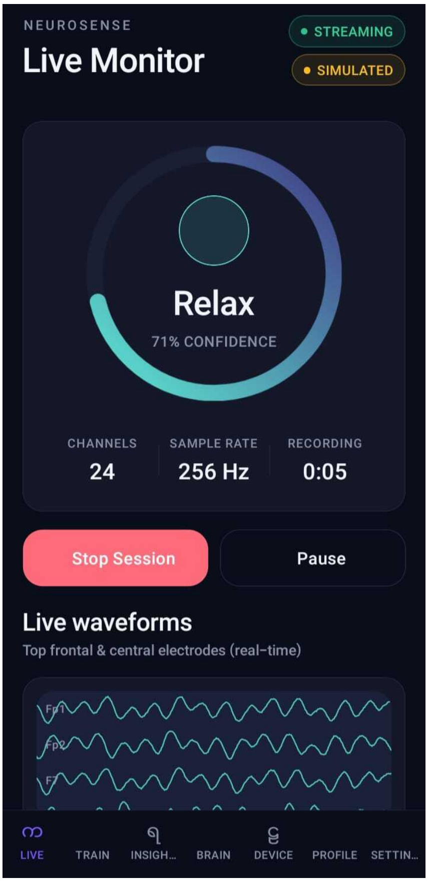
Predicted Emotion: Happy 😊

🟢 High Confidence

Figure 4.3: User interface of the EEG emotion recognition dashboard showing different views

Figure 4.3 shows The custom built UI, which displays EEG signals live along with the classification results has been built on the Streamlit platform. It has several features that allows it to accept signals, display live EEG graphs along with the detection of the emotions Happy, Sad and Stress using the prediction outputs from a CNN trained model. Streamlit is Python's web application framework. The structure of the app accepts the input data to feed to the signal processing algorithm and also to provide a live interactive front-end to display EEG signal graphs along with the predicted values.

4.8 Application Design



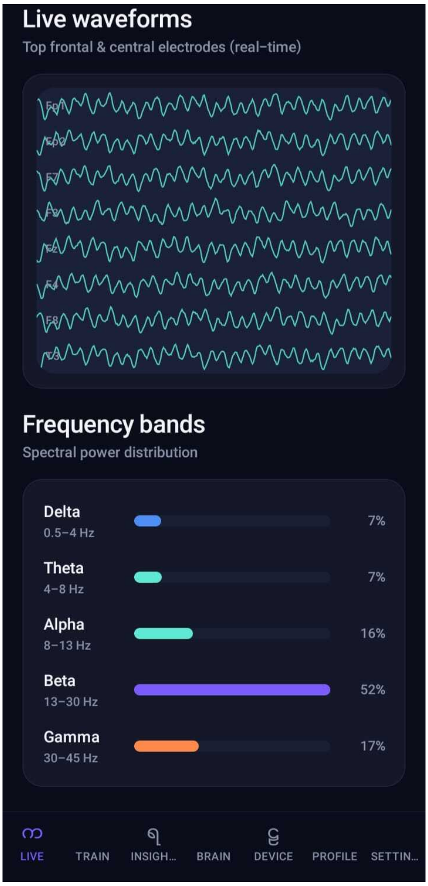
Relax
71% CONFIDENCE

CHANNELS 24
SAMPLE RATE 256 Hz
RECORDING 0:05

Live waveforms
Top frontal & central electrodes (real-time)

Figure 4.4: Real-time EEG Emotion Monitoring Interface

The figure 4.4 illustrates Figure 1 displays the graphical user interface of the constructed EEG monitoring system, showing a live plot of the EEG, a real-time analysis of the EEG on the different frequency bands and the current mental state. The interface provides the predicted state and the confidence, shown here as "Relaxed" and with 71% confidence. It displays the key recording parameters, like 24 channels, 256 Hz sampling rate and recording time, while providing the live visualization of real-time EEGs from electrodes in the frontal and central regions of the brain. The system operates on live stream and simulation modes, meaning it allows real-time signal recording, as well as being tested in offline mode, and allows control through start, pause and stop buttons.


Live waveforms

Top frontal & central electrodes (real-time)

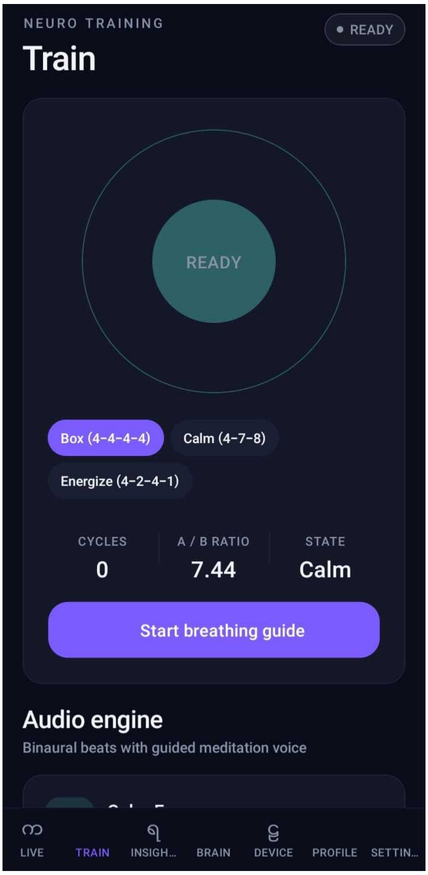
Frequency bands

Spectral power distribution

Delta 0.5–4 Hz	7%
Theta 4–8 Hz	7%
Alpha 8–13 Hz	16%
Beta 13–30 Hz	52%
Gamma 30–45 Hz	17%

Figure 4.5: Live waveforms with frequency bands

Figure 4.5 illustrates real-time waveform signals across various frequency bands such as delta (0.5-4 Hz), Theta (4- 8 Hz), Alpha (8-13Hz), Beta (13- 30 Hz), and Gamma (30-45 Hz) presenting dynamic variations in neural activity associated with emotional responses. The visualization enables observation of how signal amplitudes and frequencies fluctuate over time during various emotional states.



CYCLES 0

A / B RATIO 7.44

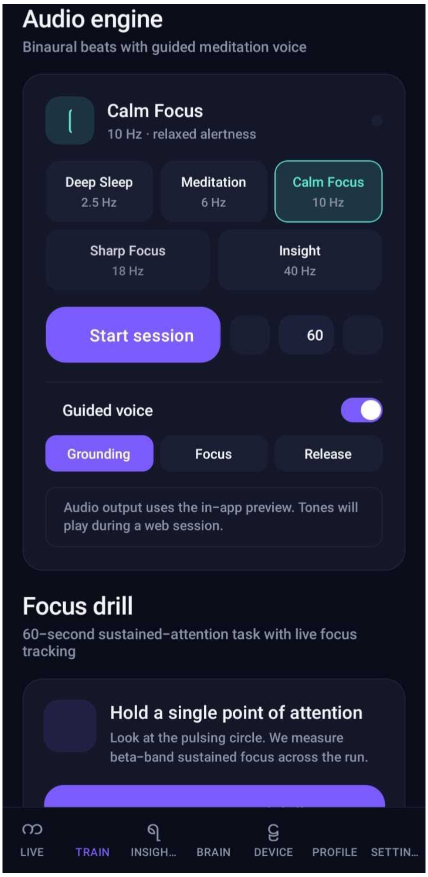
STATE Calm

Audio engine

Binaural beats with guided meditation voice

Figure 4.6: Train the participant to calm and Energize

The figure 4.6 illustrates the training interface designed to help participants regulate their emotional states by transitioning between calm and energized conditions.



Binaural beats with guided meditation voice

Calm Focus: 10 Hz · relaxed alertness

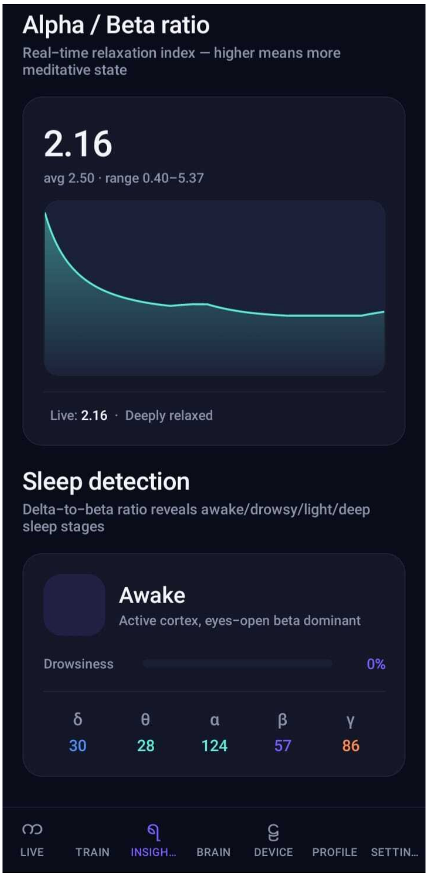
Audio output uses the in-app preview. Tones will play during a web session.

60-second sustained-attention task with live focus tracking

Look at the pulsing circle. We measure beta-band sustained focus across the run.

Figure 4.7: Audio Engine and focus drill

The figure 4.7 illustrates the audio engine module integrated with a focus training drill. The system uses auditory feedback mechanisms to guide the user into improved concentration states by responding to real-time EEG signals. The focus drill provides structured cognitive exercises designed to increase attention and mental engagement.



Alpha / Beta ratio

Real-time relaxation index — higher means more meditative state

2.16

avg 2.50 · range 0.40–5.37

Live: 2.16 · Deeply relaxed

Sleep detection

Delta-to-beta ratio reveals awake/drowsy/light/deep sleep stages

Awake

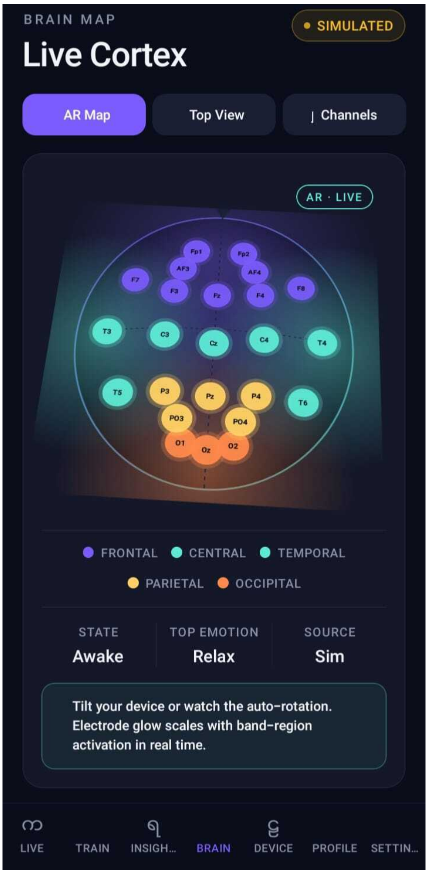
Active cortex, eyes-open beta dominant

Drowsiness 0%

δ	θ	α	β	γ
30	28	124	57	86

Figure 4.8: Alpha Beta Detection and sleep detection

The figure 4.8 tells us the detection of alpha and beta brainwave activity with sleep state monitoring. To identify the system analyze relaxation (alpha activity), active thinking (beta activity), and sleep-related patterns. This enables both cognitive state classification and basic sleep detection functionality.

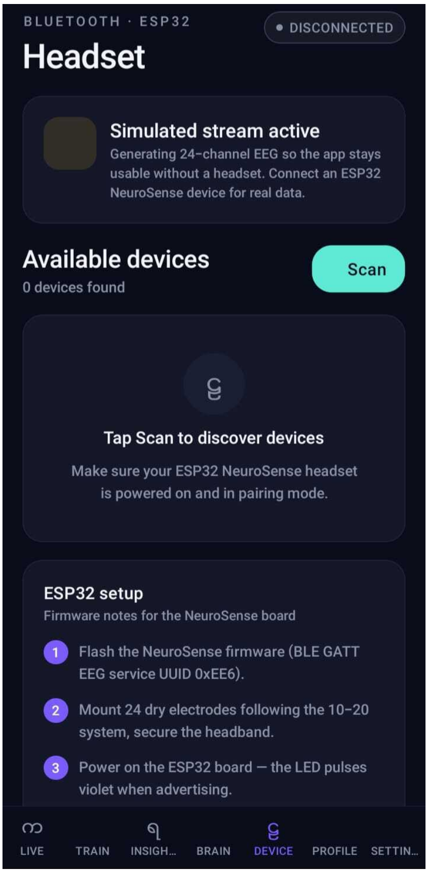


STATE	TOP EMOTION	SOURCE
Awake	Relax	Sim

Tilt your device or watch the auto-rotation. Electrode glow scales with band-region activation in real time.

Figure 4.9: Live Cortex

This figure 4.9 illustrate a live cortex visualization interface that represents ongoing brain activity in real time. The visualization maps EEG signal intensity and patterns onto a cortical model, allowing participants to observe dynamic neural responses during different mental and emotional states.


BLUETOOTH · ESP32

● DISCONNECTED

Headset

Simulated stream active

Generating 24-channel EEG so the app stays usable without a headset. Connect an ESP32 NeuroSense device for real data.

Available devices

0 devices found

Scan

Tap Scan to discover devices

Make sure your ESP32 NeuroSense headset is powered on and in pairing mode.

ESP32 setup

Firmware notes for the NeuroSense board

1. Flash the NeuroSense firmware (BLE GATT EEG service UUID 0xEE6).
2. Mount 24 dry electrodes following the 10–20 system, secure the headband.
3. Power on the ESP32 board — the LED pulses violet when advertising.

Figure 4.10: Heaset connection with bluetooth

This figure 4.10 depicts the wearable EEG headset establishing a wireless connection through Bluetooth. The interface confirms successful pairing and data transmission between the EEG device and the processing system, setting real-time signal streaming for analysis.


REFLECTIVE

Deep Thinker

Slow waves dominate — reflective and contemplative.

9 SESSIONS

9 MINUTES

93% ADAPT

Composure	36
Drive	63
Positivity	23
Intensity	100
Insight	58

The model learns from every session you record and gradually personalises predictions to your unique brain baseline.

Cloud sync

Multi-device tracking and replay

Cloud sync

Stream sessions across every signed-in device

Sessions are saved locally on this device only. Enable cloud sync to mirror data across phone, tablet, and desktop in real time.

Figure 4.11: Deep thinker and cloud syn

Figure 4.11 illustrates the ”Deep Thinker” mode provides system capabilities for advanced cognitive state assessment by handling the EEG data more extensively. This mode allows for real time processing of the brain signals and storage, along with synchronization, of the output data in long-term and enables continuous monitoring and observing of the changes in cognitive state over a longer time frame. Through the data stored the long term comparison can be performed and accuracy checked, and the patterns or trend of the cognitive performance and emotional status of the user in sessions compared.

4.9 External Interfaces

The interaction with the external components can be performed using the wireless communication protocols, Wi-Fi and Bluetooth through the use of the ESP32 module. The signals acquired through the wearable EEG headset can then be transmitted in real-time to a mobile based interface for data visualization and analysis. Through Bluetooth the headset can be connected to a mobile application, on the mobile application, the EEG signal is processed and the emotional states are displayed in real-time. This is different from systems that operate with a dataset, since this application doesn't need a previous set of acquired data recorded within the application, rather it takes in direct live EEG signals from the hardware. Alongside the communication with hardware it interacts with a machine learning backend, on which a Convolutional Neural Network (CNN) is able to analyze the extracted EEG features and provide output emotions that is passed on to the user interface.

Chapter 5

System Implementation

5.1 System Architecture

The proposed EEG based emotion detection system uses multiple layer architecture namely; Acquisition layer, processing layer, communication layer and user interface. First the human EEG signal is captured from the scalp of a human using dry-comb electrode and amplified by INA129 instrumentation amplifier because the amplitude of the human EEG signal is very low. Later the analog signal from the instrumentation amplifier is converted into digital form using the ADS1256 ADC module. ESP32 microcontroller acts as communication intermediary for transmitting the digitized EEG signal from the human scalp into a mobile or computer by means of a Bluetooth module. For the software part the collected EEG data is filtered, normalized and feature extracted by Python modules in real time and passed to the Convolutional Neural Network (CNN) for emotion classification. The estimated emotions and their confidence score are visualized in the user interface for real-time monitoring.

5.2 Tools and Technology Used

5.2.1 Hardware Components

Table 5.1 presents the key hardware components used in the EEG-based emotion recognition system along with their descriptions and functional roles.

Table 5.1: Hardware Components of EEG System

Component	**Description**	**Function**
Dry EEG Electrodes	Non-invasive scalp sensors	Capture brain signals
INA129	Instrumentation amplifier	Amplifies weak EEG signals
ADS1256	24-bit ADC	Converts analog signals to digital
ESP32	Microcontroller with WiFi	Data transmission & control

5.2.2 Software Tools

Table 5.2 presents the software tools and technologies used in the development of the EEG-based emotion recognition system along with their respective purposes in the overall implementation.

Table 5.2: Software Tools Used in EEG System

Tool / Software	**Purpose**
Arduino IDE	Programming ESP32 firmware
Proteus	Simulation of electronic circuit
Google Colab (Python)	CNN model training (cloud-based Python environment)
Python	Data processing and machine learning
NumPy	Numerical computations
Pandas	Data handling
MNE	EEG signal processing
TensorFlow	Deep learning (CNN model)
Scikit-learn	Machine learning utilities
Streamlit	Dashboard and application interface

5.3 Development Environment/Languages Used

High-level scripting languages and embedded programming are used in the development of the system. The Arduino IDE is used to write the C/C++ firmware for the ESP32, allowing for effective hardware component communication. In terms of software, Colab uses Python for machine learning, data analysis, and signal processing. Magnetoencephalography and Electroencephalography Python library (MNE-Python) is used for EEG-specific processing, whereas libraries like NumPy and Pandas are used for data handling. The convolutional neural network (CNN) model for classifying emotions is designed and trained using TensorFlow. Streamlit was used to make the dashboard application, and a unique interactive interface to show and examination the model outputs.

5.4 Processing Logic/Algorithms

The system follows a structured signal processing and classification pipeline for EEG-based emotion recognition.

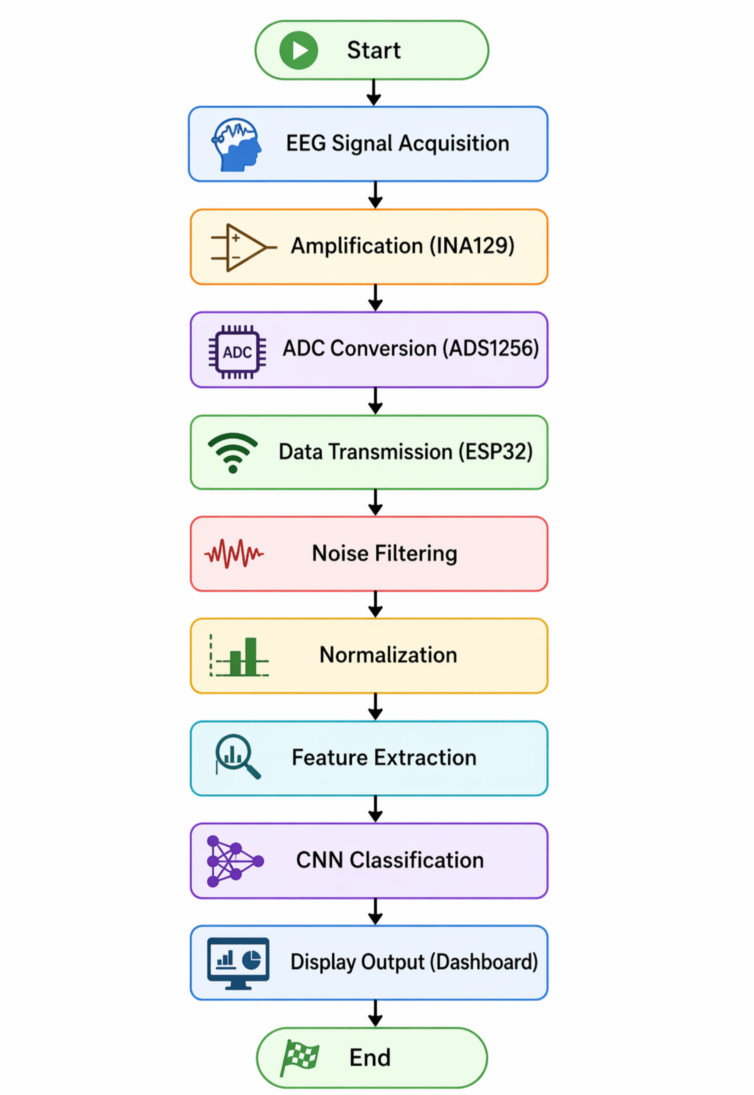


Figure 5.1: Flowchart of the EEG signal processing and emotion classification pipeline

Figure 5.1 presents the processing flow of the designed system that is organized as an organized pipeline and takes the EEG signal to finally categorize it into emotions. After the system receives signals from the human scalp through dry electrodes, the signals are first amplified and digitized to further undergo in digital processing. Following the digitization, signals are then forwarded to the processing part and subjected to a pre-processing that helps to remove noise from the EEG signal, normalized to refine the quality of signal and then features are extracted to represent important characteristic of the signal and then the extracted features is provided to CNN for classifying the emotions.

1. **Signal Acquisition**

   EEG signals are captured from the human scalp using electrodes.

2. **Signal Amplification**

   The weak EEG signals are amplified using the INA129 instrumentation amplifier.

3. **Analog-to-Digital Conversion**

   The ADS1256 converts the analog EEG signals into digital form for further processing.

4. **Noise Filtering**

   Bandpass filters are applied to remove noise and unwanted artifacts from the signals.

5. **Normalization**

   The data is normalized to enhance the performance and stability of the machine learning model.

6. **Feature Extraction**

   Relevant features are collected from the EEG signals to represent important characteristics.

7. **Classification**

   A Convolutional Neural Network (CNN) model is designed for classify the EEG signals into different emotional states.

5.5 Database Security

EEG data and model results are mainly handled via files. Controlled file access and adequate data processing steps were adopted to maintain data security. Furthermore, the dataset being used in this system is fully anonymous and privacy of all the subjects is one of the primary constraints; hence, no personal identification data (name or any related personal information) of any of the subjects will be stored or saved anywhere at any time. The system handles EEG data and model outputs mostly using file-based storage. Controlled file access and appropriate data processing procedures guarantee security.

Chapter 6

System Testing and Evaluation

6.1 Introduction

The main purpose of the assessment is to detect the reliability, accuracy, and real-time performance of the given system within the practical condition. Hence, the system signal acquisition with machine learning-based classification. In the assessment by taking real-time participants and detecting their emotional state. Initially, in the assessment and the consent is filled by the participant and their personal identification is not revealed. The testation was done in 24 young youth to examine their emotional states. The headset was worn by the participant and then signals are determined afterwards data set was put into Python for classification stage using CNN model. The output comes in this screen with their report. The app gives real- time emotional classification detection by using the alpha, beta, gamma, and Theta frequency bands. It is a human-computer interface. The EEG headset is connected via a wire to the processing device via the ESP32 module which transmit the EEG signals collected in real time. Subsequently, the emotional classification is performed by a 1D Convolutional Neural Network (CNN1D) model that extracts patterns from the processed EEG data. This model, which was trained on the dataset, determines emotional states from the collected data. This assessment process completely focuses on various key components such as classification accuracy, and robust of the system within real world conditions. This evaluation phase is quantitative, and qualitative methods are determining performance model in terms of accuracy and precision loss and prediction emotion probability distribution graph and qualitative assessment for a new user experience or for our own user experience. This contributes to an evaluation approach by measuring the strength and limitation of the given system in a structured manner.

6.2 Evaluation Methodology

The evaluation of this given EEG emotion recognition system is done through a structured methodology of the given system that conducts reliability, accuracy and precision under both controlled and real-world conditions. While the system gives multiple components including EEG hardware, signal processing algorithm, microcontroller-based data acquisition and a deep learning-based classification model. EEG signals are collected from participants using the designed wearable headset. These signals are then analyzed through a CNN-based deep learning model. The output is presented in real time using a Streamlit-based dashboard. The evaluation process includes:

1. Real-time acquisition of EEG signals
2. Emotion classification using a CNN-based model
3. Visualization of prediction results
4. User interaction through a graphical application interface

6.3 Participant-Based Testing

To validate the real-world performance of the system, testing was conducted on 24 participants. Each participant wore the EEG headset while brain's electrical activity was recorded under controlled conditions.

EEG data was successfully captured by the system, which was then able to categorize emotional states including happy, sad, stress, angry, relax and focused. The EEG-based emotion detection system does not directly retrieve emotions from brain signals. Instead, it acquires brain signals with 24 EEG channels, which are the brain's electrical activities derived from various parts of the brain. The brain signals are obtained when participants undergo someemotion elicitation procedure to evoke a specific emotion in participants including happy, sad, stress, angry, relax and focused. The acquired EEG signal is annotated with its corresponding emotional state for forming a structured dataset used to train. The 1D Convolutional Neural Network (CNN1D) extracts the signals of multiple channels in order to discover the patterns, and maps them to a certain emotion. As a result, the prediction of emotion is performed by recognizing its features in the EEG signals rather than directly collecting the emotion from either the quantity of channels or the raw signals. When it came to identifying patterns in EEG signals, the CNN model performed admirably and produced reliable findings for a variety of users.

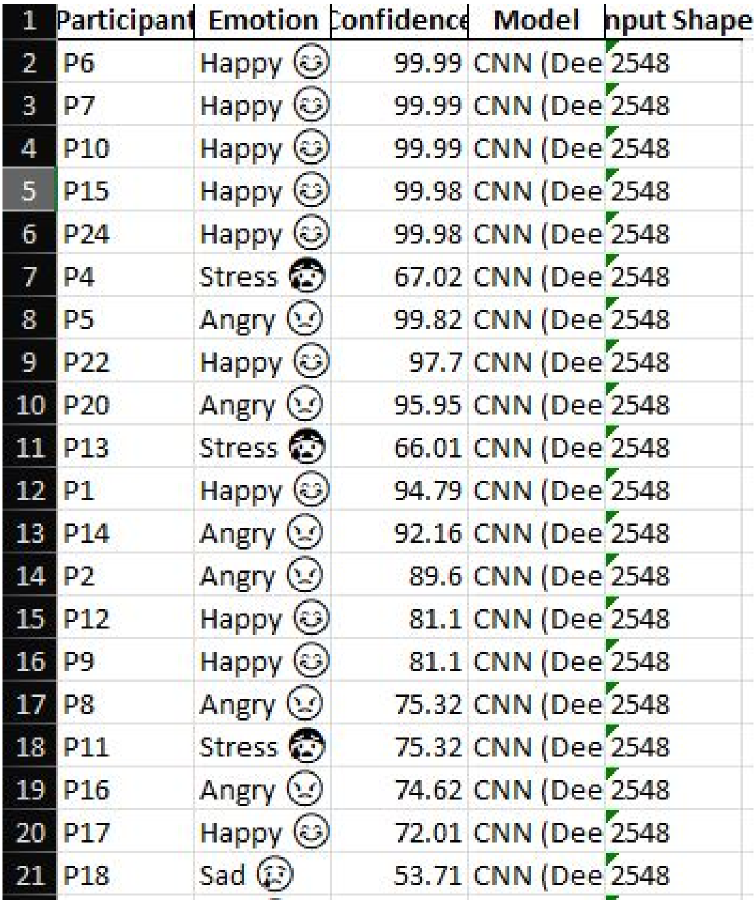
Figure 6.1: Participant wearing EEG headset during testing session

Figure 6.1 Illustrates the hardware testing setup in which EEG signals were recorded from over 24 participants using the proposed wearable EEG headset for emotion recognition analysis.

6.3.1 Results

The following table summarizes the emotion classification results obtained from participants during real-time testing of the EEG system.

Figure 6.2: EEG-based emotion classification results



1	Participant	Emotion	Confidence	Model	nput Shape
2	P6	Happy 😆	99.99	CNN (Dee	2548
3	P7	Happy 😆	99.99	CNN (Dee	2548
4	P10	Happy 😆	99.99	CNN (Dee	2548
5	P15	Happy 😆	99.98	CNN (Dee	2548
6	P24	Happy 😆	99.98	CNN (Dee	2548
7	P4	Stress 😫	67.02	CNN (Dee	2548
8	P5	Angry 😠	99.82	CNN (Dee	2548
9	P22	Happy 😆	97.7	CNN (Dee	2548
10	P20	Angry 😠	95.95	CNN (Dee	2548
11	P13	Stress 😫	66.01	CNN (Dee	2548
12	P1	Happy 😆	94.79	CNN (Dee	2548
13	P14	Angry 😠	92.16	CNN (Dee	2548
14	P2	Angry 😠	89.6	CNN (Dee	2548
15	P12	Happy 😆	81.1	CNN (Dee	2548
16	P9	Happy 😆	81.1	CNN (Dee	2548
17	P8	Angry 😠	75.32	CNN (Dee	2548
18	P11	Stress 😫	75.32	CNN (Dee	2548
19	P16	Angry 😠	74.62	CNN (Dee	2548
20	P17	Happy 😆	72.01	CNN (Dee	2548
21	P18	Sad 😢	53.71	CNN (Dee	2548

Figure 6.2 shows that the results demonstrate that the proposed system successfully classified emotional states based on EEG signals.

6.4 Signal Visualization Results

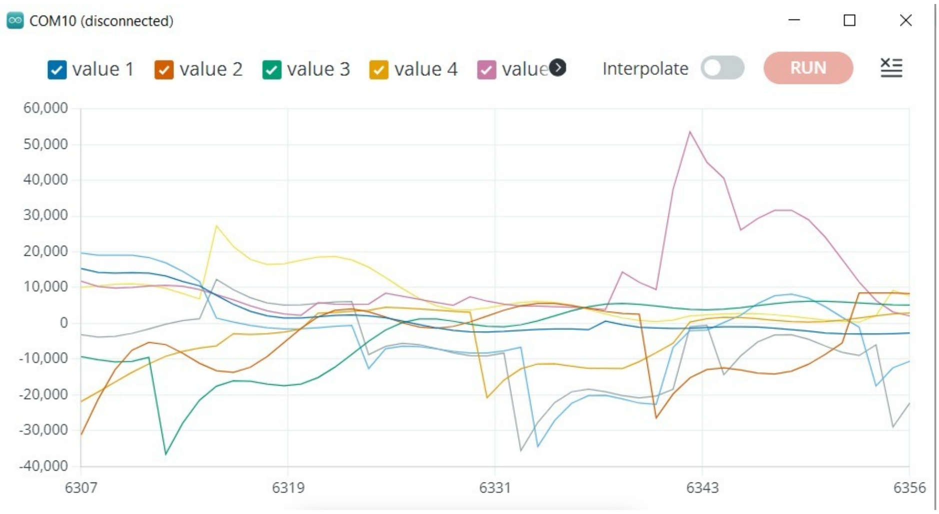


Figure 6.3: EEG-based emotion classification results

Figure 6.3 shows real-time signal data extracted from the EEG channels for the test subjects throughout the test run, as multiple EEG channels (value 1, value 2, value 3, and value 4) shown in time-series format. The graph displays the electrical activity in the brain at various intervals of time, extracted via the EEG headset system and processed through the attached system. Different colored signals represents different channels of data, as brain activity fluctuates in various signals and is continually being influenced by various neural activity. The signals are then preprocessed and feature extracted before being feed to the CNN to detect emotions.

6.5 Real-Time Application Testing

A real-time Streamlit-based application was formulated to simplify system interaction. The application allows users to input EEG data and instantly view predicted emotions.

The dashboard displays:

1. Predicted emotion label
2. Confidence score
3. Probability distribution graph
4. Downloadable report show participant emotions or emotion history.

6.6 Performance Analysis of CNN Models

Classifying and extracting information from EEG signals is the responsibility of the system's central component, a Convolutional Neural Network (CNN).

Class	Precision	Recall	F1-Score	Support
Happy	0.89	0.80	0.84	10
Angry	0.78	0.78	0.78	9
Sad	0.67	0.80	0.73	5
Accuracy	-	-	0.80	24
Macro Avg	0.78	0.79	0.78	24
Weighted Avg	0.81	0.80	0.80	24

Figure 6.4: Model Performance Metrics including Accuracy, Precision, Recall, and F1-score

Figure 6.4 this graph illustrates the proposed CNN model for EEG-based emotion recognition is evaluated quantitatively in this section. The accuracy, precision, recall, and F1-score are used to quantify the classification performance of the model to the emotion class.

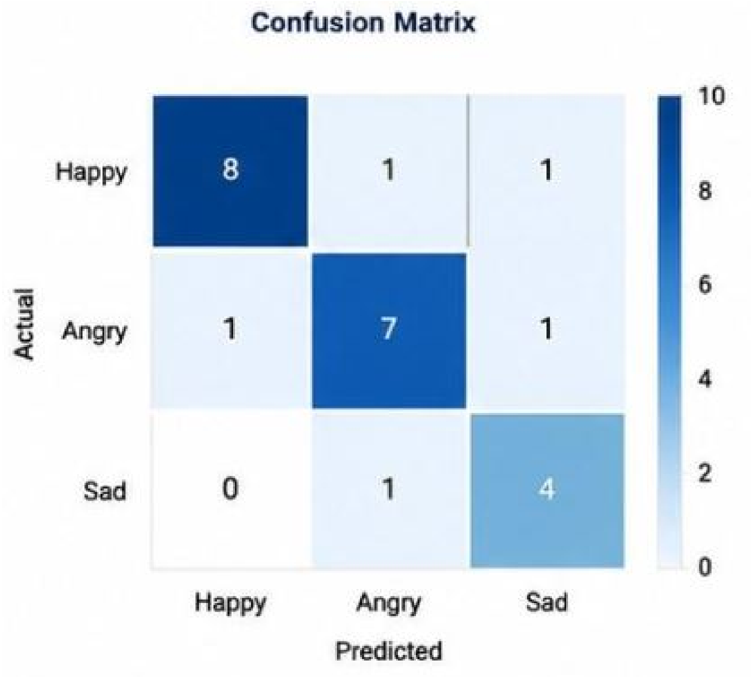


Figure 6.5: Confusion Matrix for CNN-based EEG Emotion Recognition Model

Figure 6.5 illustrates confusion matrix the classification performance of the proposed CNN-based EEG emotion recognition system. It provides a detailed breakdown of correctly and incorrectly predicted emotion classes, highlighting model strengths and misclassification patterns.

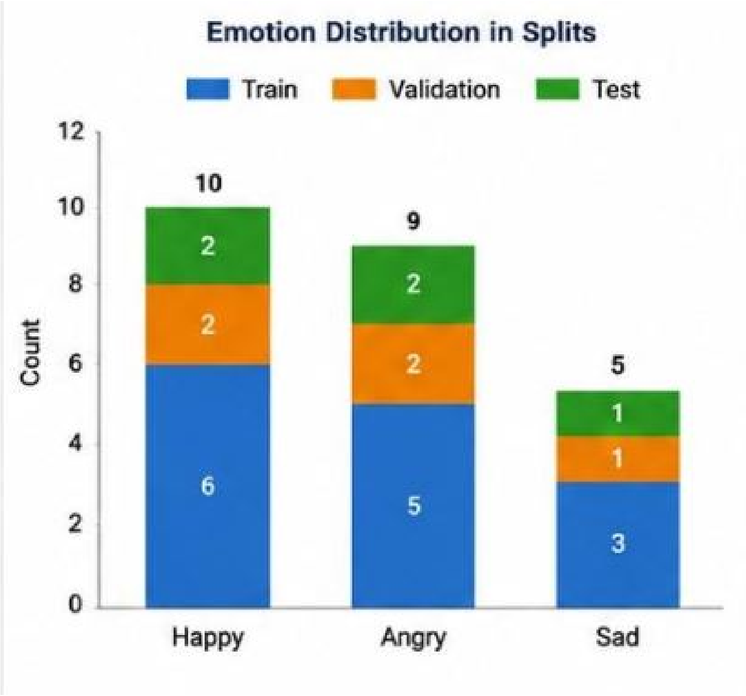


Figure 6.6: Comparison of Validation and Test Accuracy for EEG Emotion Classification

Figure 6.6 illustrates that performance comparison between validation and test sets for the proposed CNN-based EEG emotion recognition model. Validation results are used during training to tune the model, while test results represent final unseen data performance.

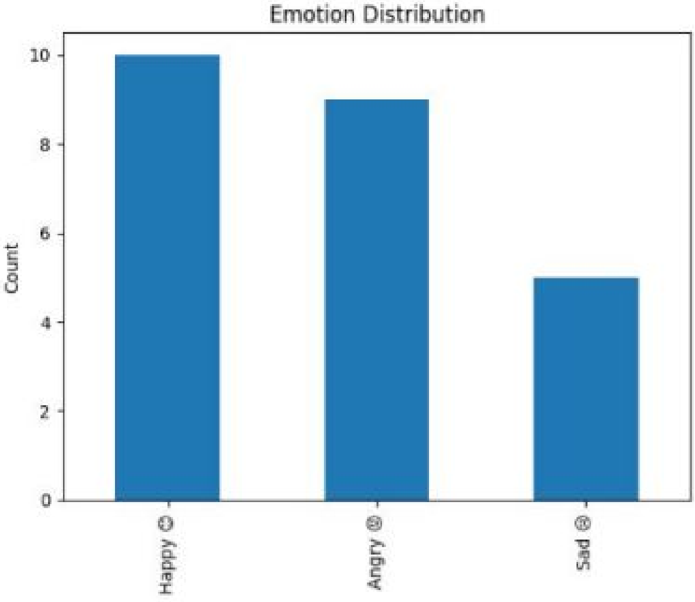


Figure 6.7: Distribution of Predicted Emotions in EEG Dataset

Figure 6.7 shows this graph shows how each 24 participant's projected emotional states(happy, angry, stress and sad) are distributed. It provides an overview of dataset balance and model prediction trends by displaying the number of samples that fall into each emotion category. Stronger classification presence in the dataset is indicated by a higher frequency of a specific emotion.

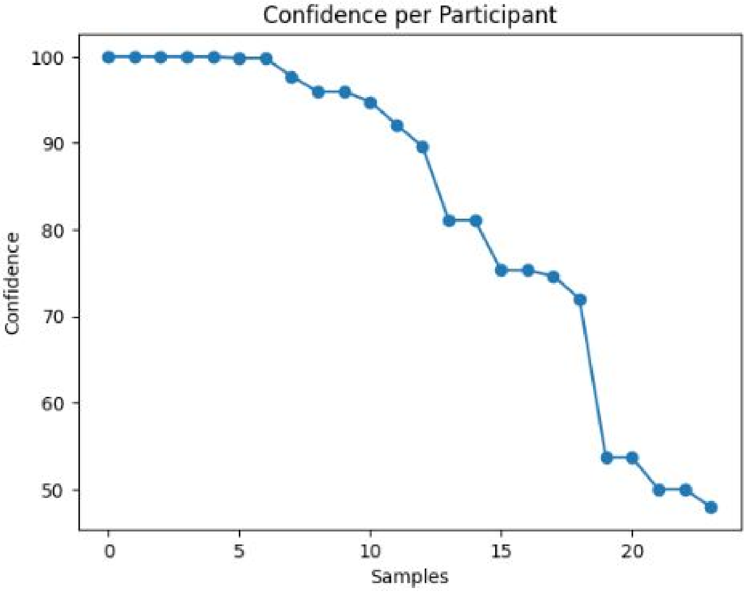


Figure 6.8: Confidence Scores of CNN Model Predictions per Participant

Figure 6.8 this graph illustrates the confidence levels generated by the CNN model for each participant's EEG-based emotion prediction. Confidence values indicate how strongly the model is certain about its predicted class. Higher values reflect stronger feature matching between EEG signals and learned patterns.

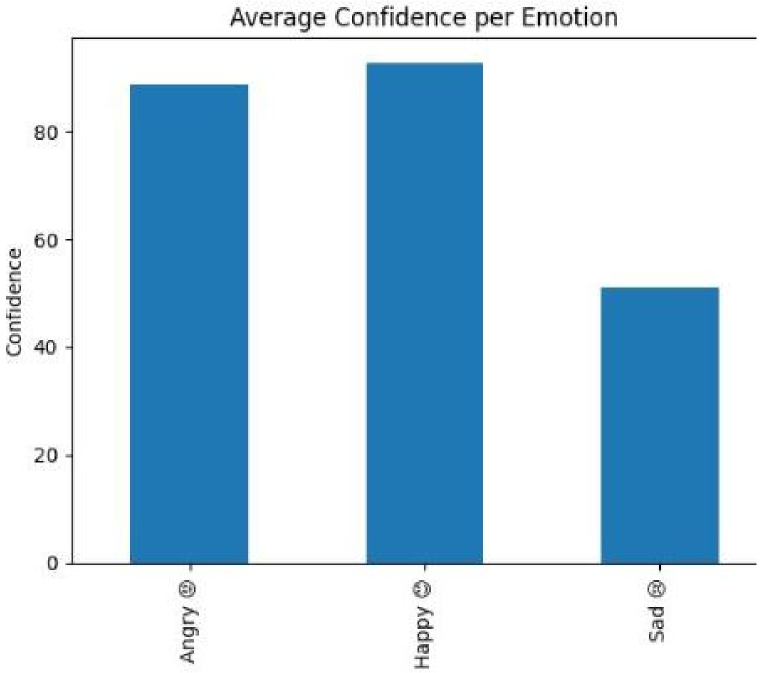


Figure 6.9: Average Confidence Level Across Different Emotion Classes

Figure 6.9 the average confidence score for each emotion category (happy, angry, and sad) is displayed in this graph. It facilitates the analysis of model performance in various emotional states. Better categorization reliability for that particular emotion class is indicated by higher average confidence.

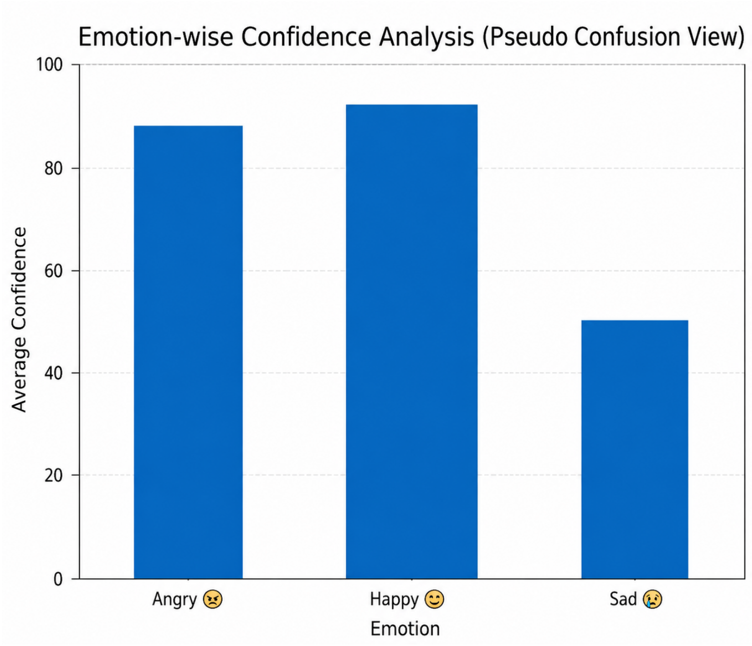


Figure 6.10: Confusion-matrix Graph

Figure 6.10 shows this graph displays a confidence analysis by class for each emotion, illustrated by way of pseudo confusion matrix, which depicts the mean confidence of the model for each predicted emotion class. The model yields robust results for the 'Happy' class with highest confidence of approximately 90-92%, followed closely by 'Angry' class with confidence of roughly 88-90%. However, considerably lower confidence scores are observed for 'Sad' class (around 50-52%), signifying that the model is not able to determine the class with sufficient accuracy. This is pseudo confusion view and does not count the numbers or misclassifications in actual classification. The level of confidence represents how confident the model is about the given predicted class. The variability of confidence may signify a class imbalance, overlapping feature of emotions and lack of appropriate representative examples for 'Sad' class in the training set, which indicates one aspect for the further improvement. The CNN model automatically learns important patterns from EEG data without the need for manual feature engineering. This leads to fast and efficient signal processing, improved emotion classification accuracy, and reduced computational complexity compared to traditional methods. As a result, the system can reliably detect and display multiple emotional states such as happiness, sadness, stress, focus, and relaxation based on real-time brainwave patterns. The system displays various emotional states such as happiness, sad, stress, focused, relaxed etc. Especially when the signals come and done the preprocessing and normalization techniques are followed.

6.7 Hardware Testing

The hardware system is composed of the dry-comb EEG electrodes, INA129 amplifier, ADS1256 ADC, and the ESP32 micro controller. The hardware was tested when the participant wore the headset. It successfully determines the weak EEG signals, which is amplified by signal acquisition and transmitted them when its preprocessing is done in real-time. Successful integration takes place when the hardware and software synchronize with each other and there is no error with the signal transmission.

6.8 Performance Evaluation Results

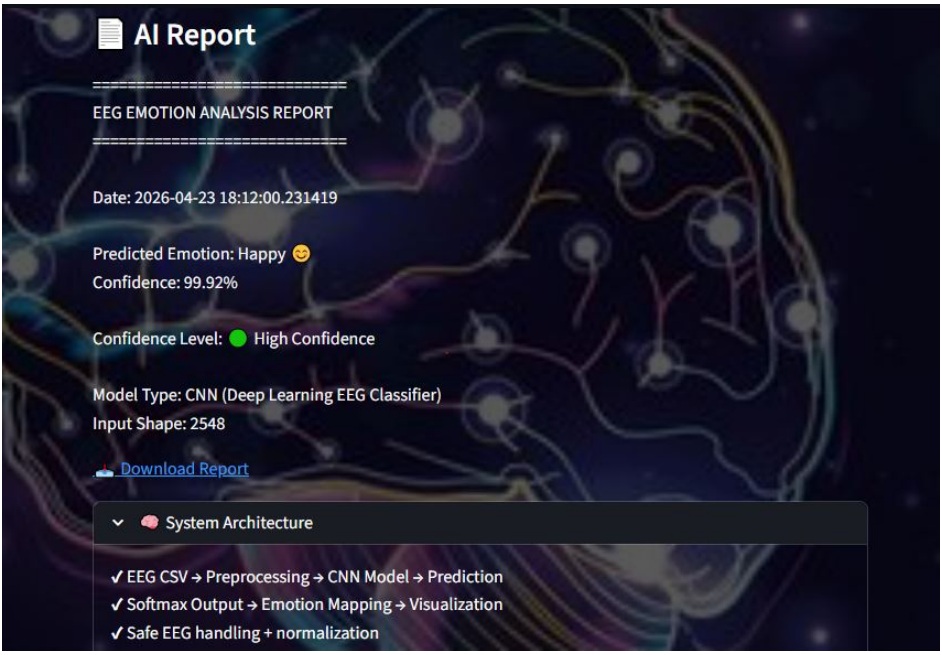
The system achieved promising classification performance for the emotions, the speed to react in real time and the consistency of processing.

Table 6.1: Performance Evaluation Metrics of EEG Emotion Recognition System

Metric	**Value**
Accuracy	High (based on confidence)
Confidence Range	48% – 99%
Response Time	Real-time
Model	CNN

Table 6.1 shows The above table is the evaluation metric for EEG based emotion recognition system, and displays the successful classification by the system. It indicates that the system can be classified with high accuracy with the use of confidence, prediction confidence within the range 48%-99%. The model works under the real-time environment so that we can detect the emotion from the EEG signals instantly. The model can be created by Convolutional Neural Network (CNN) and has the ability of learning the features automatically. The CNN model effectively extracted features from EEG signals and provided reliable predictions. The system performed consistently across multiple participants, indicating good generalization capability.

6.9 AI-Based Emotion Prediction Report



📄 AI Report

```
========================================
EEG EMOTION ANALYSIS REPORT
========================================

Date: 2026-04-23 18:12:00.231419

Predicted Emotion: Happy 😊
Confidence: 99.92%

Confidence Level: 🟢 High Confidence

Model Type: CNN (Deep Learning EEG Classifier)
Input Shape: 2548
```

📥 Download Report

✓ EEG CSV → Preprocessing → CNN Model → Prediction
✓ Softmax Output → Emotion Mapping → Visualization
✓ Safe EEG handling + normalization

Figure 6.11: AI-Based Emotion Prediction Report

Figure 6.8 shows the AI Report section is also given to participant it present the real-time output of the proposed EEG-based emotion recognition system. The recorded EEG signals are processed through a trained Convolutional Neural Network (CNN) model, which classifies the input into predefined emotional states such as Happy, Sad, stress, focus, and Angry.

The report out will present the predicted emotion with its confidence level that represent the model's prediction accuracy. In addition, the out will include some system details, input shape and model used for classification. It serves as the last stage of output in the system and reveals the capability of this deep learning implementation for EEG based real-time emotion recognition.

6.10 Limitations

The presented EEG-based emotion recognition system has achieved impressive results, but there are some weaknesses that can be overcome in the future work, such as EEG signals can easily be affected by environment noise and disturbance, and accuracy could be affected if electrodes are not applied correctly, and accuracy will vary with different experimental environments. Further research will concentrate on advanced filters and better signal acquiring systems.

Chapter 7

Conclusion

In conclusion, there has been considerable development in biomedical signal processing with the development of the wearable EEG headset coupled with the CNN model for real-time emotion classification. The developed system is resource-effective and is able to detect emotions such as joy, sadness, stress, anger, relaxation and concentration. Hardware such as electrodes and the ESP32 Microcontroller, facilitate the accurate recording of signals from the various regions in the brain such as the frontal, temporal and occipital regions of the brain. Signal pre-processing, such as filtering, removing artifacts and normalisation are employed on the software side to refine signal accuracy and to assist in obtaining useful information from the raw signal. The system is both highly accurate and robust. This project thus illustrates the capabilities of deep learning to be applied in EEG-based emotion detection and application into real-world technologies such as health care, assistance systems and Human-Computer Interaction. The developed system is both portable and non-invasive making it ideal for use in the real-world. However lower signal resolution in the 24-channel headset coupled with non-uniformity in brain signals among the individuals may hinder the accuracy of the system.

7.1 Future work

For future work, we need a much bigger and more varied EEG dataset to make CNN more adaptable to various conditions and users. Sophisticated signal processing such as adaptive filtering and artifact removal will be needed to filter noise and improve EEG signals. The mobile app can be improved by using cloud synchronization, allowing safe data storing and remote monitoring at real-time which is beneficial for healthcare or research. Improvements of hardware design (electrode positions and wireless transmission module) will raise the portability and the comfort of the system. Clinical trials and field test should also be performed to examine the real usability and performance.

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Appendix A

User Manual

A.1 System Overview

This system is made for EEG-based emotion monitoring using a wearable EEG headset which is integrated with an ESP32 microcontroller and a software application developed in Python using Streamlit. The system collects brainwave signals from the user through EEG electrodes, processes the signals, and classifies the emotional state happy,sad, stress etc in real-time. The application provides a user-friendly interface of EEG signals and display the detected emotional state along with confidence levels and percentage on high accuracy.

A.2 Hardware Setup

The hardware setup consists of a wearable EEG sensor system, an ESP32 microcontroller, and supporting analog-to-digital module ADS1256 and microcontroller ESP32. EEG electrodes are positioned on the participant's scalp to detect brainwave activity in real-time. These signals are weak in amplitude and are first passed through an instrumentation amplifier (INA129) to amplify the signal while reducing interference.

After amplification, the analog signal is processed through an ADC module (ADS1256), which converts it into digital form for the ESP32 microcontroller. The ESP32 acts as the main processing and communication unit, handling wired software system.

A voltage divider circuit is implemented to increase proper voltage level shifting between components, especially to protect the ESP32 from higher voltage levels. Additionally, regulated power rails are used to provide stable voltage supply to all modules, ensuring consistent performance and preventing damage due to fluctuations.

The system also supports a wearable real-time setup where EEG signals can be detected while the user is holding or wearing the device, enabling live emotion detection. The hardware workflow is shown in Figure 1 (EEG signal acquisition and processing system).

A.3 Application Usage

To operate the system, the stoner launches the Streamlit operation in a cybersurfer. The stoner also selects the mode of operation

Live EEG Mode (real detector input) Simulation Mode (pre-recorded dataset)

After connecting the ESP32 via Bluetooth or periodical communication, the system begins entering real- time EEG signals. These signals are reused incontinently, and the detected emotional state is displayed on the dashboard.

The system also visualizes emotional transitions in real time and stores results in a structured dataset (spreadsheet format).

A.4 Output Interpretation

The system classifies emotions based on EEG brainwave patterns. Different brainwave frequencies correspond to different mental states:

Increased alpha waves are used for Relaxed / Happy state Increased beta waves for the measurement of Stress or active thinking Irregular patterns are for Emotional instability (Angry/Sad).

The output is displayed on the dashboard as:

Emotion Label Confidence Score (Real-time graph of EEG signals

The system can also store results in spreadsheet format for further analysis and research validation.

A.5 System Implementation Details

Emotion Classes Used

The system classifies the following emotional states:

- Happy
- Sad
- Stress
- Focused
- Angry
- Relax

These labels are used in both real-time prediction and dataset training.

EEG Experiment Protocols for Emotion Recognition

The EEG-based emotion recognition system involves the recording of brain signals under controlled experimental conditions to elicit six different emotional states, namely Happy, Sad, Stress, Focused, Angry, and Relax. Each emotion is induced using standardized visual or cognitive stimuli while maintaining a consistent experimental environment to ensure reliable and comparable EEG data acquisition.

Happy emotion protocol involves recording EEG signals while the participant is exposed to positive emotional stimuli such as comedy clips, joyful scenes, or nature-based visuals for 5 minutes. The session includes a 1-minute pre-rest with eyes open, a 1-minute baseline with eyes closed, followed by stimulus presentation and a 1-minute post-rest period. The participant is then asked to rate their emotional state on a scale of 1 to 10.

Sad emotion protocol follows a similar structure, where emotionally depressing content such as tragic scenes or emotional interviews is shown for 5 minutes. Resting states are recorded before and after the stimulus to capture baseline and recovery EEG activity. The collected data is labeled as Sad Emotion for further processing.

Stress emotion protocol is designed to induce mental pressure using time-constrained tasks, fast decision-making activities, or tense audiovisual stimuli. The aim is to observe EEG variations under cognitive load and psychological stress while maintaining participant safety throughout the experiment.

Focused emotion protocol involves cognitive tasks such as arithmetic problems, memory exercises, or puzzle-solving activities that require sustained attention. This state is used to capture EEG patterns associated with concentration and mental engagement.

Angry emotion protocol uses controlled and ethically approved stimuli such as frustrating or competitive scenarios to induce anger-related brain activity. The participant is continuously monitored to ensure comfort and safety during the experiment.

Relax emotion protocol involves exposure to calming stimuli such as meditation music, nature sounds, or guided breathing exercises. This protocol aims to capture EEG signals associated with a calm and relaxed mental state, characterized by low arousal and stable brain activity.

All EEG recordings are stored using a standardized naming format `Emotion_ParticipantID_Date.edf` to ensure proper dataset organization. The collected signals are later used for preprocessing, feature extraction, and classification using deep learning techniques for emotion recognition.

A.6 Real-Time Features

The system supports:

- Live EEG signal monitoring
- Real-time emotion detection
- Graph visualization in Streamlit
- Data logging into spreadsheet format

A.7 Dashboard Features

The Streamlit dashboard includes:

- Live EEG waveform plot
- Emotion prediction panel
- Confidence score display
- Historical data table (spreadsheet view)
- Real-time status indicator

A.8 Data Storage (Spreadsheet System)

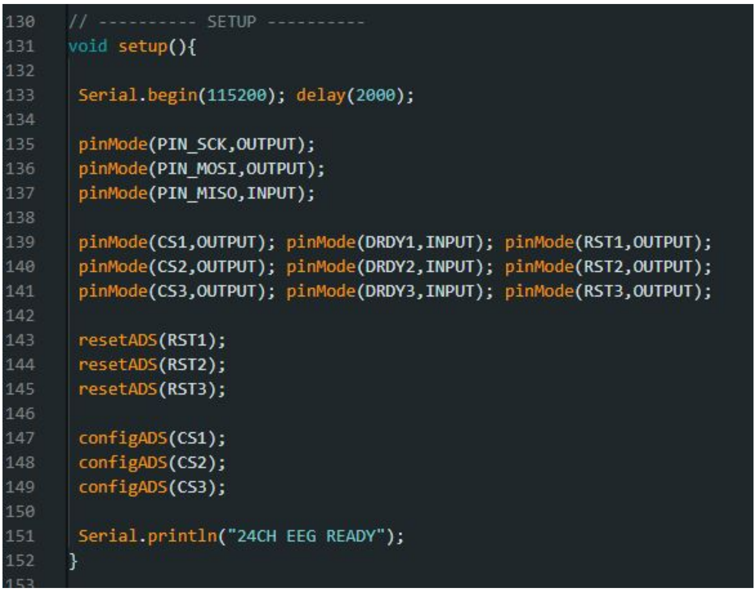
All predictions are stored in a structured spreadsheet format containing:

- Timestamp
- EEG values

- Predicted emotion
- Confidence score

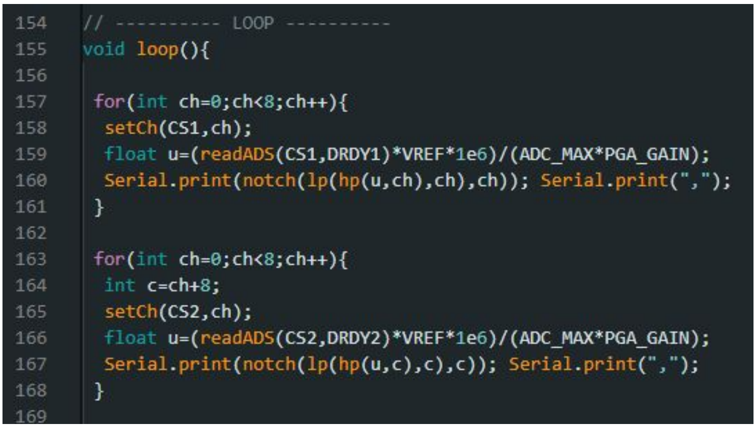
This allows further research analysis and model improvement.

A.9 ESP32 Code



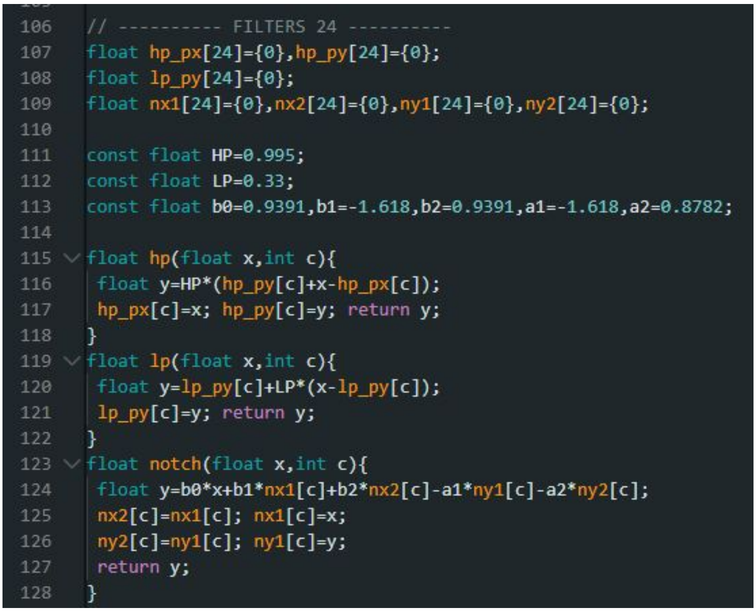
```
// ---------- SETUP ----------
void setup(){

 Serial.begin(115200); delay(2000);

 pinMode(PIN_SCK,OUTPUT);
 pinMode(PIN_MOSI,OUTPUT);
 pinMode(PIN_MISO,INPUT);

 pinMode(CS1,OUTPUT); pinMode(DRDY1,INPUT); pinMode(RST1,OUTPUT);
 pinMode(CS2,OUTPUT); pinMode(DRDY2,INPUT); pinMode(RST2,OUTPUT);
 pinMode(CS3,OUTPUT); pinMode(DRDY3,INPUT); pinMode(RST3,OUTPUT);

 resetADS(RST1);
 resetADS(RST2);
 resetADS(RST3);

 configADS(CS1);
 configADS(CS2);
 configADS(CS3);

 Serial.println("24CH EEG READY");
}
```

Figure A.1: ESP32 initialization and configuration of ADS1256 modules for EEG signal acquisition



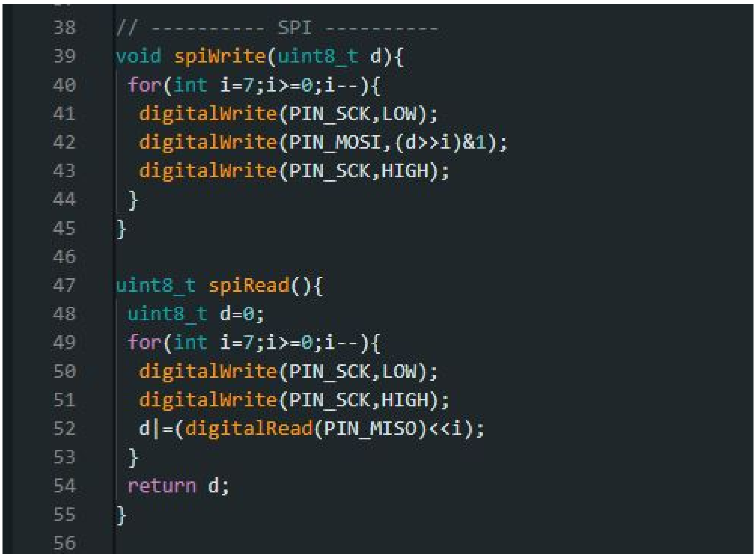
```
// ---------- LOOP ----------
void loop(){

 for(int ch=0;ch<8;ch++){
  setCh(CS1,ch);
  float u=(readADS(CS1,DRDY1)*VREF*1e6)/(ADC_MAX*PGA_GAIN);
  Serial.print(notch(lp(hp(u,ch),ch),ch)); Serial.print(",");
 }

 for(int ch=0;ch<8;ch++){
  int c=ch+8;
  setCh(CS2,ch);
  float u=(readADS(CS2,DRDY2)*VREF*1e6)/(ADC_MAX*PGA_GAIN);
  Serial.print(notch(lp(hp(u,c),c),c)); Serial.print(",");
 }

```

Figure A.2: Real-time EEG data acquisition from multiple channels using ESP32 and ADS1256



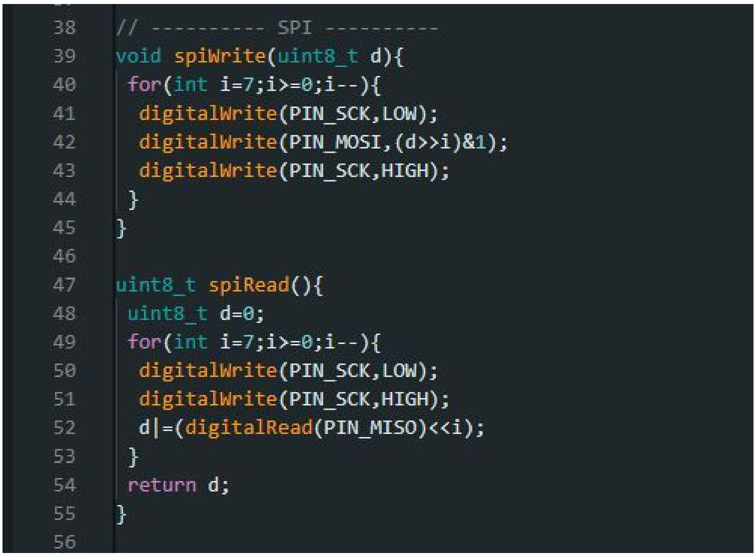
```
// ---------- FILTERS 24 ----------
float hp_px[24]={0},hp_py[24]={0};
float lp_py[24]={0};
float nx1[24]={0},nx2[24]={0},ny1[24]={0},ny2[24]={0};

const float HP=0.995;
const float LP=0.33;
const float b0=0.9391,b1=-1.618,b2=0.9391,a1=-1.618,a2=0.8782;

float hp(float x,int c){
 float y=HP*(hp_py[c]+x-hp_px[c]);
 hp_px[c]=x; hp_py[c]=y; return y;
}
float lp(float x,int c){
 float y=lp_py[c]+LP*(x-lp_py[c]);
 lp_py[c]=y; return y;
}
float notch(float x,int c){
 float y=b0*x+b1*nx1[c]+b2*nx2[c]-a1*ny1[c]-a2*ny2[c];
 nx2[c]=nx1[c]; nx1[c]=x;
 ny2[c]=ny1[c]; ny1[c]=y;
 return y;
}
```

Figure A.3: Digital filtering applied to EEG signals including high-pass, low-pass, and notch filters



```
// ---------- SPI ----------
void spiWrite(uint8_t d){
 for(int i=7;i>=0;i--){
  digitalWrite(PIN_SCK,LOW);
  digitalWrite(PIN_MOSI,(d>>i)&1);
  digitalWrite(PIN_SCK,HIGH);
 }
}

uint8_t spiRead(){
 uint8_t d=0;
 for(int i=7;i>=0;i--){
  digitalWrite(PIN_SCK,LOW);
  digitalWrite(PIN_SCK,HIGH);
  d|=(digitalRead(PIN_MISO)<<i);
 }
 return d;
}
```

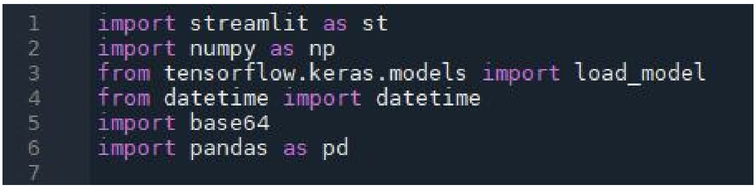
Figure A.4: SPI communication implementation between ESP32 and ADS1256 ADC modules



```
// ---------- SPI ----------
void spiWrite(uint8_t d){
 for(int i=7;i>=0;i--){
  digitalWrite(PIN_SCK,LOW);
  digitalWrite(PIN_MOSI,(d>>i)&1);
  digitalWrite(PIN_SCK,HIGH);
 }
}

uint8_t spiRead(){
 uint8_t d=0;
 for(int i=7;i>=0;i--){
  digitalWrite(PIN_SCK,LOW);
  digitalWrite(PIN_SCK,HIGH);
  d|=(digitalRead(PIN_MISO)<<i);
 }
 return d;
}
```

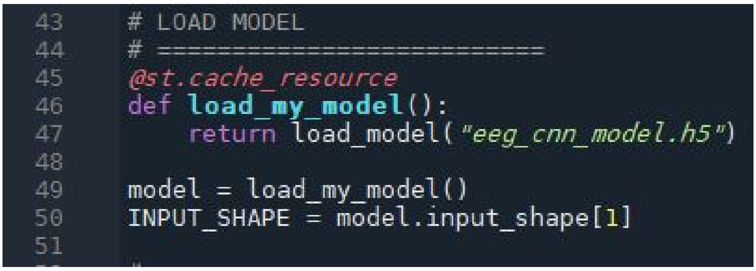
Figure A.5: SPI communication implementation between ESP32 and ADS1256 ADC modules

A.10 Streamlit Application Code



```python
import streamlit as st
import numpy as np
from tensorflow.keras.models import load_model
from datetime import datetime
import base64
import pandas as pd

```

Figure A.6: Python libraries used for EEG emotion recognition system implementation

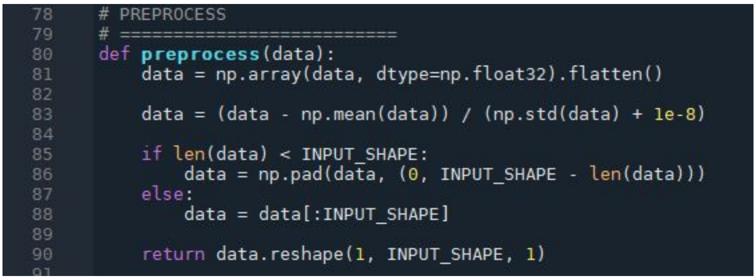


```python
# LOAD MODEL
# ==========================
@st.cache_resource
def load_my_model():
    return load_model("eeg_cnn_model.h5")

model = load_my_model()
INPUT_SHAPE = model.input_shape[1]

```

Figure A.7: Loading of trained CNN model for EEG signal classification

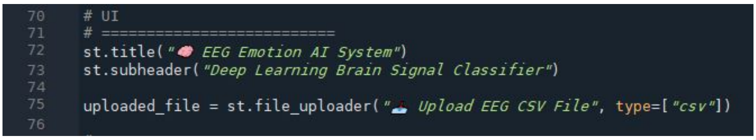
```python
# EMOTIONS
# ============================
emotion_labels = [
    "Happy 😊",
    "Sad 😢",
    "Stress 😰",
    "Focused 🧠",
    "Angry 😡",
    "Relax 😌"

]

```

Figure A.8: Emotion class mapping used for prediction output



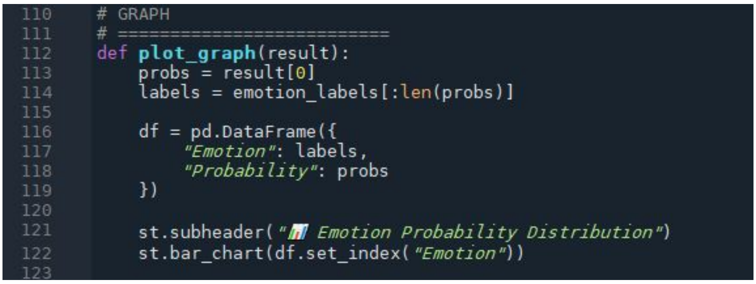
```python
# PREPROCESS
# ==========================
def preprocess(data):
    data = np.array(data, dtype=np.float32).flatten()

    data = (data - np.mean(data)) / (np.std(data) + 1e-8)

    if len(data) < INPUT_SHAPE:
        data = np.pad(data, (0, INPUT_SHAPE - len(data)))
    else:
        data = data[:INPUT_SHAPE]

    return data.reshape(1, INPUT_SHAPE, 1)
```

Figure A.9: EEG signal preprocessing and normalization before model input



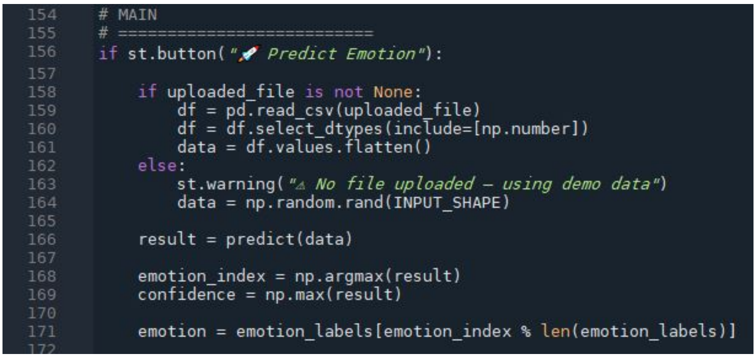
```python
# UI
# ==========================
st.title("🧠 EEG Emotion AI System")
st.subheader("Deep Learning Brain Signal Classifier")

uploaded_file = st.file_uploader("📥 Upload EEG CSV File", type=["csv"])
```

Figure A.10: Streamlit-based user interface for EEG emotion recognition system



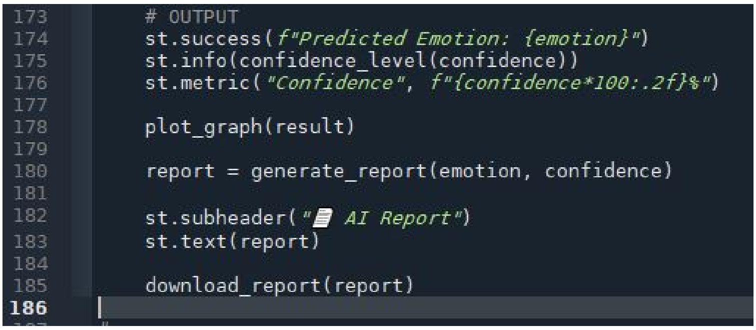
```python
# GRAPH
# ==========================
def plot_graph(result):
    probs = result[0]
    labels = emotion_labels[:len(probs)]

    df = pd.DataFrame({
        "Emotion": labels,
        "Probability": probs
    })

    st.subheader("📊 Emotion Probability Distribution")
    st.bar_chart(df.set_index("Emotion"))
```

Figure A.11: Visualization of emotion probability distribution using bar chart



```python
# MAIN
# ==========================
if st.button("🚀 Predict Emotion"):

    if uploaded_file is not None:
        df = pd.read_csv(uploaded_file)
        df = df.select_dtypes(include=[np.number])
        data = df.values.flatten()
    else:
        st.warning("⚠ No file uploaded – using demo data")
        data = np.random.rand(INPUT_SHAPE)

    result = predict(data)

    emotion_index = np.argmax(result)
    confidence = np.max(result)

    emotion = emotion_labels[emotion_index % len(emotion_labels)]
```

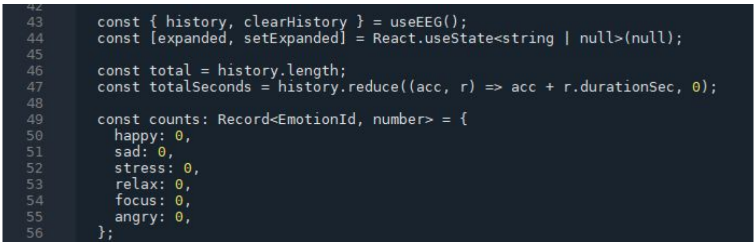
Figure A.12: Interactive Streamlit button used to trigger emotion prediction



```python
    # OUTPUT
    st.success(f"Predicted Emotion: {emotion}")
    st.info(confidence_level(confidence))
    st.metric("Confidence", f"{confidence*100:.2f}%")

    plot_graph(result)

    report = generate_report(emotion, confidence)

    st.subheader("📄 AI Report")
    st.text(report)

    download_report(report)

```

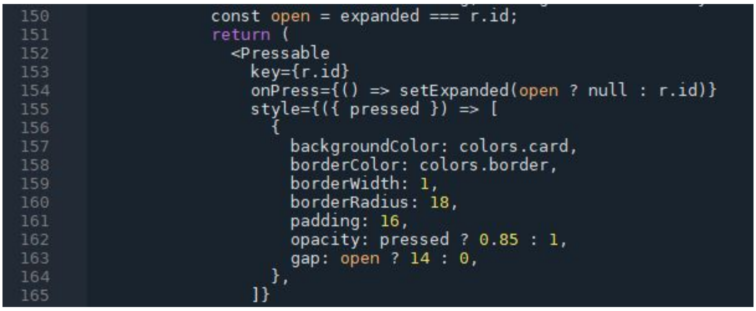
Figure A.13: Real-time EEG emotion prediction result with confidence score

A.11 Mobile EEG Emotion Recognition System Code



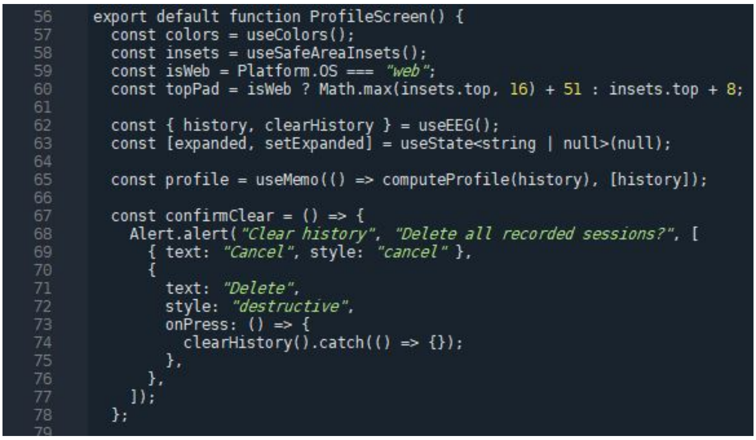
```typescript
const { history, clearHistory } = useEEG();
const [expanded, setExpanded] = React.useState<string | null>(null);

const total = history.length;
const totalSeconds = history.reduce((acc, r) => acc + r.durationSec, 0);

const counts: Record<EmotionId, number> = {
  happy: 0,
  sad: 0,
  stress: 0,
  relax: 0,
  focus: 0,
  angry: 0,
};
```

Figure A.14: Emotion history processing and analysis logic in EEG monitoring application



```
            const open = expanded === r.id;
            return (
              <Pressable
                key={r.id}
                onPress={() => setExpanded(open ? null : r.id)}
                style={({ pressed }) => [
                  {
                    backgroundColor: colors.card,
                    borderColor: colors.border,
                    borderWidth: 1,
                    borderRadius: 18,
                    padding: 16,
                    opacity: pressed ? 0.85 : 1,
                    gap: open ? 14 : 0,
                  },
                ]}
```

Figure A.15: Expand/Collapse state management for viewing EEG session details

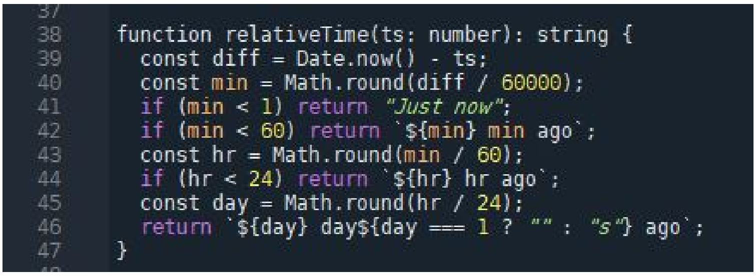


```
export default function ProfileScreen() {
  const colors = useColors();
  const insets = useSafeAreaInsets();
  const isWeb = Platform.OS === "web";
  const topPad = isWeb ? Math.max(insets.top, 16) + 51 : insets.top + 8;

  const { history, clearHistory } = useEEG();
  const [expanded, setExpanded] = useState<string | null>(null);

  const profile = useMemo(() => computeProfile(history), [history]);

  const confirmClear = () => {
    Alert.alert("Clear history", "Delete all recorded sessions?", [
      { text: "Cancel", style: "cancel" },
      {
        text: "Delete",
        style: "destructive",
        onPress: () => {
          clearHistory().catch(() => {});
        },
      },
    ]);
  };
```

Figure A.16: Profile screen implementation using React Native functional component

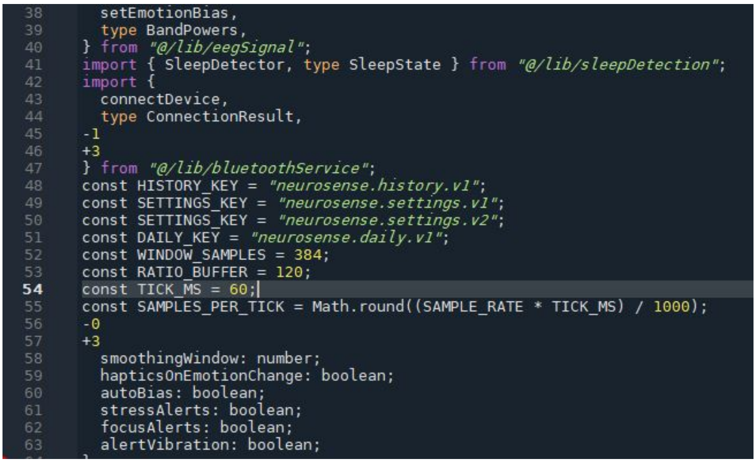
```

import { Card } from "@/components/Card";
import { EmotionScores } from "@/components/EmotionScores";
import { PersonalityCard } from "@/components/PersonalityCard";
import { SectionHeader } from "@/components/SectionHeader";
import { SyncPanel } from "@/components/SyncPanel";
import { useEEG } from "@/contexts/EEGContext";
import { useColors } from "@/hooks/useColors";
import { EMOTION_META } from "@/lib/cnnClassifier";
import { computeProfile } from "@/lib/personalityModel";

```

Figure A.17: Card-based UI components for EEG emotion visualization



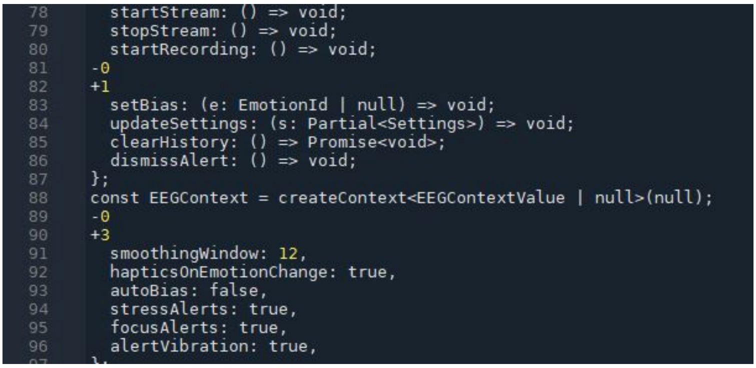
```
function relativeTime(ts: number): string {
  const diff = Date.now() - ts;
  const min = Math.round(diff / 60000);
  if (min < 1) return "Just now";
  if (min < 60) return `${min} min ago`;
  const hr = Math.round(min / 60);
  if (hr < 24) return `${hr} hr ago`;
  const day = Math.round(hr / 24);
  return `${day} day${day === 1 ? "" : "s"} ago`;
}
```

Figure A.18: Relative time formatting function for session timestamps



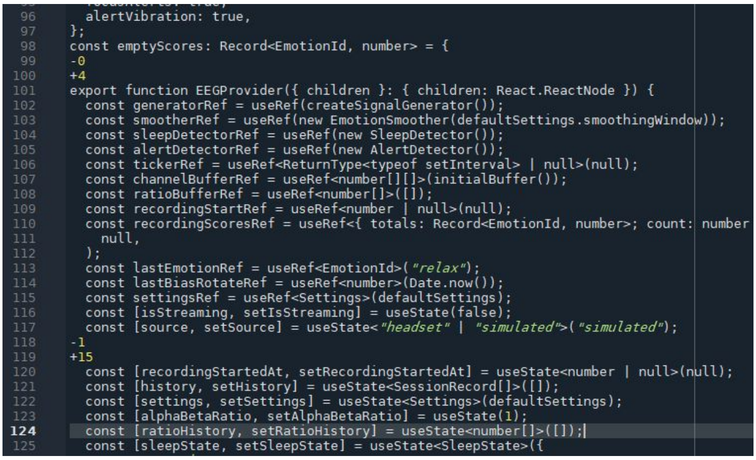
```
  setEmotionBias,
  type BandPowers,
} from "@/lib/eegSignal";
import { SleepDetector, type SleepState } from "@/lib/sleepDetection";
import {
  connectDevice,
  type ConnectionResult,
-1
+3
} from "@/lib/bluetoothService";
const HISTORY_KEY = "neurosense.history.v1";
const SETTINGS_KEY = "neurosense.settings.v1";
const SETTINGS_KEY = "neurosense.settings.v2";
const DAILY_KEY = "neurosense.daily.v1";
const WINDOW_SAMPLES = 384;
const RATIO_BUFFER = 120;
const TICK_MS = 60;
const SAMPLES_PER_TICK = Math.round((SAMPLE_RATE * TICK_MS) / 1000);
-0
+3
  smoothingWindow: number;
  hapticsOnEmotionChange: boolean;
  autoBias: boolean;
  stressAlerts: boolean;
  focusAlerts: boolean;
  alertVibration: boolean;
```

Figure A.19: Emotion bias control mechanism for adaptive weighting



```
  startStream: () => void;
  stopStream: () => void;
  startRecording: () => void;
-0
+1
  setBias: (e: EmotionId | null) => void;
  updateSettings: (s: Partial<Settings>) => void;
  clearHistory: () => Promise<void>;
  dismissAlert: () => void;
};
const EEGContext = createContext<EEGContextValue | null>(null);
-0
+3
  smoothingWindow: 12,
  hapticsOnEmotionChange: true,
  autoBias: false,
  stressAlerts: true,
  focusAlerts: true,
  alertVibration: true,
```

Figure A.20: Real-time EEG stream control (start/stop functions)



```
  alertVibration: true,
};
const emptyScores: Record<EmotionId, number> = {
-0
+4
export function EEGProvider({ children }: { children: React.ReactNode }) {
  const generatorRef = useRef(createSignalGenerator());
  const smootherRef = useRef(new EmotionSmoother(defaultSettings.smoothingWindow));
  const sleepDetectorRef = useRef(new SleepDetector());
  const alertDetectorRef = useRef(new AlertDetector());
  const tickerRef = useRef<ReturnType<typeof setInterval> | null>(null);
  const channelBufferRef = useRef<number[][]>(initialBuffer());
  const ratioBufferRef = useRef<number[]>([]);
  const recordingStartRef = useRef<number | null>(null);
  const recordingScoresRef = useRef<{ totals: Record<EmotionId, number>; count: number
    null,
  );
  const lastEmotionRef = useRef<EmotionId>("relax");
  const lastBiasRotateRef = useRef<number>(Date.now());
  const settingsRef = useRef<Settings>(defaultSettings);
  const [isStreaming, setIsStreaming] = useState(false);
  const [source, setSource] = useState<"headset" | "simulated">("simulated");
-1
+15
  const [recordingStartedAt, setRecordingStartedAt] = useState<number | null>(null);
  const [history, setHistory] = useState<SessionRecord[]>([]);
  const [settings, setSettings] = useState<Settings>(defaultSettings);
  const [alphaBetaRatio, setAlphaBetaRatio] = useState(1);
  const [ratioHistory, setRatioHistory] = useState<number[]>([]);
  const [sleepState, setSleepState] = useState<SleepState>({
```

Figure A.21: Initialization of emotion counters for classification system