Brainwave Monitoring and Stress Alert System with AI Smart Therapy

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Abstract

Anxiety and metal stress is the critical health challenges particularly for people with mental disabilities and unable to communicate effectively. The standard healthcare-based evaluations are inconsistent and failed to detect the early stress. This proposed work uses a wearable EEG-based monitoring system integrates Artificial Intelligence (AI) and Internet of Things (IoT) technologies to classify five mental states: normal, low stress, medium stress, high stress and anxiety. The EEG signals are collected from the wearable headband, preprocessed using band-pass and notch filtering which converted into physiological and statistical features such as mean, standard deviation, peak amplitude, entropy, heart rate and RR variance. Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) are the two models evaluated for classification performance. MLP used to implement low interference latency and stable performance on lightweight hardware in real-time. The classified mental states are transmitted to the healthcare people through cloud dashboard. When the critical states are detected, triggering the local SOS buzzer using ESP32. Additionally, the smart therapy is activated automatically to provide treatments. The experimental evaluation demonstrates the stress classification accuracy above 85% with real-time alert latency approximately 2-3s supports continuous monitoring and proactive method.

Keywords: EEG, Stress Detection, Anxiety Monitoring, IoT, ESP32, Smart Therapy, MLP, CNN, HRV, Real-time Alert System

1. Introduction

Mental stress, anxiety and mood swings become a major health issues in modern society. The impact is more severe among individuals with mental disabilities, autism spectrum disorders or cognitive limitations makes difficult to communicate. In these cases, healthcare providers commonly depend on physical monitoring, as it is inaccurate and may fail to recognize early symptoms of stress development. [2], [5]

Electroencephalography (EEG) is a simple method collects brainwave activity and widely used for cognitive and emotional state analysis. Research shows that EEG frequency bands such as Alpha, Beta, Theta, Delta and Gamma demonstrate quantifiable modifications under stress and anxiety conditions. For example, stress conditions show increased Beta activity and reduced Alpha power. [1], [11]

Recent advances in AI enable accurate stress classification from EEG signals using machine learning and deep learning techniques. However, many existing studies focus on classification and unable to provide closed-loop intervention or real-time safety alert mechanisms. Moreover, several EEG systems require huge clinical devices is inappropriate for continuous monitoring. [3-6].

In the proposed work, both Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) models are implemented to analyze EEG data and classify mental stress levels. The MLP model performs feature-based classification by learning non-linear connections among statistically and physiologically extracted EEG parameters including mean, standard deviation, peak amplitude, heart rate and RR variance.

1.1 Research Gap

Most of the existing studies focused on offline stress classification accuracy using lab EEG datasets with limited wearable monitoring in real-time environments. These systems are depending on clinically-based EEG devices which are not suitable for extensive use for individuals with metal disabilities [17]. The previous works handled the stress detection in an analytical way lacks closed-loop system design integrates real-time alert, safety methods and automated intervention. It will consider the isolated EEG signals avoid the support of physical indicators like heart rate variability can improve resilience and reduce fake detections [18]. These issues will be solved by developing lightweight wearable and real-time stress monitoring

system capable of integrating multimodal physiological signals with AI-based classification and automated response mechanisms. The proposed system combines EEG signal acquisition, preprocessing, feature extraction, AI-based stress classification, IoT-enables healthcare alerts and smart therapy activation in a unified architecture. When integrating EEG and HRV features with embedded hardware such as ESP32, the system enables continuous monitoring and immediate action when critical stress is detected. This provides a real-time and deployable solution extends beyond the conventional offline EEG classification methods.

1.1 Objectives

The objectives of this proposed work is

- Monitoring the brainwave signals continuously using EEG
- Classification of stress levels using AI algorithms
- Providing real-time alerts to caregivers
- Activating Smart Therapy automatically

2. Related Work

In recent years, numerous studies have explored brainwave monitoring and its application in assessing human stress levels. Electroencephalography (EEG) has emerged as a key technique for detecting neural activity, allowing researchers to correlate specific brainwave patterns such as alpha, beta, theta, delta and gamma waves with emotional and psychological states [9]. Early research by various neuroscientists demonstrated that stress and cognitive load leads to an increase in beta wave intensity, whereas relaxation and calm states are associated with alpha and theta waves. These findings formed the basis for modern stress detection systems that utilize EEG signals to assess user health in real time. [19]

The existing systems integrated EEG sensors with machine learning algorithms for stress classification. For instance, portable EEG headsets like the Muse and NeuroSky MindWave devices have enabled real-time monitoring through Bluetooth communication with mobile or desktop applications [6]. These systems capture raw EEG signals and process them using techniques such as Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT) and Power Spectral Density (PSD) analysis to extract significant characteristics. Researchers have applied classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN)

and Neural Networks to distinguish between stressed and relaxed states with high accuracy. Additionally, several studies have examined multimodal approaches combining EEG with other physiological parameters such as heart rate variability (HRV), galvanic skin response (GSR) and respiration rate. This hybrid system enhance reliability and reduce false detections by cross-verifying neural data with autonomic responses. Recent works have also explored the integration of cloud computing and Internet of Things (IoT) platforms to enable continuous monitoring and data analytics for healthcare and workplace stress management [20].

EEG-based stress detection has been widely examined the ability of EEG to represent cortical activation patterns. The work demonstrated that EEG features can be used to classify stress effectively using deep learning and feature-based methods. Deep learning approaches such as CNN performed well for EEG classification because they learn spatial and temporal patterns directly from EEG segments. This system that CNN-based methods reduce dependency on customized features [7]. Wearable EEG devices and BCI systems have been used in stress monitoring, but most of the systems focus on monitoring and visualization without intervention. The study reported wearable EEG-based monitoring but not include automated therapy activation. IoT-based healthcare monitoring systems support remote supervision and alert delivery, but many solutions depend on cloud dashboards and unable to provide emergency local response mechanisms. Another system proposes AI-based IoT monitoring but lacked EEG-driven therapy automation. [8,10]

3. Proposed Work

The manuscript follows the structured methodological system establishes logical connectivity between physiological signal acquisition, feature extraction, machine learning classification and real-time system. The proposed system collects EEG signals through the wearable headband and performs preprocessing using band-pass and notch filtering to remote noise and signal interference. The filtered signals are transformed into statistical and physiological features such as mean, standard deviation, peak amplitude, Shannon entropy, heart rate and RR interval variance.

These features represent the neural activity and autonomic nervous system response associated with stress. The extracted features are used as input to AI-based classifiers like CNN and MLP models learn non-linear connectivity between physiological patterns and mental

stress states. After classification, the predicted state is integrated with an IoT communication system using ESP32 generate alerts and activate smart therapy when the critical stress conditions are detected. This sequential integration from signal acquisition to smart intervention forms an integrated theoretical and architectural system supports the development of a real-time wearable stress monitoring system. The proposed system consists of four modules:

- EEG Signal Acquisition & Preprocessing
- AI-Based Stress Classification
- Smart Therapy & Feedback
- IoT Data Transmission & Alert System

3.1 EEG Signal Acquisition

Electroencephalography (EEG) is a technique used to measure electrical activity generated by neurons in the brain. In this proposed stress monitoring system, EEG signals are collected continuously using a wearable EEG headband sensor placed on the scalp. The sensor detects voltage variations generated by neural activity and converts them into digital signals for further analysis. The acquisition model plays an important role because the quality of the captured EEG signals directly influences the accuracy of stress detection and classification. The wearable EEG headband used in this system ensures continuous monitoring by maintaining user comfort and ability [12].

In the proposed system, EEG signals are transmitted through bluetooth communications from the wearable headband to the processing device. This enables the real-time monitoring and analysis without limiting user movement. The below table 1 illustrates the EEG signals contain different frequency components associated with physical and emotional states.

Table 1. Brainwave Frequency Range and Mental State

Brainwave	Frequency range	Mental state
Delta	0.5-4Hz	Deep sleep
Theta	4-8Hz	Drowsiness
Alpha	8-13Hz	Relaxation
Beta	13-30Hz	Stress

Gamma	>30Hz	Cognitive processing

During the stress condition, the beta wave activity increases and the alpha decreases make EEG effective for physiological signals and stress detection. The EEG acquisition model in proposed system continuously provide brainwave to the signal processing unit where the preprocessing and feature extraction are performed to prepare the signal for AI-based classification.

3.1.1 EEG Signal Preprocessing

Raw EEG signals are collected from sensors contain various types of noises that can distract the actual brain activity data. These disturbances can affect the accuracy of machine learning models if it is not properly removed. The common sources of noise include,

- Baseline drift
- Power line interference
- Muscle anomalies (Electromyography)
- Eye movements (Electro-oculography)
- Motion anomalies

The preprocessing is required to filter the EEG signal and improve signal quality before feature extraction and classification.

3.1.2 EEG preprocessing

The preprocessing steps are mainly used to filter noise, normalize the signal and prepare it for feature extraction.

1. Band-Pass Filtering

Band-pass filtering used to maintain EEG frequency components and remove irrelevant low-frequency and high-frequency noise. In the proposed system, the 0.5Hz-50Hz band-pass filter is used.

- Removes baseline drift below 0.5Hz
- Removes high-frequency noise above 50Hz
- Preserves important EEG bands such as alpha, beta and theta.

This filter will ensure brainwave signals are stored for further analysis.

2. Notch Filtering

Electrical devices and power supplies establish interference at the power line frequency (50Hz). This noise is detected as a high level in the EEG spectrum must be removed. A 50 Hz notch filter is used to reduce this interference related to frequency components. This method significantly improves signal quality reducing noise contamination.

3. Artifact Removal

Artifacts are negative signals produced by non-brain activity such as muscle contractions, blinking or head movement [13]. The proposed method uses threshold-based artifact reduction in EEG sections overcome the established amplitude threshold. For example,

If

|EEG amplitude| > threshold

Then

Signal segment = rejected

This method helps in reducing the number of abnormal signal pulses related to brain function.

4. Signal Normalization

After filtering and artifact reduction, the EEG signals are normalized to maintain consistency across various data and subjects [14]. The proposed system uses Z-score normalization, defined as:

$$Z = \frac{X-\mu}{\sigma} \tag{1}$$

Where:

X - raw EEG sample

μ - mean of the signal

σ - standard deviation

Normalization changes the data ensuring the mean is zero and the variance is in unit [15]. This improves machine learning model integration and provides an equal feature comparison. Figure 1 represents the system preprocessing module diagram.
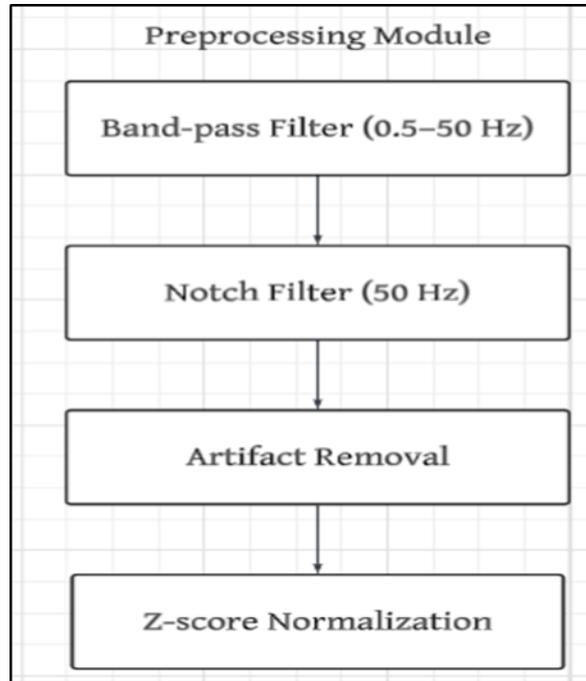

Figure 1. Preprocessing Module

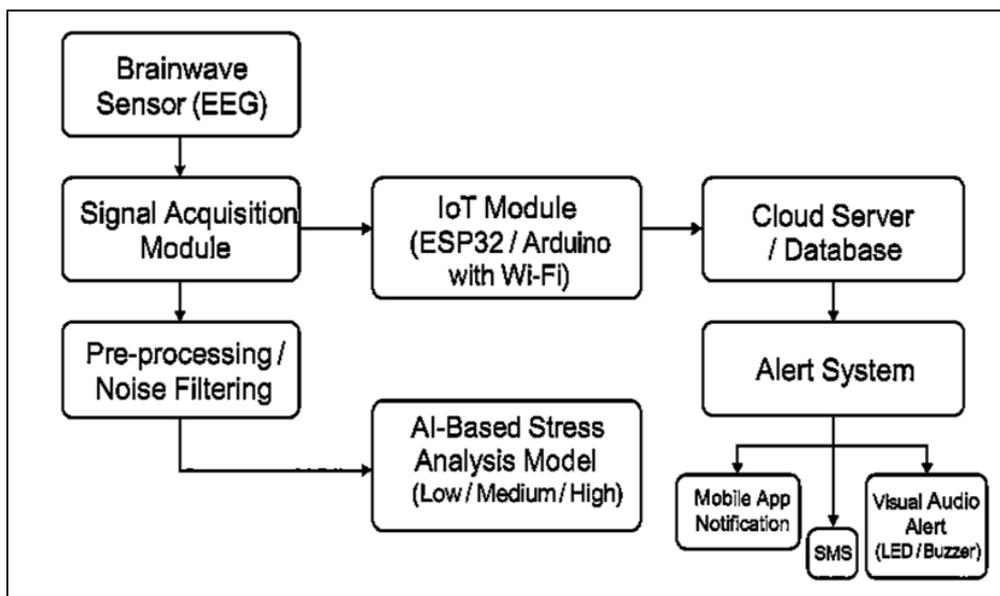The below figure 2 shows the overall architecture of the proposed system.

Figure 2. System Architecture Diagram

Figure 3 represents the overall flow of the work. It consists of four major modules:

- EEG Signal Acquisition and Preprocessing.

- AI-Based Stress Classification.

- Smart Therapy and Feedback.

- Data Transmission and Alert System

Figure 3. Workflow of the proposed work

3.1 Feature Extraction

In the proposed work, feature extraction is performed using time-domain statistical features derived from EEG signals including mean, standard deviation, peak amplitude and Shannon entropy along with physiological indicators such as heart rate (HR) and RR interval variance obtained from Heart Rate Variability (HRV). These features selected due to their computational efficiency, physiological relevance and suitability for real-time wearable systems. The frequency-domain techniques such as Faster Fourier Transform (FFT), Power Spectral Density (PSD), Discrete Wavelet Transform (DWT), Time-domain features are evaluated directly from raw EEG samples without complex signal transformations. This will reduce the computational complexity and allows rapid processing on lightweight hardware platforms. The proposed system aims to achieve a real-time prediction latency of 2-3s approximately, lightweight feature computation for maintaining continuous monitoring performance. The EEG- collect data from portable handband sensor contain noise caused by motion artifacts, electrode impedance variations and environmental interference.

HRV Signal Representation

It measures the variation in time intervals between consecutive heartbeats. These intervals are called RR intervals and are obtained from ECG or heart-rate sensors

$$R = \{r_1, r_2, r_3, \ldots \ldots r_n\} \tag{2}$$

represent the sequence of detected R-peaks in the cardiac signal.

The RR interval sequence is computed as

$$RR_i = r_{i+1} - r_i \tag{3}$$

Where

RR_i is the time difference between two consecutive R-peaks

r_i is the time index of ith heartbeat

Thus the HRV signal represented as

$$RR = \{RR_1, RR_2, RR_3, \ldots \ldots RR_n\} \tag{4}$$

Heart Rate (HR) Computation

Heart rate represents the number of beats per minute (BPM). It is computed from the RR intervals as

$$HR = \frac{60}{\overline{RR}}$$

Where

$$\overline{RR} = \frac{1}{N} \sum_{i=0}^{n} RR_i \tag{5}$$

RR Interval Variance

RR variance quantifies the variability between heartbeats and is a key HRV feature.

$$RR_{var} = \frac{1}{N-1} \sum_{i=0}^{N} (RR_i - \overline{RR})^2 \tag{6}$$

HRV Standard Deviation

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N} (RR_i - \overline{RR})^2} \tag{7}$$

This measure reflects overall autonomic nervous system activity.

EEG Feature Representation

Let the preprocessed EEG signal be represented as

$$EEG(t) = \{x_1, x_2, x_3, ...x_n\} \tag{8}$$

Where x_i is the amplitude of the EEG sample at time i. The extracted EEG features include

Mean

$$\mu = \frac{1}{M}\sum_{i-1}^{M} x_i \tag{9}$$

Standard Deviation

$$\sigma = \sqrt{\frac{1}{M-1} \sum_{i=0}^{M}(x_i - \mu)^2} \tag{10}$$

Peak Amplitude

$$Peak = max(x_i) \tag{11}$$

Shannon Entropy

$$Entropy = -\sum_{i=1}^{k} p_i \log_2(p_i) \tag{12}$$

Where

P_i probability distribution of EEG amplitude levels.

K is the number of amplitude bins.

Entropy measures increased signal complexity during cognitive load and stress.

Additionally, the proposed system integrates HRV-based physiological parameters such as heart rate and RR variance to implement EEG and HRV multimodal fusion. Stress responses involve both neurological and autonomic physiological processes. While EEG captures the primary brain activity, HRV reflects the autonomic nervous system particularly balances between sympathetic and parasympathetic activity. During stress, the sympathetic activity increases heart rate and decreases the HRV results in reduced RR interval variance. When combining the EEG and HRV features, the system collects data from neural and physiological responses by improving stress detection and reducing false classifications. This

multimodal feature fusion provides a more comprehensive representation of the user's mental and physiological state compared using EEG signals. Table 2 illustrates the time-domain features used for stress detection and figure 4 represents the EEG and HRV Multimodal Feature Fusion system

3.2 EEG and HRV Multimodal Feature Fusion System

The system combines neural features from EEG with physiological features from HRV to improve stress classification reliability.

$$F_{EEG} = [\mu, \sigma, Peak, Entropy] \tag{13}$$

The above equation represents the EEG features

$$F_{HRV} = [HR, RR_{var}] \tag{14}$$

The above equation represents the HRV features

The multimodal fusion feature vector is defined as

$$F_{fusion} = [\mu, \sigma, Peak, Entropy, HR, RR_{var}] \tag{15}$$

Table 2. Time-Domain Features used for Stress Detection

| Features	Signal Source	Explanation	Impact of Stress
Mean	EEG	Average signal amplitude	Reflects baseline neural activity
Standard Deviation	EEG	Variance of EEG amplitude	Indicates neural fluctuations
Peak Amplitude	EEG	Maximum signal intensity	Detects sudden neural spikes
Shannon Entropy	EEG	Measure of signal	Higher entropy may indicate cognitive
Heat Rate (HR)	HRV	Beats per minute	Stress increases the heart beat
RR variance	HRV	Variability between heartbeats	Stress reduces HRV variability
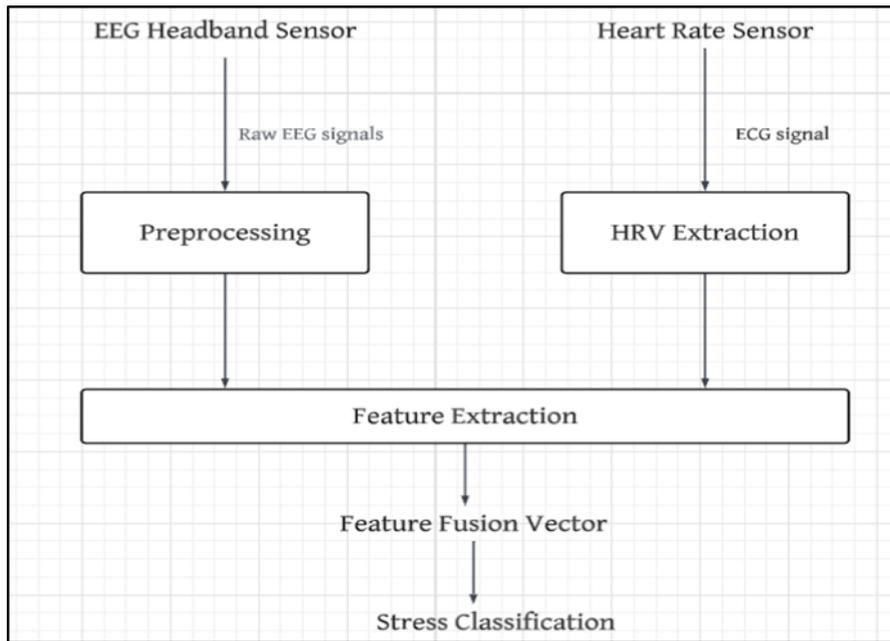
Figure 4. EEG and HRV Multimodal Feature Fusion System

3.3 Stress Level Detection and Alert System

Once the system determines that the user is under stress, an alert is generated through a connected device. Alerts can be visual (LED indication, mobile notification) or sensory (buzzer, voice message). Additionally, the system can include stress stages in a database for long-term tracking and pattern analysis.
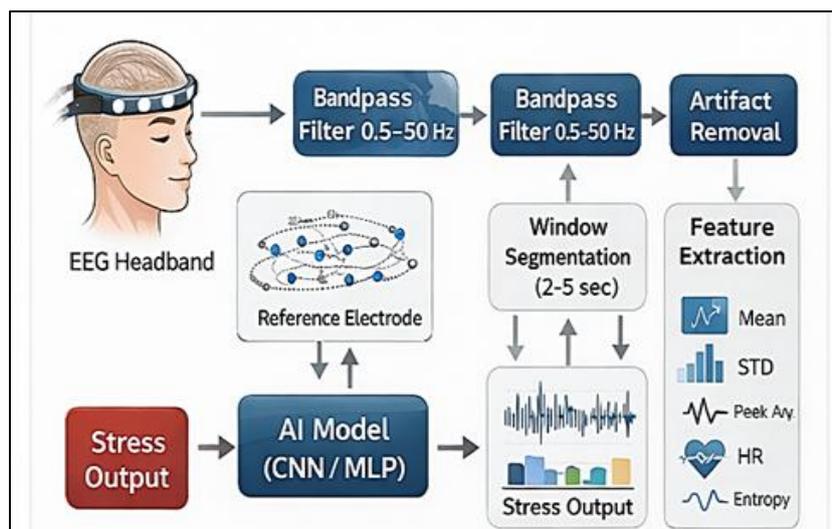

Figure 5. Stress Prediction System

This feedback loop helps users become more aware of their stress patterns and encourages proactive management. Experiments are performed with multiple persons under controlled stress and relaxing situations to validate system performance. Evaluation metrics such as accuracy, precision, recall and F1-score are used to assess the model's effectiveness. The system's responsiveness and real-time detection capability are also tested to ensure reliability. Figure 5 shows the stress prediction system.

3.4 CNN vs MLP Performance and Real-Time Stability

In the proposed stress classification system, both Convolutional Neural Network (CNN) and Multilayer Perceptron (MLP) models were evaluated to analyze EEG-based features and classify mental stress levels. The experimental results show that the CNN model achieved higher classification accuracy (87%) compared to the MLP model (85%).

This performance improved to CNN's ability that automatically learn spatial and temporal patterns from EEG signals. CNN architectures apply convolutional filters that collect local signal variations, waveform patterns and temporal dependencies within EEG segments. These filters enable the model to detect neural oscillations and patterns that may not be represented in manual statistical features. Consequently, CNN models achieve higher accuracy when analyzing complex biomedical signals such as EEG.

Table 3. Performance Comparison of CNN and MLP Models

Parameter	CNN	MLP
Classification accuracy	87%	85%
Feature Learning	Automatic features extraction	Uses pre-extracted features
Computational complexity	High	Low
Memory Requirement	High	Low
Real-Time Sustainability	Moderate	High
Dataset Requirement	Need large dataset	Works in small datasets

The proposed system requires rapid inference to generate alerts and activate therapy mechanisms within a short latency frame. The MLP model provides rapid inference speed and lower processing overhead, allowing the system to maintain a prediction latency of approximately 2–3 seconds during continuous monitoring. Additionally, MLP models perform more consistently with smaller datasets whereas CNN models typically require larger datasets

to avoid overfitting. Therefore, CNN demonstrates higher accuracy in experimental evaluation and the MLP model was selected for final implementation because it provides better stability, lower latency and efficient operation for real-time wearable stress monitoring systems. Table 3 represents the performance comparison between CNN and MLP. Figure 6 represents the MLP vs. CNN stress classification architecture.
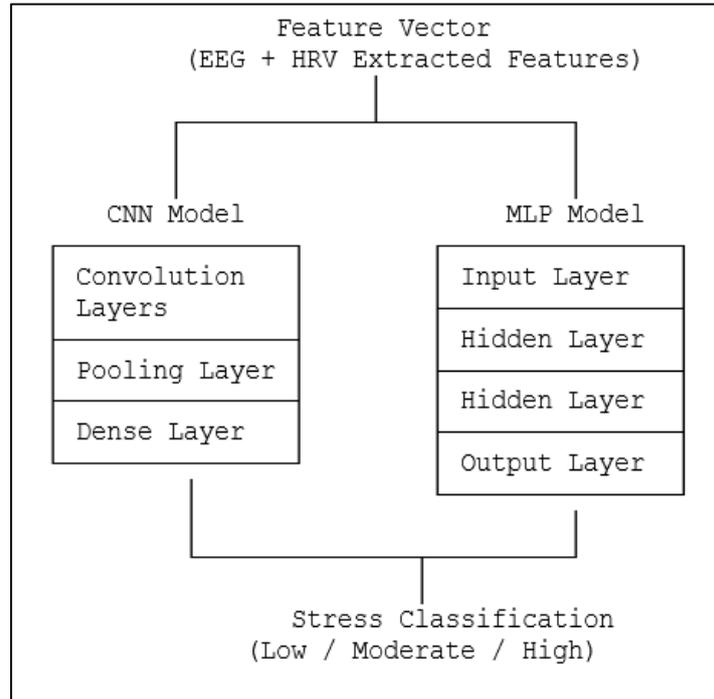

Figure 6. CNN Vs MLP Stress Classification Structure

3.5 IoT Alert and SOS Alarm Module

The ESP32 module acts as a real-time safety node. When the predicted state is high stress or anxiety, the system:

1. Sends alert to cloud dashboard
2. Triggers SOS buzzer locally
3. Displays emergency status in healthcare provider portal

This ensures that even if internet connectivity is weak, the buzzer provides immediate local warning.

Pseudocode: ESP32-Based SOS Alert Mechanism

1. Initialize ESP32 GPIO pins for buzzer control.
2. Receive mental state prediction from AI module.
3. If predicted state is Normal, continue monitoring.
4. If predicted state is Stress or Anxiety, activate SOS alert.
5. Turn ON emergency buzzer for predefined time interval.
6. Turn OFF buzzer automatically after alert duration.
7. Resume continuous monitoring.

This algorithm ensures real-time alert generation with minimal latency and low computational overhead, making it suitable for embedded healthcare monitoring applications.

3.7 Smart Therapy Activation

Smart Therapy is activated automatically when stress or anxiety is detected. Therapy includes:

- Music relaxation
- Guided breathing prompts
- Lighting therapy
- Aroma Therapy
- Mindfulness suggestions

The objective is to provide immediate stress reduction without waiting for healthcare provider response.

4. Hardware Description

4.1 Node MCU ESP32

ESP32 [figure 7] is a single 2.4 GHz Wi-Fi-and-Bluetooth combo chip designed with the TSMC ultra-low-power 40 nm technology [16]. The ESP32 series of chips includes ESP32-D0WD-V3, ESP32-D0WDQ6-V3, ESP32-D0WD, ESP32-D0WDQ6, ESP32-D2WD, ESP32-S0WD and ESP32-U4WDH, among which, ESP32-D0WD-V3, ESP32-D0WDQ6-V3 and ESP32-U4WDH are based on ECO V3 wafer.
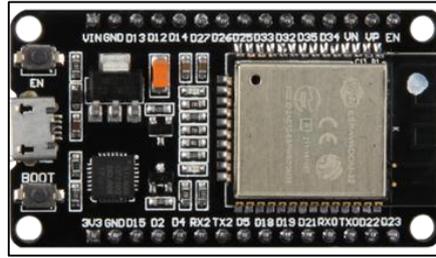
Figure 7. ESP32 Kit

4.2 EEG sensor module

EEG sensor [figure 8] is a compact, consumer based device used to detect and amplify the low electrical brainwave signals (EEG) from the scalp for applications like concentration tracking, meditation and biofeedback. The key features include 32-bit processing, wireless Bluetooth connectivity and low power consumption.

Figure 8. EEG Sensor Module

4.3 Buzzer

Buzzer [figure 9] is the audio device or apps generate loud, attention-creating sounds to signal emergencies, security attacks for user safety. They range from electronic, battery-powered components in devices to smartphones application send alerts, GPS location and SMS messages.

Figure 9. SOS Buzzer

4.4 Battery

Battery [figure 10] provides versatile, rechargeable DC/AC power for off-grid, camping or emergency requirements. This ranges from compact 88Wh packs to massive 100Wh featuring multiple USB-A/C, AC outlets and solar charging compatibility.

Figure 10. Battery

4.5 Software Requirements

- Python 3.10+
- TensorFlow / Keras
- NumPy, SciPy, Pandas
- Flask / FastAPI backend
- Firebase / Cloud DB
- Web dashboard (React)

5. RESULTS AND DISCUSSION

This section discusses both qualitative and quantitative validation of the proposed system. The results of EEG signal observation, evaluation of MLP and CNN, alert messages, real-time circuit execution and EEG dashboard is implemented. This proposed system achieved the continuous data acquisition and processing in real-time.

5.1 EEG Signal Observation

The collected EEG waveforms illustrated in table 4 with variations in frequency and amplitude to each mental state

Table 4. Prediction Levels

State	EEG Value	Mean Value	Std. Dev.	Peak Amp (µV)	Heart Rate (bpm)	RR Variance (ms²)	Entropy
Normal	0 – 320	0.45 – 0.65	0.08 – 0.18	40 – 80	65 – 85	220 – 320	0.65 – 0.80
Low Stress	321 – 500	0.55 – 0.70	0.12 – 0.22	70 – 100	80 – 95	170 – 250	0.55 – 0.70
Medium Stress	501 – 700	0.60 – 0.80	0.16 – 0.26	90 – 120	90 – 105	120 – 200	0.45 – 0.65
High Stress	701 – 900	0.65 – 0.85	0.20 – 0.30	110 – 150	100 – 115	80 – 150	0.35 – 0.55
Anxiety	901 – 1024	0.70 – 0.95	0.24 – 0.35	130 – 180	110 – 130	50 – 120	5.25 – 0.45

5.2 Quantitative Evaluation

The machine learning evaluation used to accurately verify performance of the proposed stress classification system. The four components of confusion matrix such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are measured. The evaluation metrics include accuracy, precision, recall and F1-score. Table 5 illustrates the overall evaluation metrics.

Accuracy

Accuracy measures the overall correctness of the classification model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (16)$$

Precision

Precision evaluates the predicted stress states are actually correct.

$$Precision = \frac{TP}{TP+FP} \qquad (17)$$

Recall

Recall measures the ability of the model to correctly identify actual stress cases.

$$Recall = \frac{TP}{TP+FN} \qquad (18)$$

F1–Score

The F1-score represents the harmonic mean of precision and recall, providing a balanced measure of model performance.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \qquad (19)$$

Table 5. Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
MLP	0.85	0.84	0.83	0.83
CNN	0.87	0.86	0.85	0.85

The MLP model provides rapid inference suitable for embedded real-time applications for implementation. Furthermore, the real-time capability was experimentally verified using continuous monitoring setup with a complete processing system from EEG acquisition for prediction and dashboard update required approximately 2-3s. This latency measurement monitoring and give alert messages in wearable healthcare environments.
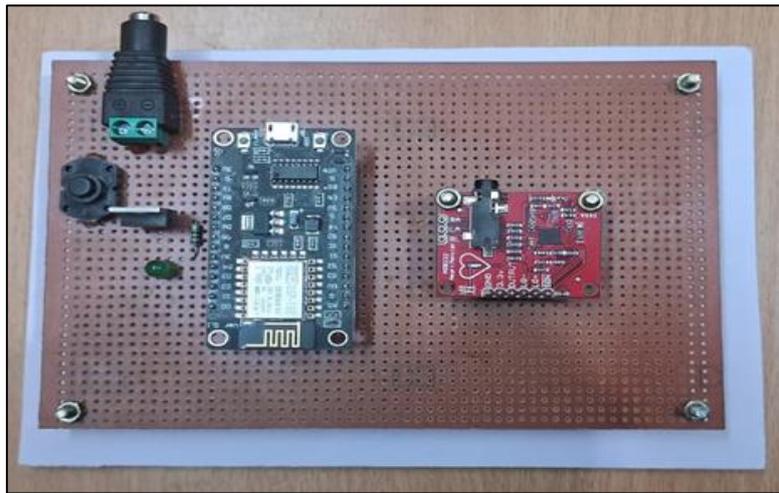

Figure 9. EEG Board Kit

Figure 9 shows the real-time EEG signal acquisition interface when the raw brainwave signals are continuously collected from wearable EEG sensor. The waveform visualization confirms that the stable signal acquisition with minimal noise, indicates effective sensor and signal preprocessing. This interface validates the collection of EEG data required for stress analysis in real-time.

Figure 10. EEG Headband

Figure 10 illustrates the extracted EEG features includes mean value, standard deviation, peak amplitude, entropy, heart rate and RR variance. These features are updated from collected EEG signals demonstrate accurate real-time evaluation. The extracted features form the primary input for AI-based stress classification.
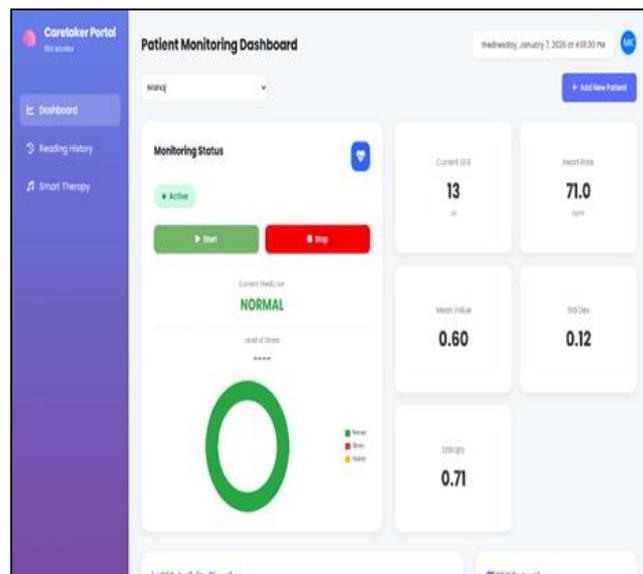

Figure 11. EEG Dashboard Page

Figure 11 shows the EEG dashboard displaying live EEG value and stress detection features. The panel confirms that real-time readings are collected continuously stored for visualization and extracted features such as mean, standard deviation, peak amplitude, HR, RR variance and entropy. These values are sent into the MLP classifier determines mental state.
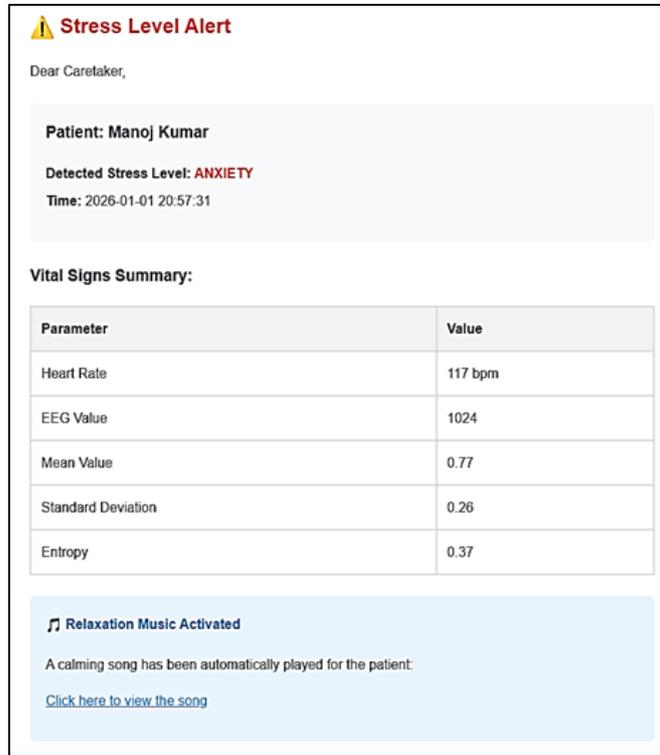

Figure 12. Mail Alert Message

Figure 12 shows the Smart Therapy interface. When stress is detected, the treatment options such as music and breathing exercises are displayed automatically supports immediate intervention and the SOS alarm activation logic. When high stress or anxiety is detected, the ESP32 triggers a buzzer alert and updates the healthcare people dashboard status in real time. This system was tested under continuous monitoring with 2s window size and 1-second overlap. The end-to-end time from EEG capture to dashboard update was measured as 2–3 seconds on average using MLP.

6. Conclusion

This paper developed a wearable EEG-based stress and anxiety monitoring system integrates AI, IoT and smart therapy. This system mainly focused on classification of five metal states using EEG and HRV features which triggers the cloud alerts and local SOS buzzer using

ESP32 to activate the treatment automatically. The EEG signals are collected from wearable headband and preprocessed to produce a statistical feature. That features are further classified to find the mental state using MLP and CNN models. The classified mental state transmitted to cloud dashboard. When the critical mental state is detected, the alert message or SOS buzzer will be activated. The experimental evaluations demonstrate the accuracy above 85% and real-time alerting within 2-3s. This proposed solution supports the safe and independent mental health monitoring for helpless individuals.

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