REALTIME STRESS MONITORING AND DATA ACQUISITION SYSTEM USING ELECTROENCEPHALOGRAM SENSOR

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ABSTRACT

Mental stress negatively impacts human health, necessitating early detection for timely intervention. With the advent of wearable stress monitoring devices, real-time remote patient monitoring has become increasingly feasible. This research presents a real-time EEG-based stress monitoring system designed for short-range, localized use. The system captures EEG signals, processes them, and transmits data via Bluetooth to a mobile application, providing immediate feedback within the monitoring range. Unlike cloud-based remote monitoring solutions, this system operates in a proximity environment and does not store data on external servers or facilitate remote physician accessibility. The proposed methodology involves EEG signal acquisition using a ThinkGear ASIC Module (TGAM), signal preprocessing for artifact removal, feature extraction based on frequency domain analysis, and classification of stress levels using threshold-based metrics. The system was tested on seven individuals under various conditions, with EEG parameters analyzed to determine stress levels. Sensitivity analysis was performed to assess the sensor's accuracy in detecting brainwave activity. Results indicate a correlation between stress levels and EEG signal variations, confirming the system's viability for mental health applications. The study contributes to remote health monitoring and lays the groundwork for future advancements in stress assessment tools.

Keywords: Electroencephalography, Bluetooth, Brainwave, mental health.

DOI: 10.63748/FETiCON2025.v3i1p5

1. INTRODUCTION

People undergo stress in everyday life. This must be triggered by demanding physiological activity. This is always not only a negative process, as it can also accompany unexpected success, lifestyle changes, or unpredictable opportunities. However, under certain circumstances, it becomes a threat to mental health (Vanitha and Krishnan 2016). Smaller biomedical device development has recently increased because of the rising demand for novel physiological and health monitoring approaches that maximize user comfort (Valenti et al 2023). Three categories of stress have been identified in the literature: acute, episodic, and chronic. Acute stress is associated with brief exposure and is safe. When the stimulus is more frequent for a brief period, episodic stress occurs. Chronic stress, on the other hand, is the most harmful kind and is brought on by ongoing and persistent stressors (Colligan 2006). Numerous neuroimaging methods have been employed to measure brain activity either directly or indirectly to evaluate mental stress. These consist of electroencephalography (EEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS) (Zhang X et al 2019).

Feature extraction and stress categorization are the two main components of a standard EEG stress evaluation approach. Time-domain, frequency-domain, and synchronicity-domain features are the three types of EEG features. The time-domain characteristics use the amplitude associated with energy, variability, coefficient of variation, Hjorth feature, fractal dimension feature, and higher-order crossing feature to capture the temporal information. Conversely, the EEG signal's therapeutic frequency bands, including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (30–50 Hz), yield the most utilized frequency-domain information (Kulkarni et al 2020).

This paper explores the use of such EEG sensors, focusing on the extraction of relevant data that can be indicative of stress. This system's mobility and versatility are largely due to the integration of Bluetooth and a Mobile Application. The Bluetooth technology makes it easier to wirelessly collect EEG data from TGAM sensor and, guaranteeing that the data is available for analysis regardless of location. The paper aims to contribute to the expanding field of remote health monitoring and lay the groundwork for future research and development in stress assessment tools by utilizing current advances in wireless communication and EEG technologies.

2. THEORETICAL ANALYSIS

To provide real-time stress assessment, researchers aim to detect stress based on EEG, as there is a clear connection between stress and EEG. The Hilbert-Huang Transform (HHT) is used to extract pertinent time-frequency information from the EEG signal after it has been pre-processed to remove artefacts (HHT). Stress levels were identified by manipulating the collected characteristics with a hierarchical Support Vector Machine (SVM) classifier. The outcomes demonstrated how well the technique worked to use their brain waves to identify stress in real time. (Vanitha and Krishnan 2016). Researchers suggest an approach for measuring human stress using EEG signals, and it incorporates treatments to teach stress-reduction strategies. The K-means clustering method was employed in the study to quantify stress, which assisted in classifying the participants and determining their level of stress. The advancement of this research aids in lowering the amount of time and labour needed to identify the appropriate advice and stress-reduction strategy. (Neeta et al, 2017). With the need for continuous stress monitoring, the study validates an EEG-based metric for real-time stress measurement. It was tested during a multitasking session and then validated during a realistic driving task. The Neuro-metric was compared with other stress 15 measurements, like SCL- and machine learning-based measures calibrated using both an intrasubject and cross-task approach. Moreover, the proposed measure does not need calibration and can be used in real time both in and out of a laboratory to measure stress levels. (Sciaraffa et al 2022).

Researchers aim to detect stress using brainwaves and take measures to reduce it in the early stages and to reduce the damage caused by stress in the long term. It uses stress detection using EEG signals and Power Spectral Density values of Theta, Alpha, and Beta frequency bands, and stress reduction methods like Music Therapy, Yoga, Meditation, and Exercise. In conclusion, stress can be relieved through various methods like music therapy, yoga, meditation, exercise, etc. (Shreya et al, 2022). Unlike these previous studies that incorporated advanced classification models and large-scale validation, this study focuses on the development of a portable, real-time EEG-based prototype for basic stress monitoring. The system lays the groundwork for future integration of machine learning and stress classification frameworks while remaining accessible and low-cost for early testing.

3. MATERIALS AND METHODOLOGY

The system being developed is able to transmit detected and monitor brain signals at short distances. It employs the use of two electrodes: the dry EEG electrode, which records brain signal from the scalp, and the reference (ear clip) electrode, which tells the EEG device what “no brain signal” looks like (i.e. baseline). Main objective of this system is to design and construct stress detector device using various sensors to collect, transmit data to be observed/analysed by professionals as and when needed. Figure1 gives the block diagram of an EEG sensor system. The designed architecture describes how the system is going to work and how the sensor gets the values which is used to measure stress levels. The power supply is given to the Think Gear ASIC Module (TGAM) and all sensors are connected to it. When neurons in the brain are stimulated, they generate electrical signals that can be interpreted as small voltages in the range of millivolts. The susceptibility of these signals to interference from external sources necessitates the implementation of signal filtering. Additionally, EEG signals are often captured from multiple brain lobes to mitigate the impact of external signals or electrostatic noise. In this work, a single electrode is to be used to record signals, during the recording process a single LED light is on display. The recorded data is transmitted to a mobile app using the Bluetooth module and displayed in real time graphical manner. Figure 2 is a flow chart of detailing the numerous steps required to collect data from the sensor, connection of the TGAM with the Bluetooth, processing of the data and displaying the data on the mobile app.

For this paper, multiple tests were carried out on six individuals (males within the age of 18 – 26) under different scenarios to get values for evaluation of brainwave signals as well as attention and meditation levels ranging from 0 to 100, indicating different stress levels. For the evaluation, the frequency wave bands in Table 1 and the EEG eSense meters will be used.

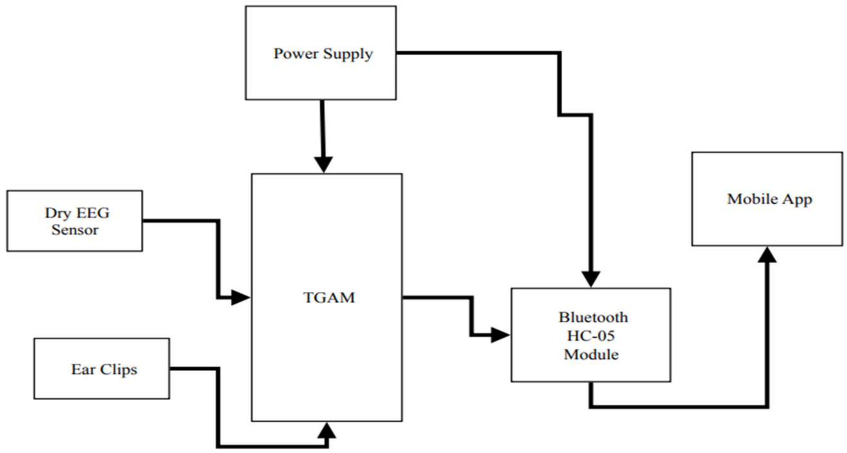

Figure1: Block Diagram of an EEG Sensor Device

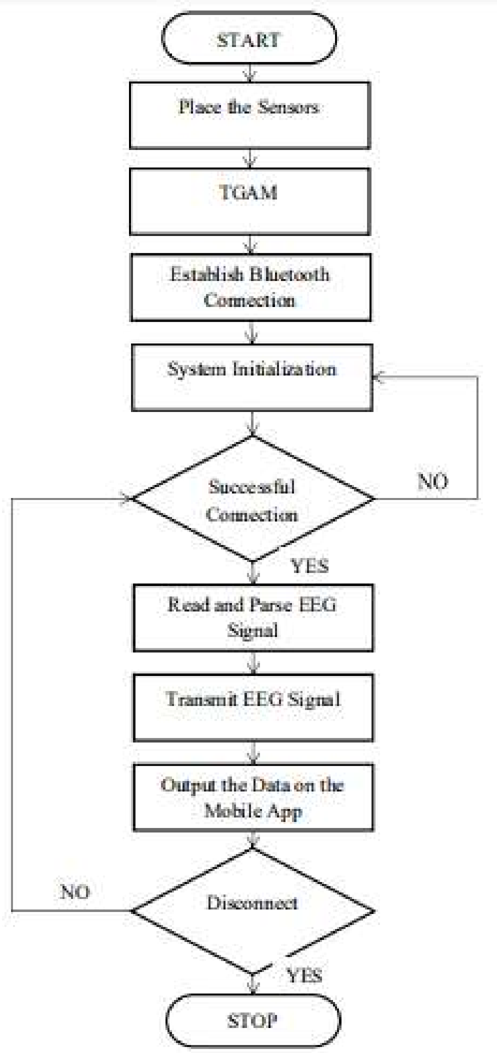

Figure 2: Flowchart of an EEG Sensor for real-time stress monitoring

Table 1: EEG Related Brainwave (Neeta et al, 2017)

Brainwave	Frequency	Mental States
Delta	0.5 - 2.75 Hz	Non-REM Sleep, Unconscious
Theta	3.5 - 6.75Hz	Fantasy, imaginary, dream
Low Alpha	7.5 - 9.25Hz	Balance between relaxation and alertness
High Alpha	10 - 11.75Hz	Deeper relaxation, during meditation or when the mind is quiet
Low Beta	13 - 16.75Hz	Relaxed yet focused, integrated
High Beta	18 - 29.75Hz	Alertness, Agitation
Low Gamma	31 - 39.75Hz	Focus on external stimuli or internal thoughts
High Gamma	41 - 49.75Hz	Higher mental performance, learning and problem-solving

4. RESULTS AND DISCUSSION

This section presents the comprehensive results from the brainwave activity tests conducted on six distinct participants. For each individual, their measured brainwave data is provided, accompanied by a detailed interpretation of these findings. This allows for a nuanced understanding of how different individuals respond under similar testing conditions. Each participant is designated a subject for the purpose of this manuscript.

4.1. Subject 1

In an intriguing study, as depicted in Figure 3, an individual's neurophysiological responses were monitored via eSense meters while they watched a movie. The data revealed a compelling dichotomy: attention levels consistently hovered between 50 and 60, while meditation levels were significantly higher, ranging from 80 to 90. Further analysis of the brainwave frequencies indicated a prevalence of high gamma and low alpha waves. This suggests a state of focused engagement (high gamma) coupled with a remarkable sense of relaxed awareness or internal calm (low alpha). Such a unique combination of brainwave activity during movie-watching hints at a deeply immersive yet simultaneously tranquil experience

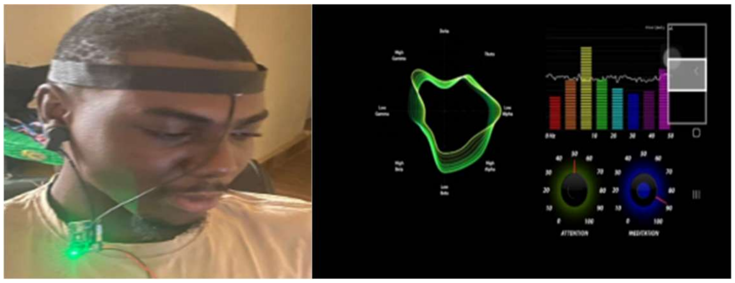

Figure 3 Testing of the first individual

4.2. Subject 2

Figure 4 illustrates the results of a second experiment, this time conducted on a different participant engaged in a study state. During this focused activity, the eSense meters registered remarkably high attention levels, consistently falling within the 90-100 range. Concurrently, meditation levels were observed to be between 50-60. Analysis of the brainwave frequencies during this study session revealed a predominance of low alpha and delta waves. This intriguing combination suggests a state of deep concentration (low alpha) combined with a profound state of relaxation or even subconscious processing (delta). The data implies that while intensely focused, the participant maintained a level of calm and potentially accessed deeper cognitive states conducive to learning.

Figure 4: Testing of the second individual

4.3 Subject 3

Figure 5 presents the results of a third test, performed on a football player immediately after a match to assess their vital signs and brain activity. During this post-exertion period, the eSense meters recorded attention levels consistently within the 50-60 range. Simultaneously, meditation levels were observed to be between 60-70. Analysis of the brainwave frequencies during this session revealed a predominant presence of high gamma waves. This combination suggests that while the player exhibited moderate attention, they also maintained a significant level of mental calm or recovery. The high gamma activity might indicate continued cognitive processing or rapid neural firing associated with recent intense physical and mental exertion, even as the body begins to wind down.

Figure 5: Testing of the third Participant

4.4 Subject 4

Figure 6 illustrates the results of the fourth test, conducted on an individual engaged in their regular daily activities. During this observation, the eSense meters registered both attention and meditation levels consistently within the 50-60 range. Analysis of the brainwave frequencies during these routine activities revealed a broad spectrum, encompassing delta, low alpha, high alpha, low gamma, and high gamma waves. This diverse presence of frequencies suggests a dynamic and flexible cognitive state, characteristic of everyday functioning. It indicates that the individual was likely navigating various levels of focus and relaxation as they moved through their daily tasks, demonstrating the brain's adaptability in balancing attentiveness with a sense of calm.

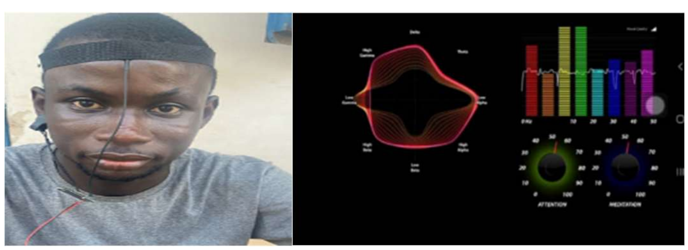

Figure 6: Testing of the fourth individual

4.5 Subject 5

Figure 7 illustrates the results of the fifth test, conducted on an individual in a relaxed state, listening to music. During this period, the eSense meters registered remarkably low attention levels, consistently falling within the 30-40 range. Conversely, meditation levels were exceptionally high, ranging from 90-100. Analysis of the brainwave frequencies revealed a prominent presence of low alpha, low beta, and high beta waves. This unique combination suggests a state of profound relaxation and internal calm (high meditation, low attention), where the brain is still actively processing the auditory input (beta waves) but in a non-demanding or contemplative manner (low alpha). It paints a clear picture of the brain settling into a deeply serene and receptive mode while engaging with music.

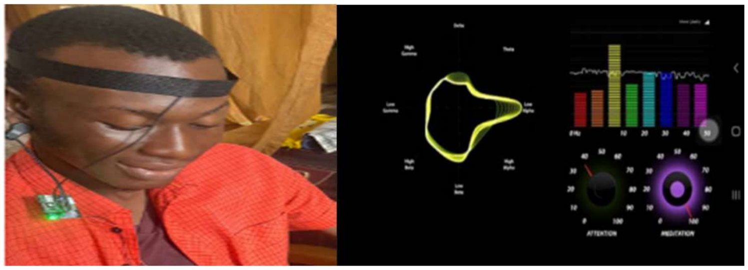

Figure 7: Testing of the fifth individual

4.6 Subject 6

Figure 8 illustrates the results of a test conducted on an individual during their regular daily activities. During this observation, the eSense meters recorded attention levels consistently within the 70-80 range, while meditation levels were observed to be between 60-70. Analysis of the brainwave frequencies revealed a broad spectrum, encompassing delta and high gamma waves. This combination suggests a dynamic cognitive state where the individual is actively engaged and focused (high attention, high gamma), yet also maintains a degree of underlying cal mness or subconscious processing (meditation, delta waves). This indicates a highly adaptive brain, efficiently managing daily tasks with both sharp focus and a subtle undercurrent of relaxed awareness.

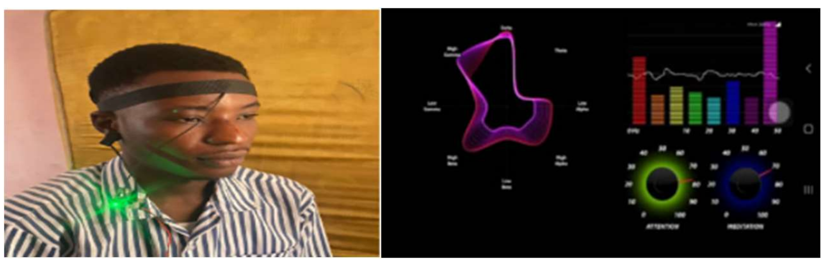

Figure 8: Testing of the sixth individual

Table 2 provides a concise summary of the comprehensive brainwave test results. The data demonstrates the study's capability to rapidly capture brainwave activity, even detecting subtle shifts related to muscle movement and changes in attention and relaxation. When comparing these findings with the frequency data presented in Table 1, it's anticipated that periods of stress would correlate with notably lower values for both attention and meditation. This highlights the system's sensitivity in reflecting distinct neurological states.

Table 2: Summary of Results and Interpretation

Subjects	Attention/Meditation	Frequency Waves
1	50 - 60 / 80 - 90	High Gamma & Low Alpha
2	90 - 100 / 50 - 60	Low Alpha & Delta
3	50 - 60 / 60 - 70	High Gamma
4	70 - 80 / 60 - 70	Delta & High Gamma
5	30 - 40 / 90 - 100	Low Alpha, Beta & High Gamma
6	70 - 80 / 60 - 70	Delta & High Gamma

5. CONCLUSION

A real-time, wearable EEG-based prototype system for stress monitoring was developed and tested. The system captures and transmits brainwave signals to a mobile application, offering immediate visualization of stress-related brain activity. Results show the system is responsive to changes in attention and relaxation, validating its potential for non-clinical, personal stress tracking. While previous research employed complex signal processing and machine learning models, this study focuses on a simplified, practical design that can serve as a foundation for more advanced systems.

6. RECOMMENDATION

Based on findings for this study, the following recommendations are made:

- Creating a dataset for more analysis on stress-related brain activity using multiple individuals.
- Performing machine learning models like KNN (K-nearest neighbours' algorithm) Model, Random Forest Classifier, SVM (Support Vector Machine), to train the dataset for better analysis.
- Combine EEG with other physiological signals like heart rate or skin conductance for a more holistic stress assessment.

ACKNOWLEDGEMENTS

The author acknowledges TETFUND, National Research Fund 2021, for the Project with reference No.TETF/ES/DR&D-CE/NRF2021/SETI/ICT/00102/VOL.1

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