

A Low-Cost EEG Sleep Monitoring System with YASA-Based Classification and LLM-Assisted Analysis

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Abstract—Electroencephalography provides valuable information on sleep dynamics, but conventional polysomnography systems are still costly and difficult to access. This paper presents the design and evaluation of a low-cost, portable EEG sleep monitoring system priced under sixty dollars, using an ESP32 microcontroller, SD card, and AD8232 with MCP602 operational amplifier for additional signal filtering and amplification as the analog front-end. The device samples and records data at a frequency of 256 hertz to an SD card for offline processing, enabling reproducibility in research and educational settings. Data analysis is performed through NeuroNap, a Gradio-based interface that visualizes EEG waveforms, filtered signals, frequency spectra, and hypnograms, with downloadable graphs for each frequency band. Sleep staging is performed using the Yet Another Spindle Algorithm (YASA) toolbox, which automatically classifies five standard stages: Wake, Non-Rapid Eye Movement (NREM) Stage 1, Stage 2, Stage 3, and Rapid Eye Movement (REM). To improve usability, an integrated large language model with retrieval-augmented generation allows users to query their results and receive explanations of the recorded data and derived sleep statistics for better understanding. The system incorporates simple feedback indicators and initialization controls to support reliable operation, demonstrating feasibility for and research use. Future work will explore multichannel EEG recording, supervised machine learning approaches, extended Wi-Fi or cloud-based functionality, improved electrode stability, and automated motion artifact removal.

Index Terms—EEG, sleep monitoring, low-cost, YASA, NeuroNap, signal processing, large language model

I. INTRODUCTION

Sleep disorders such as insomnia and sleep apnea affect a significant portion of the global population and are linked to cardiovascular risk, cognitive impairment, and reduced quality of life [1], [2]. Polysomnography (PSG) remains the clinical gold standard for assessing these conditions, combining electroencephalography (EEG), electrooculography (EOG), and electromyography (EMG) to identify wakefulness, Non-Rapid Eye Movement (N1, N2, N3), and Rapid Eye Movement (REM) sleep stages [3]. Despite its diagnostic value, PSG is costly and resource-intensive, limiting access for patients and restricting its use in routine screening, research, or education. Commercial wearable devices and bedside sensors have emerged as more accessible alternatives, but most rely on

movement, heart rate, or respiratory surrogates rather than direct EEG recordings. As a result, they cannot provide raw EEG traces or hypnograms that allow detailed stage analysis, nor do they give users or researchers the flexibility to add custom features or extend device functionality [4]–[6]. These systems are often closed platforms, leaving students, researchers, and hobbyists unable to modify acquisition pipelines or run their own algorithms, which limits their value in teaching and experimental contexts.

Recent advances in open-source and low-cost EEG designs have started to bridge this gap. Studies have demonstrated affordable portable EEG devices that enable sleep recording at a fraction of the cost of clinical systems [7], [8], while others have adapted commercial sensors such as the AD8232 for biopotential monitoring in research and teaching applications [9]. However, many of these designs compromise on sampling rate, robustness, or ease of use. Wireless systems, for example, may suffer data loss, and some implementations lack tools for visualization or interpretation, leaving users with raw signals that are difficult to analyze. Few solutions provide an integrated explanation layer that can assist non-experts in understanding sleep stage outputs or the meaning of derived statistics.

In this work, we present a portable EEG-based sleep analysis system that records at 256 Hz directly to removable storage, avoiding streaming interruptions, and pairs hardware acquisition with NeuroNap, a Gradio-based software interface. NeuroNap provides visualizations of EEG waveforms, filtered signals, frequency spectra, and hypnograms, with the option to download stage-specific band plots. Sleep staging is performed using the Yet Another Spindle Algorithm (YASA) open-source toolbox, enabling standardized classification into Wake, N1, N2, N3, and REM [10]. To assist with sleep analysis interpretation, the system incorporates a large language model enhanced with retrieval-augmented generation, enabling users to query their recordings and receive explanations of the derived sleep statistics, making sleep stage outputs and statistical measures easier to understand in both home and research settings.

II. LITERATURE REVIEW

A. Wearable and Commercial Sleep Monitoring Technologies

Consumer wearables and bedside sensors have become popular alternatives to clinical systems, since they are more affordable and easy to use. However, these devices typically rely on motion, heart rate, or respiratory proxies rather than direct EEG recordings [4]. Lee et al. evaluated 11 consumer sleep trackers and found that while they provide useful sleep metrics, they do not allow users to access raw EEG or detailed hypnograms [4]. De Zambotti et al. emphasized that these systems are closed platforms incapable of customization, which limits their usefulness for research or instructional purposes [6]. Canali et al. further discussed challenges such as data quality, interoperability, and equitable access, pointing out that open-source solutions are needed to broaden capability and fairness in health devices [5].

B. Low-Cost EEG and Open-Hardware Systems

To bridge the gap, low-cost EEG systems have been proposed to deliver raw brain signals affordably. Pretel et al. (2024) developed a single-channel, 3-electrode portable sleep device using ESP32, with SD card and Wi-Fi options, validated against research equipment at 256 Hz sampling [7]. Mendes Junior and colleagues examined the AD8232 sensor for biopotential monitoring in open-source educational systems [9]. Yu and Guo [8] proposed a 4-channel wireless EEG system for virtual reality environments, showing versatility but facing potential data loss during wireless transmission. The OpenBCI Cyton Board provides 8-channel, 250 Hz sampling [11], but its cost and technical setup make it less accessible for educational contexts. These designs demonstrate progress toward affordability and openness but often sacrifice ease of use or user guidance.

C. Automated Sleep Staging and Analysis Tools

Automated sleep staging has matured thanks to tools like the YASA library, introduced by Vallat and Walker [10], offering performance comparable to manual scoring with open access for researchers. Studies confirm YASA's accuracy varies with preprocessing, channel selection, noise reduction, and sleep conditions, such as sleep restriction [12]. Comparisons of automated and manual scoring in portable devices also highlight improvements in agreement with polysomnography [15]. Despite these advances, most systems produce graphs without built-in interpretability, leaving non-expert users without guidance on data meaning.

D. Explainability, User Interaction, and Gaps

Beyond data accuracy, interpretability is key. Retrieval-augmented generation (RAG) models use document-grounded responses to improve factual reliability and context relevance [13]. Applications of large language models (LLMs) in biomedical analysis show promise for automated explanation and education, but challenges remain in validation and user trust [14]. Few low-cost EEG systems combine visualization

TABLE I
COMPARISON WITH PRIOR LOW-COST EEG SYSTEMS

System	Cost (\$)	Ch.	Rate (Hz)	Storage	Key Features
Pretel et al. (2024) [7]	<100	1	256	SD Card, Wi-Fi	Open HW, GUI
Yu & Guo [8]	60	4	250	Wi-Fi	VR use
OpenBCI Cyton [11]	499	8	250	USB, PC	Research-grade
Mendes Jr. [9]	-	1	100–250	USB	AD8232 eval
Proposed system	<60	1	256	SD Card	GUI, LLM, YASA

with interpretive assistance, limiting accessibility for students and general users.

E. Summary and Opportunities

In summary, commercial wearables favor accessibility over fidelity, while open-source EEG devices achieve affordability but lack integrated analysis and interpretability. The proposed system, developed in this study, combines both by integrating reliable signal acquisition, intuitive visual feedback, and a context-aware explanation layer for improved accessibility and understanding.

III. METHODOLOGY

A. System Overview

The system acquires and analyzes single-channel EEG for sleep staging. EEG was recorded using a frontal-to-mastoid montage (Fz–A1) with an AD8232 amplifier and MCP602 operational amplifier for signal conditioning. The conditioned signal is digitized by an ESP32 at 256 Hz and saved to a microSD card. Offline analysis in Python uses the NeuroNap interface, built with Gradio, to preprocess the data, compute band power, and perform automated sleep staging with the YASA toolbox. NeuroNap also provides contextual explanations of the results using a retrieval-augmented language model.

A block diagram illustrating the system architecture is shown in Figure 1.

B. Materials

The system is designed to be cost-effective and portable. The components used are listed in Table II and described below:

- **ESP32 Microcontroller:** Equipped with a 12-bit analog-to-digital converter (ADC) providing a resolution of approximately 0.805 mV (3.3 V / 4096 levels) and SPI support for interfacing with the MicroSD card module. It handles EEG data acquisition and storage at 256 Hz [16].
- **AD8232 Sensor:** An ECG front-end with a gain of 100 and a common-mode rejection ratio (CMRR) of 80 dB. It serves as the initial amplification stage [17].

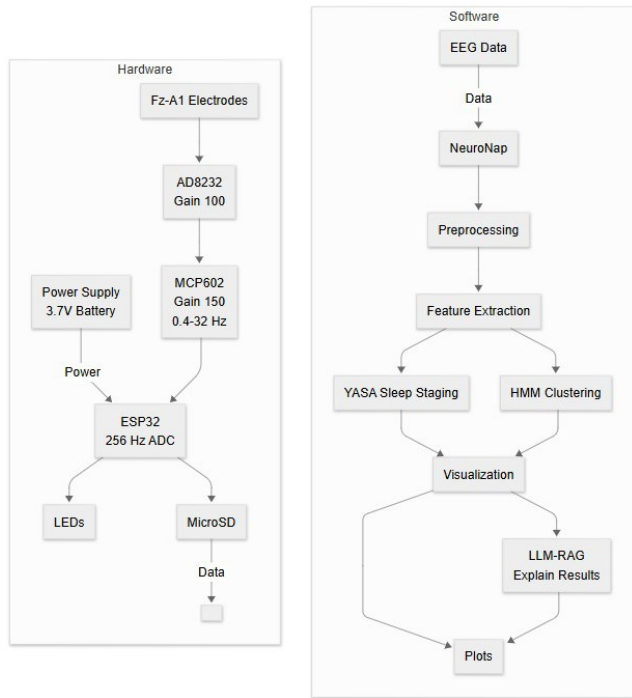


Fig. 1. Block diagram of the EEG acquisition and analysis system.

TABLE II
COMPONENT COST BREAKDOWN

Component	Cost (USD)
ESP32 Microcontroller	10
AD8232 Sensor	10
MCP602 Op-Amp	1
MicroSD Card (8 GB)	5
Battery and Charging Circuit	20
Electrodes and Accessories	4
Total	50

- **MCP602 Operational Amplifier:** A low-power dual op amp with 90 dB CMRR, configured for additional signal amplification (gain of 150) and bandpass filtering (0.4–32 Hz) to enhance the quality of the EEG signal for sleep analysis [18].
- **MicroSD Card Module:** An 8 GB MicroSD card formatted in FAT32, used for reliable offline storage of EEG data sampled at 256 Hz.
- **LEDs and Power Supply:** Green and red LEDs provide feedback for system initialization and operation status. A rechargeable battery with an integrated charging circuit ensures portability.
- **Electrodes and Accessories:** Disposable Ag/AgCl electrodes for a frontal-to-mastoid (Fz–A1) montage, along with cables and connectors for signal acquisition.

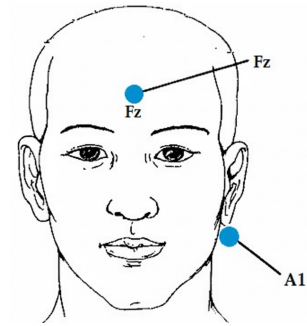


Fig. 2. Electrode placement for the Fz–A1 montage.

C. Electrode Configuration

The system uses a single-channel EEG with a frontal-to-mastoid (Fz–A1) montage, following the 10–20 system [19]. Electrode placements are shown in Fig. 2 and listed below:

- **RA Electrode:** Placed at Fz (forehead center), connected to AD8232 RA pin, secured with a headband.
- **LA Electrode:** Positioned on the left mastoid, connected to AD8232 LA pin, secured with medical tape.
- **RL Electrode:** Located on the right forehead (above eyebrow), connected to AD8232 RL pin, secured with a headband.

D. Signal Conditioning and Amplification

Typical EEG signals for sleep monitoring have amplitudes of 10–100 μV , with peaks up to 200 μV including artifacts, requiring significant amplification for digitization [10]. The AD8232 heart monitor module serves as the first amplification stage. It contains a differential amplifier with a gain of 100 (60 dB), suitable for amplifying ECG signals [17]. However, for EEG signals in the microvolt range, this gain alone is not sufficient, so an external amplification stage is added with the MCP602 operational amplifier to reach a total gain of about 15,000 ($\approx 83.5\text{dB}$). The total gain is calculated using Equation (1), combining the contributions of the AD8232 and MCP602 amplifiers. The total gain is calculated using Equation (1), combining the contributions of the AD8232 and MCP602 amplifiers.

$$G_{\text{total}} = G_{\text{AD8232}} \times G_{\text{MCP602}}, \quad (1)$$

where $G_{\text{AD8232}} = 100$ (AD8232) and $G_{\text{MCP602}} = 150$ (MCP602), yielding $G_{\text{total}} = 15,000$. This amplifies EEG signals to 0.15–1.5 V, fitting the ESP32’s 3.3 V ADC range without saturation. The bandwidth of 0.4–32 Hz captures key EEG frequency bands for sleep stage classification (Wake, N1, N2, N3, REM), as shown in Table III, while removing DC drifts (below 0.4 Hz) and high-frequency noise or aliasing (above 32 Hz) for a 256 Hz sampling rate [10]. This bandwidth ensures delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands are preserved, enabling accurate detection of sleep stage characteristics such as K-complexes (N2) and slow waves (N3).

TABLE III
SLEEP STAGES AND ASSOCIATED EEG FREQUENCY BANDS

Sleep Stage	Frequency Band (Hz)	Characteristics
Wake	Alpha (8–13), Beta (13–30)	High-frequency activity, alertness
N1	Theta (4–8), Alpha (8–13)	Light sleep
N2	Theta (4–8), Spindles (11–16)	Sleep spindles, K-complexes
N3	Delta (0.5–4)	Slow-wave sleep, deep sleep
REM	Theta (4–8), Beta (13–30)	Rapid eye movements

The analog front-end processes EEG signals using the AD8232 for initial amplification (gain of 100, output bias of 1.65 V) [17], followed by a high-pass filter (HPF) to remove the DC bias, re-biasing to center the signal at 1.65 V, and a second stage with the MCP602 operational amplifier for amplification (gain of 150) and low-pass filtering (LPF) to achieve a 0.4–32 Hz bandwidth [18]. The circuit simulated in LTSpice to mimic, amplify and filter the AD8232's EEG output, is shown in Fig. 3. The complete signal conditioning schematic is shown in Fig. 4.

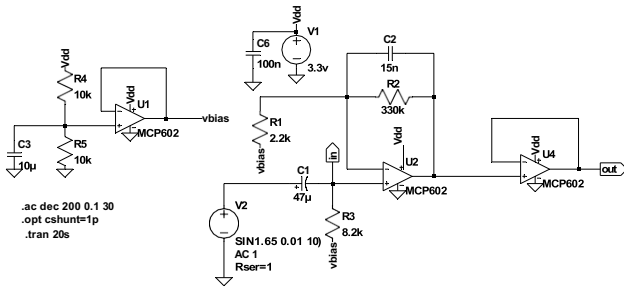


Fig. 3. Circuit simulation diagram of the amplification and filtering stages, showing HPF, re-biasing, and LPF.

1) **High-Pass Filter (HPF):** The HPF removes the 1.65 V DC bias from the AD8232 output using a 47 µF capacitor and an 8.2 MΩ resistor. The cutoff frequency, calculated using Equation (2) and is set to approximately 0.4 Hz to eliminate low-frequency artifacts.

$$f_{\text{HPF}} = \frac{1}{2\pi RC}, \quad (2)$$

where R is the resistor and C is the capacitor.

2) **Re-Biasing:** To center the signal at 1.65 V for the ESP32 ADC, an MCP602 in a buffer configuration uses a voltage divider with two 10 kΩ resistors ($R_1 = R_2$) connected between the 3.3 V supply and ground. The bias voltage, given

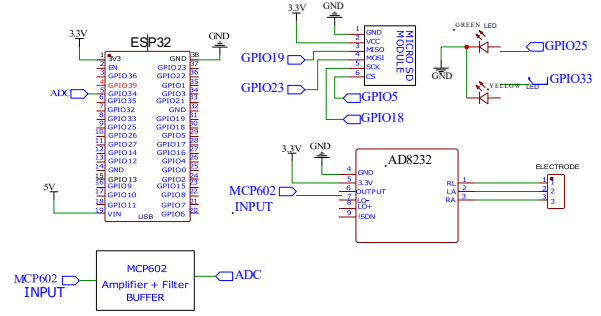


Fig. 4. Schematic diagram of the signal conditioning circuit.

by Equation (3), ensures the EEG signal remains within the 0–3.3 V ADC range.

$$V_{\text{bias}} = \frac{V_{\text{supply}}}{2}. \quad (3)$$

3) **Low-Pass Filter and Amplification (LPF):** The MCP602 is configured as a non-inverting amplifier with a gain calculated using Equation (4), where $R_f = 330 \text{ k}\Omega$ and $R_g = 2.2 \text{ k}\Omega$, yielding a gain of approximately 150.

$$G = 1 + \frac{R_f}{R_g}, \quad (4)$$

A 15 nF capacitor in parallel with R_f forms the LPF, with the cutoff frequency determined Equation (5), set at approximately 32 Hz to filter out high-frequency noise.

$$f_{\text{LPF}} = \frac{1}{2\pi R_f C_f}. \quad (5)$$

A final MCP602 buffer isolates the amplification stage from the ESP32 ADC, ensuring stable signal delivery.

E. Data Acquisition and Storage with User Feedback

The ESP32 samples the EEG signal at 256 Hz using its 12-bit ADC (0–4095, 0.805 mV per level) with a 3.906 ms sampling delay, capturing EEG bands of 0.5–30 Hz for sleep staging [16]. Data, including timestamps (ms) and ADC values, are stored in a CSV file (eegdata.csv) on an 8 GB microSD card. The firmware initializes the SD card, writes a header (time_ms,adc_value), and signals initialization with five LED blinks. A 30-second countdown establishes a baseline, and an LED indicates write operations, ensuring reliable offline storage.

F. Power Consumption

The system is powered by a 3.7 V, 1000 mAh lithium-ion battery with an integrated charging circuit, shown in Fig. 5, ensuring portability and rechargeability. The total power consumption is calculated as

$$P_{\text{total}} = V_{\text{supply}} \times (I_{\text{ESP32}} + I_{\text{AD8232}} + I_{\text{MCP602}} + I_{\text{SD}} + I_{\text{LEDs}} + I_{\text{charge}}), \quad (6)$$

where $V_{\text{supply}} = 3.3 \text{ V}$ for most components, $I_{\text{ESP32}} \approx 100 \text{ mA}$ in active mode [16], $I_{\text{AD8232}} \approx 0.17 \text{ mA}$ [17], $I_{\text{MCP602}} \approx$

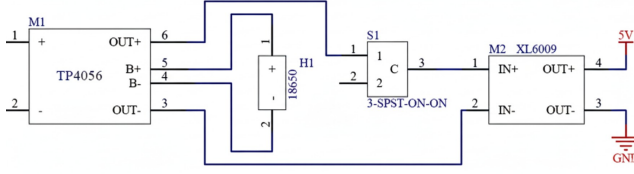


Fig. 5. Schematic diagram of the charging circuit.

0.46 mA for two channels [18], $I_{SD} \approx 20$ mA during writes, $I_{LEDs} \approx 10$ mA with minimal duty cycle, and $I_{charge} \approx 1$ mA for the charging circuit. This yields a total current of approximately 131.63 mA, or 434 mW at 3.3 V, enabling over 7 hours of operation on a 1000 mAh battery.

G. Offline Signal Processing in NeuroNap

The offline signal processing pipeline, implemented within the NeuroNap interface, processes EEG data stored on a microSD card. NeuroNap, built using Gradio [20], provides a user-friendly platform for preprocessing, feature extraction, sleep staging, and visualization of EEG signals. The pipeline ensures accurate conversion of raw ADC values to EEG voltages, applies filtering to isolate relevant frequency bands, extracts features for sleep stage classification, and generates a hypnogram using the YASA toolbox. Additionally, an integrated large language model (LLM) with retrieval-augmented generation (RAG) explains the results to users, enhancing interpretability for both researchers and nonexperts. The workflow is illustrated in Figure 1.

1) **Signal Preprocessing:** The preprocessing stage converts raw ADC values to EEG voltages, resamples the data to ensure uniform sampling, and filters noise, preparing the data for feature extraction and sleep staging.

a) **ADC to Voltage Conversion:** The raw EEG data, stored as 12-bit ADC values (0–4095), are converted to voltages using the reference voltage of ESP32 ($V_{ref} = 3.3$ V) and the total gain of the system ($G_{total} = 15000$). The voltage is calculated as follows:

$$V_{raw} = ADC \times \frac{V_{ref}}{4095}, \quad (7)$$

followed by DC bias removal:

$$V_{EEG} = V_{raw} - \bar{V}_{raw}, \quad (8)$$

where $\bar{V}_{raw}$ is the mean voltage that represents the estimated DC bias of the signal. The EEG signal in microvolts is then:

$$EEG_{\mu V} = \frac{V_{EEG} \times 10^6}{G_{total}}. \quad (9)$$

This scales the signal to 10–100 μV for the analysis of the sleep stage [10].

b) **Data Cleaning and Resampling:** Duplicate timestamps or irregular sampling intervals are addressed by averaging ADC values for identical timestamps and resampling to a uniform 256 Hz (sampling interval $\Delta t \approx 3.906$ ms) using linear interpolation. The resampled data are stored in a new DataFrame for further processing.

c) **Bandpass and Notch Filtering:** A fourth-order Butterworth bandpass filter (0.5–30 Hz) isolates sleep-relevant EEG frequencies, applied using zero-phase filtering to produce EEG_{BP}. A notch filter at 50 Hz removes power line interference, resulting in EEG_{notched}.

d) **Frequency Band Decomposition:** Specific EEG frequency bands, as defined in Table III, are extracted using fourth-order Butterworth filters, producing signals (EEG_{delta}, EEG_{theta}, EEG_{alpha}, EEG_{beta}) for visualization and feature extraction.

2) **Feature Extraction:** The filtered EEG signal is segmented into 30-s epochs, spectral and temporal features are then extracted for sleep stage classification

a) **Epoching:** The EEG signal is divided into non-overlapping 30-second epochs, each containing $N_{epoch} = 30 \times 256 = 7680$ samples. The number of epochs is:

$$N_{epochs} = \left\lfloor \frac{N_{samples}}{N_{epoch}} \right\rfloor, \quad (10)$$

where $N_{samples}$ is the total number of samples.

b) **Spectral Features:** Power spectral density (PSD) is computed using Welch's method [21] with a segment length of 1024 samples and 50% overlap. Relative band powers for delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), sigma (12–16 Hz), and beta (13–30 Hz) are calculated as:

$$P_{rel,band} = \frac{\int_{f_{low,band}}^{f_{high,band}} PSD(f) df}{\int_{f_{low,band}}^{f_{high,band}} PSD(f) df}. \quad (11)$$

c) **Temporal Features:** Temporal features include sample entropy, spindle count, and slow-wave count. Sample entropy quantifies signal complexity, while spindles (12–16 Hz) and slow waves (0.5–2 Hz) are detected using bandpass filtering and amplitude thresholding via the Hilbert transform envelope.

3) **Sleep Staging:** Each 30-second epoch is classified into sleep stages using Hidden Markov Model (HMM) or supervised classification with YASA.

a) **Unsupervised Clustering with Hidden Markov Model (HMM):** Principal Component Analysis (PCA) reduces feature dimensionality, and a Gaussian HMM [22] with 5 states is trained on the transformed features, assigning each epoch to a cluster. Users can map clusters to sleep stages based on feature summaries (e.g., high delta power for N3).

b) **YASA-Based Sleep Staging:** The YASA toolbox uses a pre-trained model to predict stages from EEG_{notched} at 256 Hz, producing a hypnogram with stages W, N1, N2, N3, or R. Sleep statistics are computed as:

$$\text{Percentage}_{stage} = \frac{N_{stage}}{N_{epochs}} \times 100, \quad (12)$$

$$\text{Duration}_{stage} = N_{stage} \times 0.5 \text{ min}, \quad (13)$$

where N_{stage} is the number of epochs per stage. The hypnogram and statistics are visualized and downloadable.

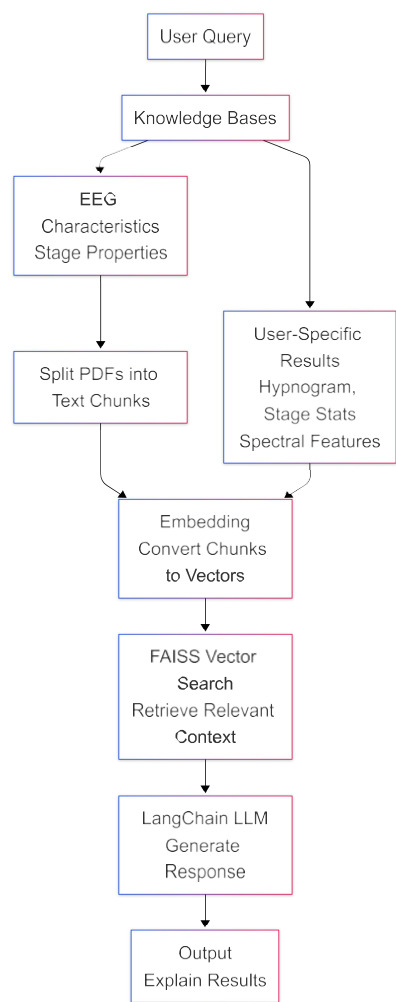


Fig. 6. LLM pipeline for result explanation in NeuroNap.

4) **LLM-Assisted Analysis Explanation:** NeuroNap integrates an LLM with retrieval-augmented generation (RAG) using FAISS [23] and LangChain [24] to explain results. It leverages two knowledge bases: sleep stage definitions/EEG characteristics and user-specific results (hypnograms, stage statistics). The LLM pipeline is shown in Figure 6.

The LLM processes queries (e.g., “What does my N3 percentage mean?”) by retrieving context and generating clear, educational responses, using exact user data values and simplified analogies for accessibility. A sample system instruction for the LLM is:

You are an expert assistant in EEG-based sleep analysis. Your task is to explain sleep staging results and EEG characteristics to users, using a clear and educational tone. Use the provided context from two knowledge bases: (1) sleep stage definitions and EEG signal properties, and (2) user-specific analysis results (hypnogram, stage percentages, durations, and spectral features). Retrieve relevant information using FAISS vector search and generate responses with LangChain. Ensure explanations are accurate,

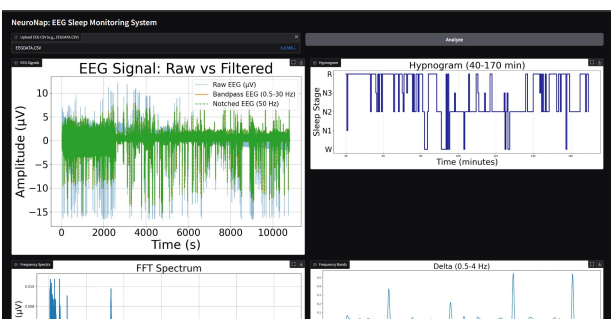


Fig. 7. NeuroNap Gradio interface for EEG data visualization and analysis.

TABLE IV
SUMMARY OF RECORDED EEG DATA CHARACTERISTICS

Parameter	Value
Duration	179.417 057 min (2.99 h)
Sample count	2755847
Sampling interval	3.906 25 ms
Sampling rate	256 Hz
Duplicate timestamps	6723
Estimated bias voltage	1.65 V
Negative EEG values	1532338
Positive EEG values	1223509
Zero EEG values	0
Epoch length	30 s
Total epochs	358

concise, and tailored to the user’s query. Avoid technical jargon unless necessary, and provide simplified analogies where appropriate. If the query references specific results (e.g., N3 percentage), include the exact values from the user’s data and explain their significance in the context of sleep health.

IV. RESULTS AND DISCUSSION

This section presents results from the low-cost EEG sleep monitoring system, including data acquisition, signal processing, and sleep staging using the NeuroNap Gradio interface, shown in Fig. 7. EEG data sampled at 256 Hz were processed offline, producing downloadable figures and tables, with affordability and usability also highlighted in the discussion

A. Recorded EEG Data Characteristics

The system recorded EEG data using a single-channel Fz–A1 montage at 256 Hz, stored in CSV format on an 8 GB microSD card. The recording spanned ≈179 mins, yielding 2,755,847 samples at ≈3.9 ms intervals. Preprocessing resolved 6,723 duplicate timestamps by averaging ADC values. After removing a 1.65 V bias, the EEG signal comprised of 1,532,338 negative and 1,223,509 positive values, with no zero values, suitable for sleep analysis. Table IV summarizes these characteristics.

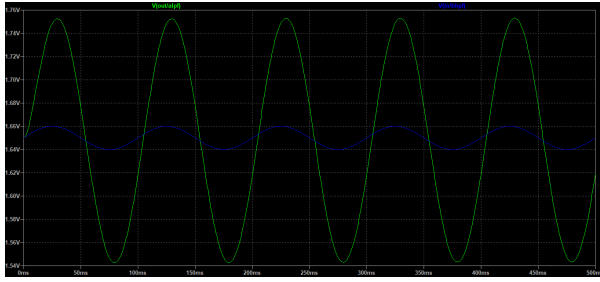


Fig. 8. V_{out} vs. V_{in} plot showing a gain of 150 for a 0.01 mV input at 10 Hz with a 1.65 V bias (transient analysis).

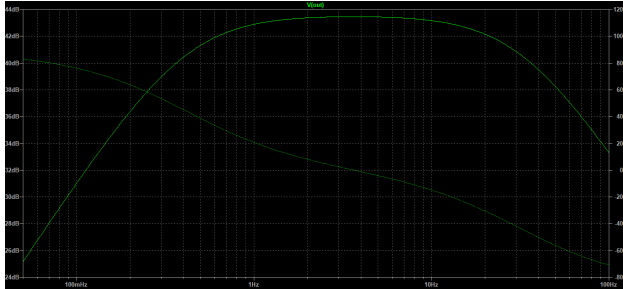


Fig. 9. Bode plot of the EEG signal chain, showing a bandwidth of 0.4 Hz to 32 Hz (frequency response).

B. Signal Conditioning and Amplification Validation

Simulations validated the amplification and filtering process. The V_{out} vs. V_{in} plot in Fig. 8 shows the transient analysis for a 0.01 mV input at 10 Hz with a 1.65 V bias. The Bode plot in Fig. 9 confirmed a frequency response of 0.4 Hz–32 Hz, capturing sleep-relevant EEG bands while filtering noise and ensuring reliable signal acquisition.

C. EEG Signal Processing and Visualization

The NeuroNap interface in Fig. 7 provided downloadable visualizations. Time-domain plots in Fig. 10 show raw, bandpass-filtered (0.5 Hz–30 Hz), and notched (50 Hz) EEG signals, demonstrating effective noise reduction. Frequency-domain analyses, including FFT and Welch PSD in Fig. 11, reveal clear spectral content within 0.5 Hz–30 Hz, with reduced 50 Hz interference. Band-specific waveforms for delta (0.5 Hz–4 Hz), theta (4 Hz–8 Hz), alpha (8 Hz–13 Hz), and beta (13 Hz–30 Hz) in a 20 s window (3000 s–3020 s) are shown in Fig. 12, aiding sleep stage identification.

D. Feature Extraction and Clustering

The EEG data were segmented into 358 epochs (30 seconds each), with eight features extracted per epoch: relative powers for each frequency bands, sample entropy, spindle count, and slow-wave count. A five-cluster Gaussian HMM was applied to the PCA reduced features to generate distinct profiles, as summarized in Table V. These clusters show characteristic EEG patterns that users can examine to assign sleep stage labels or guide further analysis.

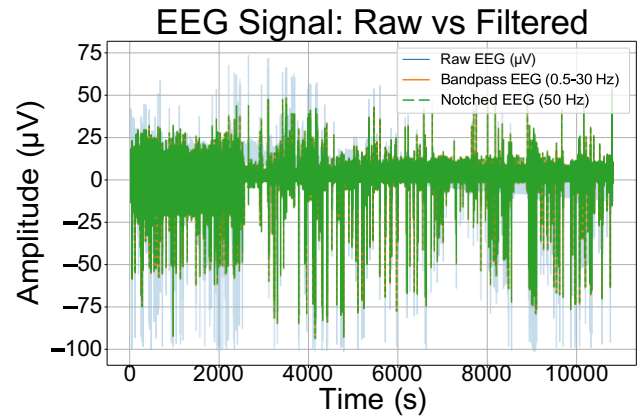


Fig. 10. Time-domain EEG signals: raw, bandpass-filtered (0.5 Hz–30 Hz), and notched (50 Hz) for noise reduction..

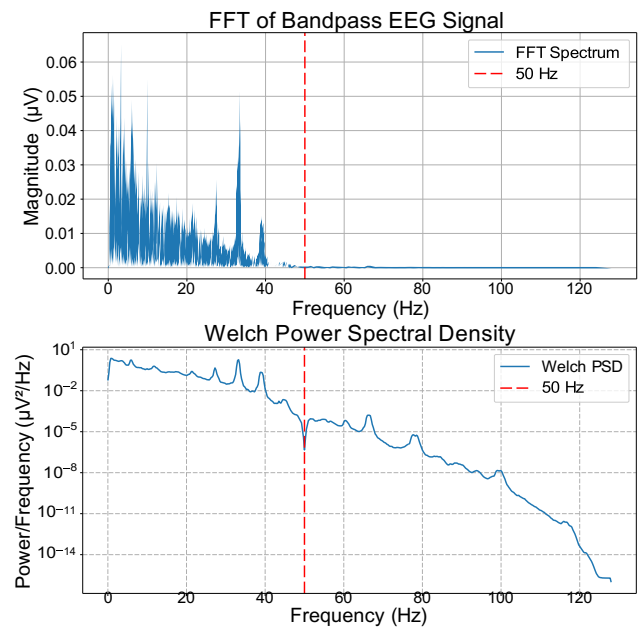


Fig. 11. Frequency-domain analysis showing FFT spectrum and Welch PSD of the filtered EEG signal.

TABLE V
MEAN FEATURE VALUES FOR HMM CLUSTERS (NORMALIZED RELATIVE POWERS)

Cluster	0	1	2	3	4
rel_delta	0.25	0.21	0.35	0.30	0.20
rel_theta	0.14	0.18	0.10	0.11	0.15
rel_alpha	0.19	0.26	0.04	0.08	0.20
rel_sigma	0.08	0.07	0.08	0.10	0.09
rel_beta	0.34	0.28	0.43	0.41	0.36
sample_entropy	1.99	1.91	1.03	1.17	1.13
spindle_count	8.20	7.40	12.00	12.33	10.20
slow_wave_count	21.60	16.80	33.00	30.33	19.80

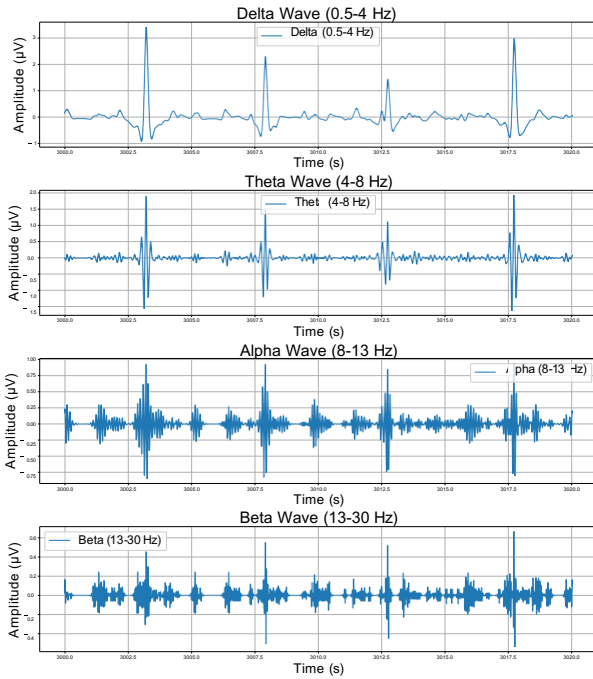


Fig. 12. Band-specific EEG waveforms for delta (0.5 Hz–4 Hz), theta (4 Hz–8 Hz), alpha (8 Hz–13 Hz), and beta (13 Hz–30 Hz) in a 20 s window.

TABLE VI
SLEEP STAGE COUNTS, PERCENTAGES, AND DURATIONS

Stage	Count	Percentage (%)	Duration (min)
Wake (W)	58	16.2	29.0 min
N1	17	4.7	8.5 min
N2	216	60.3	108.0 min
N3	46	12.8	23.0 min
REM (R)	21	5.9	10.5 min

E. YASA-Based Sleep Staging

The YASA toolbox classified 358 epochs into Wake (W), N1, N2, N3, and REM (R). The hypnogram in Fig. 13 shows sleep stage transitions from 40 min to 170 min, reflecting typical sleep cycles. Stage N2 dominated at 60.3 % (108.0 min), followed by N3 (12.8 %, 23.0 min), Wake (16.2 %, 29.0 min), REM (5.9 %, 10.5 min), and N1 (4.7 %, 8.5 min), as summarized in Table VI. A pie chart in Fig. 14 illustrates these proportions. Sleep statistics in Table VII report a Total Sleep Time (TST) of 150.0 min, Sleep Efficiency (SE) of 83.8 %, and latencies to N1 (15.0 min), N2 (16.0 min), N3 (49.0 min), and REM (79.0 min).

F. Large Language Model-Assisted Analysis Explanation

The NeuroNap interface (Fig. 7) offers clear explanations of sleep analysis results. For example, when queried about the N3 sleep percentage, the LLM responds:

According to your data, 15.3% of your sleep was spent in N3, the deepest sleep stage. Deep sleep is

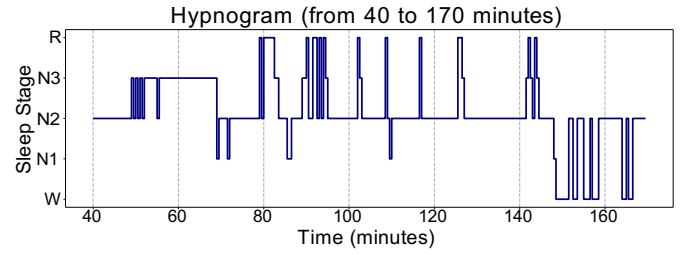


Fig. 13. Hypnogram showing sleep stage transitions from 40 min to 170 min.

Sleep Stage Percentages

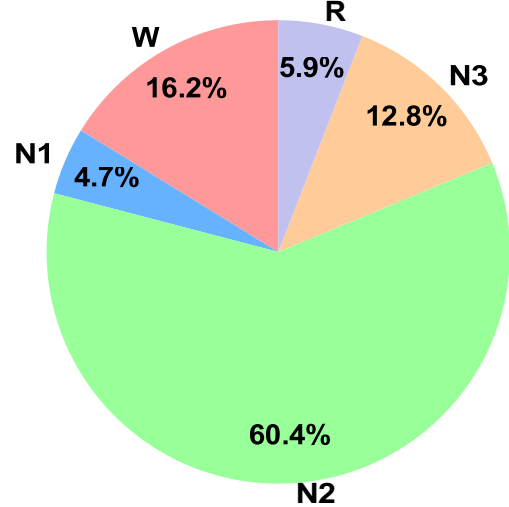


Fig. 14. Pie chart of sleep stage percentages: W (16.2%), N1 (4.7%), N2 (60.3%), N3 (12.8%), R (5.9%).

essential for repairing tissues, boosting immunity, and consolidating memories. Since this falls comfortably within the typical adult range, your body is getting a good amount of restorative sleep.

This approach enhances accessibility for non-expert users, enabling them to understand metrics like N3 percentage (indicating deep sleep) or sleep efficiency (sleep quality) in the context of their health.

V. DISCUSSION

The EEG sleep monitoring system accurately classifies sleep stages at low cost, ideal for research and personal use. Using the YASA toolbox, it categorized sleep stages into Wake (W), N1, N2, N3, and REM (R), generating a hypnogram with clear sleep cycle transitions (Fig. 13). Evaluation metrics (Table VII) report a Total Sleep Time (TST) of 150.0 minutes and a Sleep Efficiency (SE) of 83.8%, aligning with healthy adult sleep patterns.

The low-cost design expands access to sleep monitoring, unlike costlier systems [11]. The NeuroNap interface, enhanced by an LLM with retrieval-augmented generation (RAG), delivers clear explanations of metrics, making results accessible to non-experts. Visualizations and metrics, including Sleep

TABLE VII
SLEEP STATISTICS FROM YASA ANALYSIS

Metric	Value
Total Time in Bed (TIB)	179.0 min
Sleep Period Time (SPT)	162.5 min
Wake After Sleep Onset (WASO)	12.5 min
Total Sleep Time (TST)	150.0 min
N1 Duration	8.5 min
N2 Duration	108.0 min
N3 Duration	23.0 min
REM Duration	10.5 min
NREM Duration	139.5 min
Sleep Onset Latency (SOL)	15.0 min
Latency to N1	15.0 min
Latency to N2	16.0 min
Latency to N3	49.0 min
Latency to REM	79.0 min
N1 Percentage	5.7%
N2 Percentage	72.0%
N3 Percentage	15.3%
REM Percentage	7.0%
NREM Percentage	93.0%
Sleep Efficiency (SE)	83.8%
Sleep Maintenance Efficiency (SME)	92.3%

Maintenance Efficiency (SME) of 92.3% and sleep latencies (e.g., 15.0 minutes to N1) provide actionable insights surpassing manual or proxy-based devices [4]. The YASA-based automated staging ensures standardized, reproducible results, enhancing utility across applications.

VI. CONCLUSION AND FUTURE WORK

This low-cost EEG sleep monitoring system achieves precise sleep stage classification, with an 83.8% Sleep Efficiency and stage distributions (e.g., 60.3% N2, 12.8% N3). Its YASA-based staging, robust metrics (e.g., 92.3% SME), and LLM-driven explanations with RAG via NeuroNap offer reliable, user-friendly sleep analysis. The affordable design supports researchers, educators, and individuals in monitoring sleep health. Future improvements include fine-tuning the LLM for sleep-specific explanations, expanding metrics like spindle density, multichannel support, automated artifact removal, and Wi-Fi connectivity for real-time monitoring. These enhancements will further strengthen its diagnostic capabilities and utility.

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