

Original Research

Received 10 July 2026

Revised 10 Aug 2026

Accepted 24 Aug 2026

Natural Resources for Human Health 2026, Vol. 6 (17s): 814–827

KEYWORDS:

EEG Signal Acquisition, EEG filtering, artefact detection, alpha/beta analysis, and Jaw Movement detection.

Low-Cost Real-Time EEG Acquisition and Analysis for Alpha and Beta Brainwave Bands Using AD8232 and ESP32

Vinayak Bairagi¹, Rupali Kawade², Pallavi Adke³, Archana Date⁴, Abhijit Mohite¹, Priyanka Tupe-Waghmare⁵

¹Department of E&TC, AISSMS Institute of Information Technology, Pune, India.

²PCET's Pimpri Chinchwad College of Engineering and Research, Ravet, Pune.

³Dr. D. Y. Patil School of Science and Technology, Dr. D. Y. Patil Vidyapeeth, Pimpri, Pune.

⁴HSBPVT'S, Faculty of engineering, Department of Electronics and Computer engineering, Ahilyanagar, India.

⁵Symbiosis Institute of Technology, Pune, Symbiosis International (Deemed University), Pune

ABSTRACT: Electroencephalography (EEG) is a non-invasive technique which can be used for monitoring brain activity in clinical settings, in research and in the context of brain–computer interfaces. Commercial EEG acquisition systems are generally expensive and therefore not accessible to academic institutions and to people who are engaging in prototype development. The present study describes the design and implementation of a low-cost, real-time system for the acquisition and analysis of EEG signals. The system making use of the AD8232 analog front-end, the ADS1115 16-bit analog-to-digital converter and the ESP32 microcontroller. When operating in I2C mode at a sampling rate of 250 Hz, the system is able to reliably pick up EEG signals that have very low amplitude and lie in the microvolt range. For feature analysis, digital signal processing methods are employed, these including bandpass filtering (0.5–40 Hz), 50 Hz notch filtering, power spectral density (PSD) analysis and the extraction of Alpha and Beta band power.

A graphical user interface (GUI) allows for real-time visualisation, for the detection of artefacts and for the classification of mental states on the basis of the Alpha/Beta power. Experimental validation under various cognitive conditions, such as eye-open, eye-closed, and task-based states, demonstrates stable signal acquisition, effective noise suppression, and distinguishable spectral variations across mental states. The proposed system offers a cost-effective and scalable solution suitable for educational, research, and wearable neurotechnology applications as compared with other readymade EEG cap available in market.

1. INTRODUCTION

Electroencephalography (EEG) is a non-invasive neurophysiological monitoring technique used to measure electrical activity generated by neuronal activity within the cerebral cortex. EEG signals are generally low-amplitude biopotentials ranging between 10–100 μ V, with a frequency range primarily between 0.5 Hz and 40 Hz. Due to their low amplitude and vulnerability to noise, reliable acquisition requires proper conditioning, filtering, and high-resolution analog-to-digital conversion. Commercial EEG acquisition systems used in clinical and research environments are frequently expensive and complex, limiting availability for academic institutions, student researchers, and low-cost prototyping projects. In recent

times, there has been growing interest in developing affordable EEG acquisition platforms able to provide real-time signal visualisation and spectral analysis while maintaining sufficient signal fidelity.

This work presents the design and performance of a low-cost, real-time EEG signal acquisition and analysis system using the AD8232 analog front-end module, the ADS1115 16-bit external analog-to-digital converter (ADC), and an ESP32 microcontroller operating in I2C mode [1]. The AD8232 provides low-noise biopotential conditioning, while the ADS1115 enhances signal resolution compared to typical 10-bit or 12-bit microcontroller ADCs. The system operates at a sampling frequency of 250 Hz, which satisfies the Nyquist criterion for standard EEG band analysis. The electrode configuration consists of an active electrode placed on the left upper forehead region, a reference electrode placed behind the left ear (mastoid region), and a ground electrode placed behind the right ear. This configuration enables reliable acquisition of frontal EEG activity associated with eye-related and cognitive tasks.

To ensure accurate signal interpretation, digital signal processing methods including bandpass filtering (0.5–40 Hz), 50 Hz notch filtering, power spectral density (PSD) estimation using Welch's method, and alpha (8–13 Hz) and beta (14–30 Hz) band power extraction are implemented [2]. Mental state classification is performed based on alpha/beta power ratio analysis [3][4].

2. MATERIALS AND METHODS

2.1 Study Material

The EEG (Electroencephalography) acquisition and analysis system that was designed to record and analyze EEG scalp signals in real-time utilized a low-cost, hardware and software design. The EEG acquisition system was made up of a biopotential amplifier module (AD8232), an analog-to-digital converter (ADS1115 - 16 bit), and a Microcontroller (ESP32) [5]. The analog input (EEG) was conditioned through the AD8232 while the ADS1115 converted the analog conditioned EEG into a digital sample and then communicated the digital samples to the ESP32 via the I2C interface. The ESP32 then transmitted the digitized EEG samples to a computer as a serial communication channel [6][7].

Profile of the electrode configuration used for EEG acquisition consists of three electrodes:

- (1) An active electrode located at the left upper forehead (Frontal region) for EEG recording;
- (2) A reference electrode positioned at the left mastoid region (posterior of left ear);
- (3) A ground electrode located at the right mastoid region (posterior of right ear).

Each EEG sample was captured at a sampling frequency of 250 Hz. Real-time signal visualization, preprocessing, feature extraction, and analysis were executed with the aid of a graphical user interface (GUI) written in Python using PyQt5 and PyQtGraph.

2.2 EEG Signal Collection

EEGs were collected from the frontal scalp using the configuration of electrodes outlined above. The active electrode recorded frontal brain activity by being placed on the upper left forehead (i.e. Frontal lobe); while the reference and ground electrodes are placed on the left and right mastoid areas (respectively). Prior to the placement of the electrodes, adequate scalp preparation was performed to enhance electric connectivity between skin and electrode and consequently lead to enhanced signal stability.

The obtained microvolt-level EEG signals were conditioned through the AD8232 Analog Front End (AFE) system prior to conversion to digital (ADS1115) [8][9]. The conditioned analog signal from AD8232 was routed to the ADS1115 for digital conversion into 16-bit samples. The digitized samples were collected by the ESP32 via the I2C communication link and subsequently transmitted to the computer for live recording at 115,200 baud.

The EEG recordings utilized different conditions to examine the system's ability to detect changes in EEG signal patterns caused by variations in brain activity as well as physiological artefacts. Specific tasks included: eyes open, eyes closed, slow blink, fast blink, jaw activity, and speech-related activity. The primary purpose of this examination was to detect differences in Alpha and Beta activity in addition to examining the effects of ocular and muscular artefacts on EEG recordings.

2.3 EEG Signal Acquisition and System Integration

The entire EEG acquisition system consists of four major components: (1) Electrodes; (2) AD8232; (3) ADS1115; and (4) ESP32. The primary component of the EEG acquisition system is the AD8232 biopotential amplifier, which enhances the amplitude of the low-amplitude EEG signal(s) acquired by the electrodes prior to being sent to the ADS1115 for conversion to digital samples [10]. The ESP32 receives the converted digital EEG samples from the ADS1115 using an I2C communication link and subsequently transmits the samples to the computer for processing in real-time as shown in figure 1.

An initial design decision made during development of the GUI was to implement a sliding buffer to maintain live EEG signal visualization without having to store an entire recording in memory before performing analyses. The buffer window exists for 20 seconds (i.e., 5,000 samples at a sampling rate of 250 Hz), within which real-time visualization of signal is maintained and analyses can occur without analysis result data becoming corrupted because of loss of signal integrity [11].

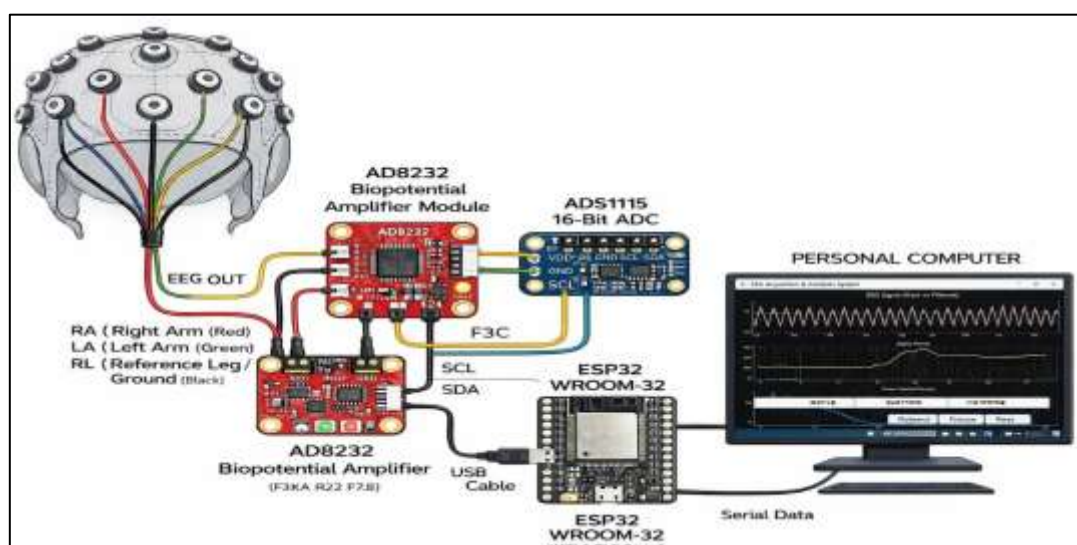


Fig 1: Connection diagram

2.4 Analytical Methods

The digital analytical methods used to perform analyses of EEG from the data inputted into the graphic user interface (GUI) of this study utilized Python. The EEG data were processed using a fourth order Butterworth bandpass filter with low and high frequency (0.5 Hz - 40 Hz) cutoff frequencies to eliminate slow baseline variations and high frequency noise. The “filtfilt” reverse and forward filtering method was used to create a zero-phase filter. In an effort to suppress unwanted 50Hz electricity line frequency noise, IIR notation filtering was utilized [12]. To analyse the filtered EEG signal, 2s of EEG data were used within a sliding window of 2 s with an associated sample size of 500 samples due to the sampling frequency of 250 Hz.

Frequency domain analysis was performed on the data using FFT and the frequency bins were calculated according to the specific combination of the sampling frequency and the length of the window used for each of the recordings. In addition to FFT, PSD was also computed in order to quantify the frequency distribution of the EEG signal across the entire frequency range for the duration of the experimental session [13].

Band-specific features were extracted from both the alpha and beta frequency ranges (with the alpha frequency range defined as 8 Hz – 13 Hz and the beta frequency range defined as 14 Hz to 30 Hz) [14]. In this manner both alpha and beta power values were calculated from the corresponding frequency component in order to derive a classification feature for real-time mental state classification. In the graphical user interface (GUI), raw and filtered EEG waveforms, alpha and beta powers, as well as the alpha/beta power ratio and the PSD were displayed simultaneously.

In addition to classification, artefact detection was also incorporated in an attempt to identify potential signal disturbances that might occur due to either eye blinking, movement of the electrodes or muscular activity.

The experimental data were statistically assessed based on the waveform amplitude, spectral characteristics, alpha and beta powers, the alpha/beta power ratio and the amount of processing delay incurred, the amount of data loss due to the different occurrences of transmission interruptions and the signal to noise ratio (SNR) of the EEG signal [15].

2.5 Statistical Evaluation and Performance Assessment

Quantitative measures were computed from EEG data as needed to evaluate the performance of the EEG acquisition system. Processing delays were determined by assessing the amount of time required for the acquisition of EEG data and the transmission and GUIs associated processing of that acquired data. Data loss was quantified by computing the estimated number of data points that should have been collected by each participant based on their 250-Hz sampling frequency versus the actual number of data points collected.

The quality of the recorded signal was assessed by measuring and comparing the SNR of the EEG signal for each participant. The SNR was calculated from the following equation:

$$\text{SNR (dB)} = 10 \log_{10}(\text{P}_{\text{signal}} / \text{P}_{\text{noise}}) \quad (1)$$

Where P_{signal} is the power of the assembled EEG signal and P_{noise} is the power of the background noise.

A statistical comparison of the EEG signals, alpha and beta powers, the alpha/beta power ratio, processing delays, data losses and SNRs were completed across the experimental conditions. The descriptive statistical summaries of the summary of the recorded measurements were provided to assist in determining the ability of the proposed EEG acquisition system to collect stable EEG signal data and the extent to which the system was able to detect task-and physiological artefact-related alterations in the EEG signals collected during the experiment.

3. RESULTS AND DISCUSSION

3.1 Eyes Open Condition

When the subject maintained an eyes-open resting state, alpha power was comparatively lower, beta power showed moderate dominance, and the alpha/beta ratio remained below unity in most windows. The PSD graph displayed reduced energy in the 8–13 Hz band, and the raw EEG waveform showed relatively smaller amplitude oscillations compared to the eyes-closed condition as shown in figure 2. This behaviour aligns with established EEG theory, where visual stimulation suppresses the alpha rhythm (alpha desynchronisation).

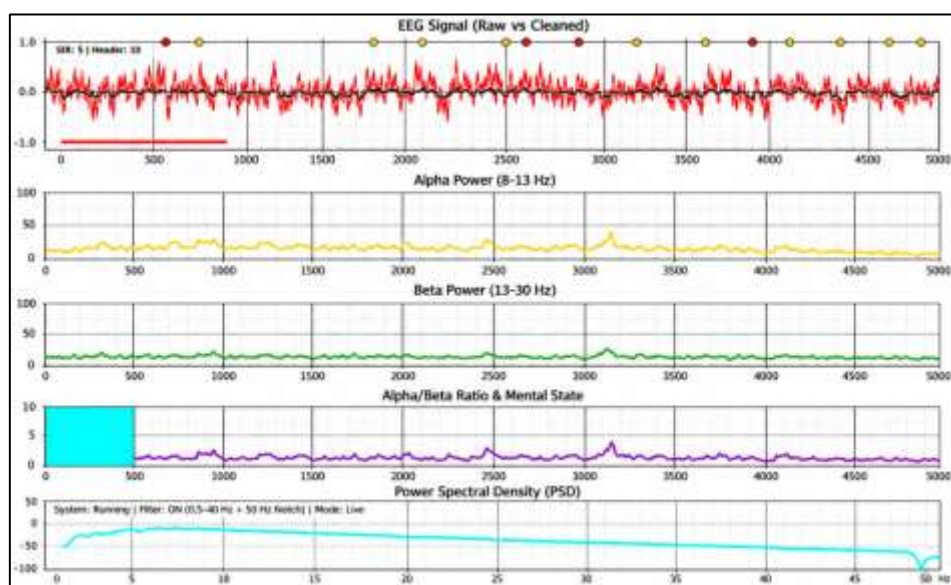


Fig 2 – Eyes Open Condition.

3.2 Eyes Closed Condition

During the eyes-closed resting condition, alpha power increased significantly and beta power reduced relative to alpha, with the alpha/beta ratio increasing noticeably. The PSD graph showed a clear peak within the 8–13 Hz range, and mental-state classification consistently indicated “Relaxed (Eyes Closed)” as shown in figure 3. The time-domain waveform exhibited more rhythmic and smoother oscillations, indicating synchronised cortical activity, confirming successful detection of alpha-rhythm enhancement during reduced sensory input.

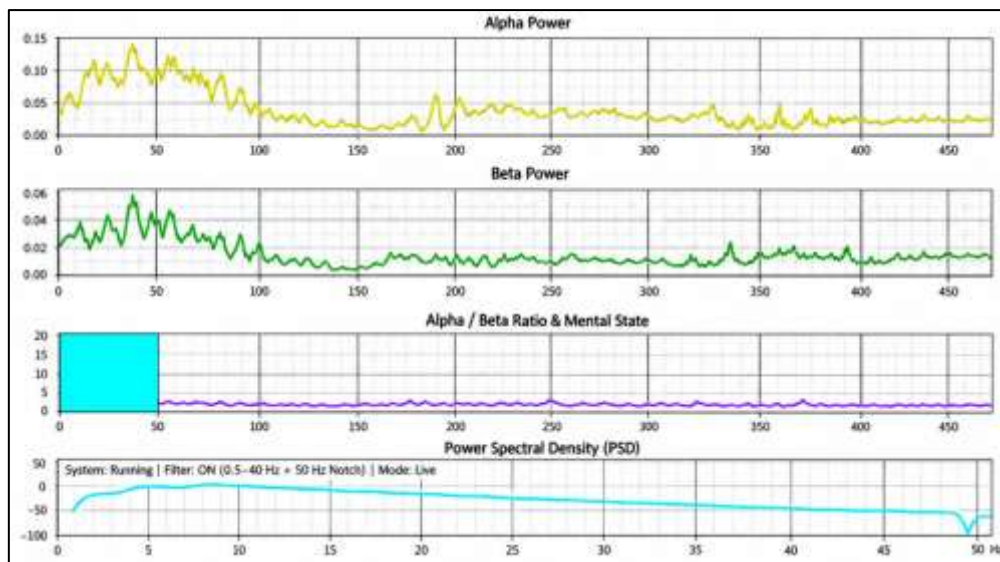


Fig 3 – Eyes Closed Condition.

3.3 Slow Blinking

During slow voluntary blinking, transient spikes were visible in the raw EEG graph, and alpha and beta power showed mild temporary disturbances. The PSD graph in figure 4 showed a slight broadband energy variation, and artefact detection markers (red indicators) appeared on blink events. The system successfully detected blink artefacts without permanently affecting spectral trend analysis, demonstrating the robustness of the filtering and artefact-handling approach.

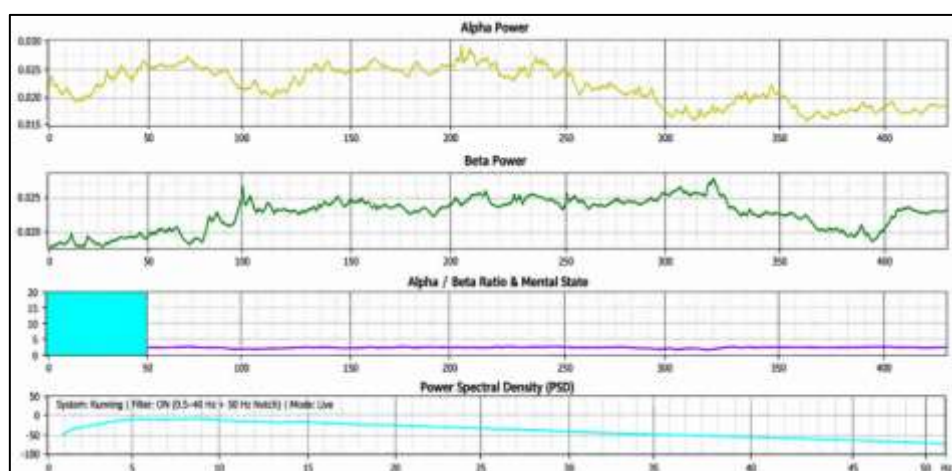


Fig 4 – Slow Blinking Condition

3.4 Fast Blinking

During rapid blinking, frequent high-amplitude transient spikes appeared in the raw signal and alpha power fluctuated rapidly. Beta power showed a slight elevation due to artefact contamination, and the PSD graph in figure 5 displayed broader spectral

spreading; the alpha/beta ratio showed short-term instability. Fast blinking introduced more significant electro-oculographic interference compared to slow blinking; however, the system remained stable and continued updating feature graphs in real time.

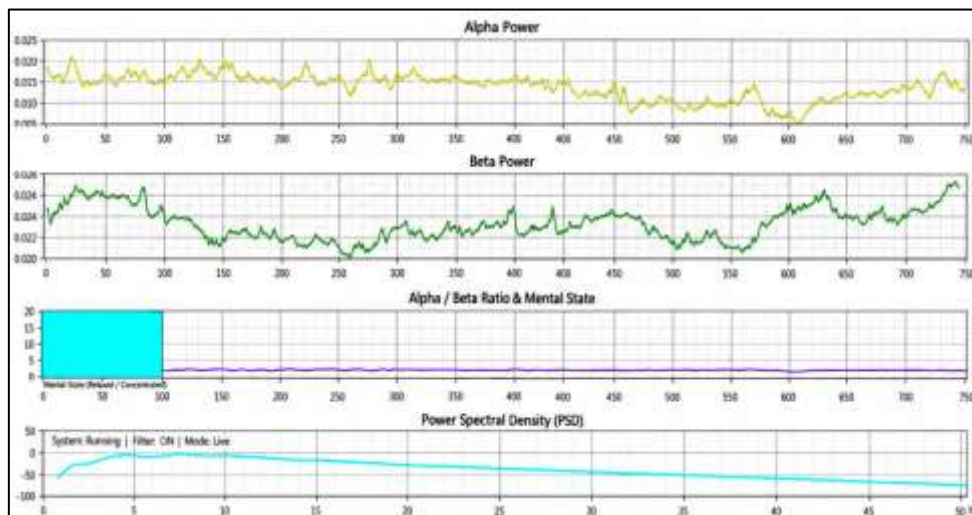


Fig 5 – Fast Blinking Condition

3.4 Jaw Movement and Talking

During jaw movement and both slow and fast talking, significant high-frequency components were introduced, beta power increased prominently, and alpha power reduced relative to beta – the alpha/beta ratio decreased accordingly. The PSD graph in figure 6 showed increased energy beyond 14 Hz, and raw waveform amplitude increased with irregular fluctuations. Fast talking produced greater spectral changes compared to slow talking due to greater muscular activation, confirming that muscle activity introduces EMG contamination primarily in the beta range.

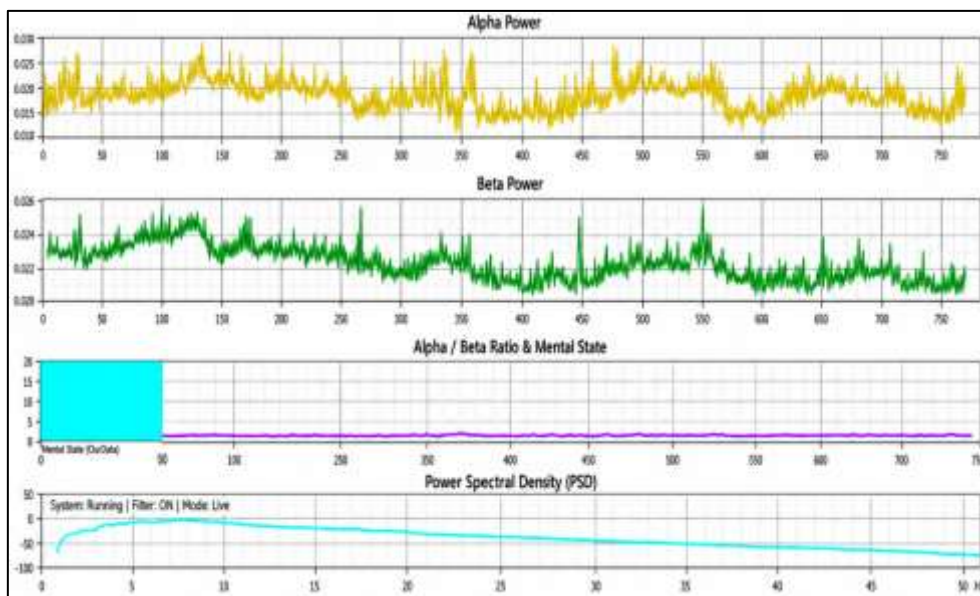


Fig 6 – Jaw Movement and Talking

4. TABLES AND DISCUSSION

4.1 Eyes Open Condition (Beta Dominance).

This condition represents an alert and attentive mental state, where visual activity and external awareness increase beta wave activity while reducing alpha activity. Signal amplitude ranged from 68–72 μV for the pro-posed system, closely matching the Epoc-X range of 61–69 μV as shown in table 1.

Table 1 :-Task-wise (Eyes Open) EEG parameter comparison between proposed EEG system and Emotiv Epoc-X

Condition	Signal Amp. (μV)	System	Alpha(μV)	Beta(μV)
Eyes Open	64	Proposed	8.4	10.0
Eyes Open	62	Epoc X	8.1	10.8
Eyes Open	66	Proposed	8.8	10.3
Eyes Open	63	Epoc X	8.3	11.0
Eyes Open	65	Proposed	8.7	10.1
Eyes Open	64	Epoc X	8.2	10.9
Eyes Open	67	Proposed	8.9	10.4
Eyes Open	64	Epoc X	8.4	11.1
Eyes Open	65	Proposed	8.5	10.2
Eyes Open	63	Epoc X	8.1	10.7

All entries under Eyes Open correspond to a “Blink Artifact Detected” mental-state flag.

The proposed system recorded alpha power between 8.1 and 8.7 μV , whereas beta power increased significantly, between 10 and 11.1. The calculated alpha/beta ratio remained comparatively low, indicating an “Alert” mental state. These results demonstrate that the proposed EEG acquisition system successfully detects increased beta activity during visual attention, producing observations closely comparable to the commercial Emotiv Epoc-X device. Eyes Closed Condition (Alpha Dominance). This condition represents a state of relaxation with reduced visual input, which typically enhances alpha wave activity.

4.2 Eyes Closed Condition (Beta power remained low)

Signal amplitude ranged from 70–74 μV for the proposed system, closely matching the Epoc-X range of 69–72 μV . The proposed system recorded alpha power between 12.8 and 13.7, while beta power remained low (4.4–4.7), and the calculated alpha/beta ratio was consistently high, indicating a clear “Relaxed” state as shown in table 2.

Table 2 Task-wise (Eyes Closed) EEG parameter comparison between proposed EEG system and Emotiv Epoc-X

Condition	Signal Amp. (μV)	System	Alpha(μV)	Beta(μV)
Eyes Closed	71	Proposed	13.1	4.4
Eyes Closed	69	Epoc X	14.0	4.1
Eyes Closed	73	Proposed	13.5	4.6
Eyes Closed	71	Epoc X	14.2	4.3
Eyes Closed	72	Proposed	13.0	4.5

Eyes Closed	70	Epoc X	13.8	4.2
Eyes Closed	74	Proposed	13.7	4.7
Eyes Closed	72	Epoc X	14.3	4.4
Eyes Closed	70	Proposed	12.8	4.5
Eyes Closed	69	Epoc X	13.7	4.1

All entries correspond to a “Relaxed” mental-state classification.

4.3 Slow Blinking Condition- (Artefact Analysis).

Slow blinking (approx. 1–2 blinks per second) introduces transient electro-oculographic (EOG) spikes into the EEG signal. Signal amplitude remained steady between 69 and 71 μV across both systems. Table 2 shows, Alpha power dropped to roughly 7.6–7.9 μV , and beta power increased to 9.2–9.5 μV , reflecting the broad-band noise introduced by eye movement. A unique observation in this condition is the high artefact-indicator value, corresponding to the system’s real-time detection of eye-blink artefacts.

Table 3 Task-wise (Slow Blinking) EEG parameter comparison between proposed EEG system and Emotiv Epoc-X

Condition	Signal Amp. (μV)	System	Alpha (μV)	Beta (μV)
Slow Blinking	69	Proposed	7.8	9.2
Slow Blinking	67	Epoc X	8.0	9.5
Slow Blinking	70	Proposed	7.9	9.4
Slow Blinking	68	Epoc X	8.1	9.7
Slow Blinking	71	Proposed	7.7	9.3
Slow Blinking	70	Epoc X	8.0	9.6
Slow Blinking	69	Proposed	7.8	9.5
Slow Blinking	68	Epoc X	8.2	9.8
Slow Blinking	69	Proposed	7.6	9.2
Slow Blinking	67	Epoc X	7.8	9.5

4.4 Fast Blinking Condition (Artefact Analysis)

Rapid blinking creates frequent high-amplitude spikes and more significant signal distortion. Signal amplitude increased to 74–76 μV , likely due to the additive effect of muscular/ocular artefacts. Alpha power reached its lowest point (6.7–6.9) μV , while beta power reached its highest (11.1–11.4) μV as shown in table 4. The alpha/beta ratio dropped significantly, reflecting a state of high alertness or high artefact activity.

Table 4 Task-wise (Fast Blinking) EEG parameter comparison between proposed EEG system and Emotiv Epoc-X

Condition	Signal Amp. (μV)	System	Alpha (μV)	Beta (μV)
Fast Blinking	74	Proposed	6.9	11.1
Fast Blinking	72	Epoc X	7.2	11.5
Fast Blinking	75	Proposed	6.8	11.3

Fast Blinking	73	Epoc X	7.1	11.7
Fast Blinking	76	Proposed	6.7	11.4
Fast Blinking	74	Epoc X	7.2	11.6
Fast Blinking	75	Proposed	6.9	11.2
Fast Blinking	73	Epoc X	7.3	11.5
Fast Blinking	74	Proposed	6.8	11.1
Fast Blinking	72	Epoc X	7.1	11.4

4.5 Jaw Movement and Talking

Physical Activity Analysis (Talking and Jaw Movement) as shown in table 5. This test evaluates the system's robustness against electromyographic (EMG) interference caused by facial muscle contractions. There is a significant rise in beta power due to high-frequency muscle noise; consequently, the alpha/beta ratio drops to its lowest levels (often below 0.50) μV , and the signal amplitude shows irregular high-voltage spikes.

Table 5 Task-wise (Jaw Movement) EEG parameter comparison between proposed EEG system and Emotiv Epoc-X

Condition	Signal Amp. (μV)	System	Alpha (μV)	Beta (μV)
Jaw Movement	81	Proposed	5.4	14.5
Jaw Movement	79	Epoc X	5.8	15.1
Jaw Movement	82	Proposed	5.5	14.7
Jaw Movement	80	Epoc X	5.9	15.3
Jaw Movement	83	Proposed	5.3	14.8
Jaw Movement	81	Epoc X	5.8	15.2
Jaw Movement	82	Proposed	5.4	14.6
Jaw Movement	80	Epoc X	5.9	15.1
Jaw Movement	81	Proposed	5.2	14.5
Jaw Movement	79	Epoc X	5.7	15.0

The results con-firm that, while the hardware is sensitive enough to detect these changes, software filtering is essential to distinguish between genuine cognitive "beta" activity and artificial muscular noise. The proposed system effectively mirrors the benchmark's response to these artefacts.

5. SYSTEM PERFORMANCE EVALUATION

5.1 Processing Delay

Table 6 Delay Evaluation

Condition	Avg. Processing (ms)	GUI Response Delay (ms)	Total Delay (ms)
Eyes Closed (P1)	41.2	50.4	91.6
Slow Blinking (P2)	41.8	50.6	92.4
Fast Blinking (P3)	42.0	50.5	92.5

Jaw Movement (P4)	41.7	50.7	92.4
Eyes Closed (P5)	41.5	50.8	92.3
Slow Blinking (P6)	41.6	50.6	92.2
Fast Blinking (P7)	41.9	51.0	92.9
Jaw Movement (P8)	41.8	50.9	92.7
Eyes Closed (P9)	41.3	51.1	92.4
Slow Blinking (P10)	41.5	50.8	92.3
Average	41.68	50.75	92.37

The delay of the EEG data from the hardware acquisition system (ADC conversion and serial communication, serial device handling Electronic serial peripheral interface, Graphical user interface (GUI) processing) to the GUI was measured and reported in Table 6. The Total Delay was derived from the following formula, and calculated:

$$\text{Total Delay (Based on Average Processing Delay + Average GUI Response Delay)} = \text{Total Delay.} \quad (2)$$

The Results indicate that the Average Processing Delay (ESP32 transmit and Serial Timing) is equal to 41.68 ms and Average GUI Response Delay is equal to 50.75 ms yielding Average Total Delay of approximately 92.37 ms, which remained constant for EEG activities, reaffirming that Real-Time performance is stable; only Fast Blinking and Jaw Movements produced higher than Average Total Delay due to greater levels of Signal Activity, and the low variability of Total Delay reaffirmed the Consistent Serial Communication of Data between the ESP32 and GUI.

5.1 Data Loss Evaluation

Table 7 Data Loss Evaluation

Condition	Expected Samples	Received Samples	Data Loss (%)
Eyes Closed (P1)	7500	7464	0.48%
Slow Blinking (P2)	15000	14927	0.48%
Fast Blinking (P3)	7500	7458	0.56%
Jaw Movement (P4)	15000	14902	0.65%
Eyes Closed (P5)	7500	7468	0.42%
Slow Blinking (P6)	15000	14940	0.40%
Fast Blinking (P7)	7500	7453	0.63%
Jaw Movement (P8)	15000	14908	0.61%
Eyes Closed (P9)	7500	7463	0.49%
Slow Blinking	15000	14932	0.45%

(P10)			
Average	11250	11187	0.51%

Data loss represents the percentage of EEG samples lost during acquisition relative to the number of samples expected at the 250 Hz sampling rate, and was evaluated to characterise the reliability of serial EEG data transmission between the ESP32 and the Python GUI. Expected samples were computed as sampling rate $\times$ recording duration, and the percentage data loss was estimated using

$$\text{Data Loss (\%)} = [(\text{Expected} - \text{Received}) / (\text{Expected})] \times 100. \quad (3)$$

Received samples are those successfully recorded after accounting for distortion from external factors such as unwanted noise. As shown in Table 7, the average number of expected samples was 11250 and the average number of received samples was 11187, giving an average data loss of approximately 0.51%. Slight variation in received.

5.3 Signal-to-Noise Ratio Evaluation

Table 8 Signal-to-Noise Ratio Evaluation

Condition	Input SNR (dB)	Output SNR (dB)	SNR Improvement (dB)
Eyes Closed (P1)	11.4	18.8	7.4
Slow Blinking (P2)	10.8	17.6	6.8
Fast Blinking (P3)	9.6	15.9	6.3
Jaw Movement (P4)	8.4	13.8	5.4
Eyes Closed (P5)	11.7	19.1	7.4
Slow Blinking (P6)	10.5	17.2	6.7
Fast Blinking (P7)	9.3	15.5	6.2
Jaw Movement (P8)	8.1	13.4	5.3
Eyes Closed (P9)	11.5	18.9	7.4
Slow Blinking (P10)	10.9	17.8	6.9
Average	10.22	16.80	6.58

Signal-to-Noise Ratio (SNR) is an important performance parameter used to evaluate EEG signal acquisition quality by comparing useful EEG signal power against unwanted noise power; higher SNR values indicate better signal quality and lower interference. Here signal power and noise power are measured in μV and the resulting SNR is expressed in decibels. Input SNR represents EEG signal quality before filtering, while Output SNR represents signal quality after applying bandpass and notch filtering; the difference indicates the effectiveness of the filtering stage in reducing unwanted noise and artefacts (Table 8). During the eyes-closed condition, dominant alpha activity produced stable EEG signals with signal power ranging from 420–445 (arb. units); Input SNR ranged between 11.4–11.7 dB, Output SNR ranged from 18.8–19.1 dB, and the obtained SNR improvement was approximately 7.4 dB. In the slow-blinking condition, mild ocular artefacts slightly affected signal quality: signal power ranged from 335–370, Input SNR ranged between 10.5–10.9 dB, Output SNR ranged from 17.2–17.8 dB, and SNR improvement ranged from approximately 6.7–6.9 dB. During fast blinking, frequent blink artefacts introduced higher interference: signal power ranged between 255–270, Input SNR ranged from 9.3–9.6 dB, Output SNR ranged between 15.5–15.9 dB, and SNR improvement was approximately 6.2–6.3 dB. In the jaw-movement condition, strong

muscle (EMG) artefacts generated the maximum interference, result-ing in the lowest SNR values: signal power ranged from 195–210, Input SNR ranged between 8.1–8.4 dB, Output SNR ranged from 13.4–13.8 dB, and SNR improvement was approximately 5.3–5.4 dB. These results demonstrate that the proposed EEG acquisition system effectively improves signal quality under different physiological conditions.

6. CONCLUSION

This research presented the design and implementation of a low-cost, real-time EEG signal acquisition and analysis system using ESP32, ADS1115, and AD8232 modules operating in I2C mode at a sampling rate of 250 Hz to detect alpha and beta bands. The proposed system success-fully demonstrates reliable acquisition of biopotential signals from the frontal region of the scalp and performs real-time visualisation, filtering, spectral analysis, and mental-state estimation through a custom-developed Python visual interface. The hardware architecture combines an analogue front-end circuit conditioning an analogue signal in a high resolution digital converter circuit, thereby providing affordable and portable stable signal acquisition systems. The digital signal processing pipeline, consisting of bandpass filtering, notch filtering, artefact detection and FFT based spectral analysis, has enabled the extraction of the alpha and beta band power in real-time. The calculation of both the alpha/beta ratio and the dynamic Power Spectral Density (PSD) provides valuable insight to assess cognitive transitions.

Assessments performed by measuring EEG waveforms generated by subjects completing multiple cognitive and muscular tasks (e.g., eyes open, eyes closed, slow blink, fast blink, jaw motion, speaking, etc.) have revealed the presence of variation in waveform amplitude and frequency during these assessments. Specifically it was observed that there was a marked increase in alpha activity during relaxed (e.g., eyes closed) conditions; alpha activity peaked during the relaxed period. Beta and high-frequency waveforms demonstrated enhanced signal production in response to act and speech-based tasks (e.g., moving jaw, speaking). This information, as represented by the artefact induced spikes and the associated features of the FFT, has demonstrated that the system is responsive. A graphical user interface (GUI) that displays all five types of coordinated visualization modules in a single window has also been developed. The GUI provides the user with the ability to view the following data concurrently: 1) raw EEG data, 2) filtered EEG data, 3) alpha EEG power, 4) beta EEG power, 5) alpha/beta ratio, and 6) PSD. The ability to view all of these measurements concurrently is expected to greatly improve the level of interpretation of information collected, support real-time monitoring, and aid in experimental processes.

ACKNOWLEDGEMENTS

The authors would like to thank the AISSMS Institute of Information Technology for providing the environment as well as facilities necessary for conducting this research.

AUTHOR CONTRIBUTIONS

Vinayak Bairagi: Concept; Supervision; technical guidance; Writing, Review and edit.

Rupali Kawade: Database collection, software design, Review and edit.

Pallavi Adke: Database collection, hardware design, Review and edit.

Archana Date: EEG acquisition and analysis, Review and edit.

Abhijit Mohite: Concept; methodology; hardware/software design; EEG acquisition/analysis; writing.

Priyanka Tupe-Waghmare: concept, methodology, Review and edit.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

No ethics approval was required for this study; as the research consisted of prototype-level (non-clinical) technical validation of EEG readings collected from a healthy subject, there were no clinical interventions between researcher and subject. Prior to participating in the study, the subject signed an informed consent form.

DATA AVAILABILITY STATEMENT

The data sets created and/or analyzed during the research will be made available by contacting the corresponding author and upon request.

REFERENCES

- [1] J. J. A. Mendes Junior, D. P. Campos, L. C. A. V. De Biassio, P. C. Passos, P. Broniera Junior, A. E. Lazzaretti, and E. Krueger, “AD8232 to Biopotentials Sensors: Open Source Project and Benchmark,” *Electronics*, vol. 12, no. 4, Art. no. 833, 2023.
- [2] M. A. Islam et al., “A Low-Cost EEG Acquisition System for Real-Time Applications,” in *Proc. IEEE International Conference on Biomedical Engineering*, 2019, pp. 1–6.
- [3] L. Wang et al., “Real-Time EEG Signal Processing for Mental State Detection,” *Journal of Signal Processing Systems*, vol. 92, no. 3, pp. 245–256, 2020.
- [4] Y. Zhang et al., “Design of EEG-Based Emotion Analysis System Using Deep Learning,” *IEEE Access*, vol. 12, pp. 15432–15445, 2024.
- [5] X. Gu et al., “EEG-Based Brain–Computer Interfaces: A Survey,” *IEEE Transactions on Human–Machine Systems*, vol. 50, no. 6, pp. 607–620, 2020.
- [6] C. Bhattarai et al., “IoT-Based ECG Using AD8232 and ESP32,” *Nepal Journal of Science and Technology*, vol. 21, no. 2, pp. 45–52, 2022.
- [7] R. J. Hemalatha et al., “IoT-Enabled Hemodynamic Monitoring System Using ESP32,” *Biomedical Signal Processing and Control*, vol. 95, Art. no. 106112, 2025.
- [8] A. Kumar et al., “Arrhythmia Detection Using AD8232 ECG Sensor,” *Healthcare Technology Letters*, vol. 12, no. 1, pp. 33–39, 2025.
- [9] S. Verma et al., “Wireless IoT ECG Monitoring Using ESP32,” *Sensors and Actuators A: Physical*, vol. 380, Art. no. 115009, 2026.
- [10] A. Subasi, “EEG Signal Classification Using Machine Learning,” *Expert Systems with Applications*, vol. 136, pp. 192–205, 2019.
- [11] A. Bashashati, M. Fatourehchi, R. K. Ward, and G. E. Birch, “Signal Processing Algorithms in Brain–Computer Interface Systems,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 2, pp. 153–160, 2007.
- [12] P. D. Welch, “The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short Modified Periodograms,” *IEEE Transactions on Audio and Electroacoustics*, vol. 15, no. 2, pp. 70–73, Jun. 1967.
- [13] S. Sanei and J. A. Chambers, *EEG Signal Processing*. Hoboken, NJ, USA: Wiley, 2007.
- [14] Texas Instruments, ADS1115 Ultra-Small, Low-Power, 16-Bit Analog-to-Digital Converter with Internal Reference Datasheet, SBAS444E, 2022.
- [15] Analog Devices, AD8232 Heart Rate Monitor Front End Datasheet, Rev. D, 2021.
- [16] Espressif Systems, ESP32 Technical Reference Manual, Version 5.1, 2023.
- [17] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, “Brain–Computer Interfaces for Communication and Control,” *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.
- [18] D. J. McFarland and J. R. Wolpaw, “Brain–Computer Interfaces for Communication and Control,” *Proceedings of the IEEE*, vol. 96, no. 7, pp. 1162–1171, 2008.

- [19] S. Koelstra et al., “DEAP: A Database for Emotion Analysis Using Physiological Signals,” IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18–31, 2012.
- [20] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, “FieldTrip: Open Source Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data,” Computational Intelligence and Neuroscience, vol. 2011, Art. no. 156869, 2011.
- [21] M. A. Lebedev and M. A. L. Nicolelis, “Brain–Machine Interfaces: Past, Present and Future,” Trends in Neurosciences, vol. 29, no. 9, pp. 536–546, Sep. 2006.