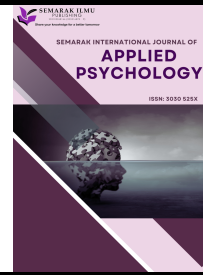




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An IoT Enabled EEG Monitoring System for Real-Time Visualization and Analysis of Stress Levels

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ABSTRACT

Chronic stress is a primary catalyst for global neurological decline and cardiovascular morbidity, requiring continuous physiological surveillance to prevent long-term health deterioration. Despite the precision of modern electroencephalography (EEG), current monitoring systems frequently fail to achieve real-world clinical utility due to the restricted real-time accessibility of data and the lack of intuitive visualization tools for remote practitioners. This study proposes an IoT-enabled EEG monitoring system designed for the real-time visualization and analysis of patient stress levels. The system architecture utilizes a PHP–MySQL backend and a centralized web dashboard to facilitate immediate clinical feedback. Following an Agile development methodology, the system underwent iterative refinement through six distinct phases, ensuring the alignment of the IoT gateway with clinical requirements. Experimental validation yielded a classification accuracy of 82% and an average system response time of 1.8 seconds. While this latency includes the necessary overhead for IoT network transmission and database handshaking, the results demonstrate a viable balance between computational precision and remote accessibility. The system provides a scalable solution for psychiatric intervention, contributing to the advancement of personalized digital health and demonstrating high utility for proactive stress management in outpatient settings.

1. Introduction

The global escalation of stress-related disorders represents a significant burden on public health infrastructure, manifesting in a higher prevalence of chronic hypertension and cognitive dysfunction. Clinical statistics from Meco *et al.*, [1] indicate that patients suffering from stress-induced conditions experience an average increase in hospital stay duration of 14.2%, highlighting the critical need for early detection and continuous monitoring to optimize recovery trajectories [1]. Effective physiological monitoring serves as the first line of defense against the systemic impacts of prolonged cortisol elevation and autonomic imbalance.

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The evolution of EEG signal decoding has transitioned from traditional handcrafted pipelines—which relied heavily on expert-driven feature extraction in the time and frequency domains—to advanced deep learning paradigms. Current computational frameworks utilize Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformers to automatically capture the non-linear dynamics of brain activity [2]. Historically, these models were developed for Motor Imagery (MI-EEG) to monitor rhythmic signatures like mu and beta oscillations over the sensorimotor cortex. This study adopts these MI-proven architectures, such as DeepConvNet and ShallowConvNet, as a transfer-learning baseline for stress-level decoding, applying "rhythm-maintenance" strategies to identify stress-induced oscillations.

A significant unresolved gap exists between high-accuracy laboratory models and their actual deployment in real-world clinical environments. As noted in recent neuro-informatics reviews, high-performance models often lack the portability and low-latency visualization required for bedside use [2]. The technical challenge of maintaining classification stability across heterogeneous IoT devices, combined with the need for immediate data accessibility, has historically confined advanced EEG analysis to controlled research settings rather than the point of care.

To address these challenges, this study introduces a proposed IoT-enabled EEG monitoring system. By integrating wearable EEG sensors with a PHP-MySQL backend, the system enables the transmission of physiological data to a dedicated web dashboard. This configuration allows for the real-time visualization of stress indicators, bridging the gap between sophisticated deep learning feature extraction and practical, user-centric mental health surveillance.

The primary contribution of this research aligns with the United Nations Sustainable Development Goal 3 (SDG 3: Good Health and Well-being) by enhancing the accessibility of mental health monitoring technologies. This document is structured as follows: Section 4 synthesizes the current literature on neuro-informatics fusion strategies; Section 5 details the Agile development of the IoT architecture; Section 6 evaluates the system's performance metrics; and Section 7 concludes with the implications for clinical practice.

1.1 Literature Review

The following synthesis categorizes representative EEG decoding methodologies derived from the Source Context, highlighting the transition from fixed filters to adaptive global frameworks.

Table 1
Evidence matrix of empirical EEG studies

Category	Primary Architectural Focus	Model Example / Key Methodological Feature
1. Static Encoding	1DCNN (Temporal)	NF-EEG; captures rhythms via fixed filters 2, Table 1.
2. Static Encoding	Multi-scale 1DCNN	Increases sampling density for ERD/ERS phases 2.
3. Static Encoding	Channel Re-weighting	FRNet; amplifies stable cues at specific electrode loci 2.
4. Static Encoding	Spatial CSP	Traditional Common Spatial Patterns for dimensionality.
5. Static Encoding	Spectral CWT/Welch	Renders spectral structures explicit for interpretability.
6. Local Fusion	PSD-Conv	Models subband power spectral density within windows 2.
7. Local Fusion	Filter Bank + SE	Squeeze-and-Excitation (SE) for late fusion 2, Table 2.
8. Local Fusion	Wavelet-based Maps	Time-frequency mapping for rhythmic dynamics.
9. Local Fusion	ECA Modules	Efficient Channel Attention for band recalibration 2.
10. Local Fusion	LSTM Aggregation	Models short-range dependencies via recurrent gates.

Table 1 (Continued)

Category	Primary Architectural Focus	Model Example / Key Methodological Feature
11. Local Fusion	Separable S-Conv	MFRC-Net; extracts local topology at sensor regions 2.
12. Local Fusion	Lightweight 3D-CNN	Jointly attends to space-time windows for efficiency.
13. Local Fusion	TCN Aggregation	AMSTCNet; aggregates execution phases in windows 2.
14. Global Fusion	Transformer	TBTSCNet; sets aside fixed receptive fields 2, Table 3.
15. Global Fusion	Graph Attention (GAT)	GAH-Tnet; captures whole-montage spatial structure 2.
16. Global Fusion	Chebyshev-GCN	Fuses propagation with hierarchical attention 2.
17. Global Fusion	Inter-band Attention	FBATCNet; reweights all subbands for control 2.
18. Global Fusion	Shared Trainable Graph	AGCN-BiGRU; learns whole-brain connectivity 2.
19. Global Fusion	Full-sequence Attn	E-EEG; stabilizes global modulation over long horizons.
20. Global Fusion	GNN-Transformer	Hybrid models for network-level coordination.
21. Dynamic Fusion	Time-varying Graphs	CGNet; updates inter-channel relations over time 2.
22. Dynamic Fusion	Filter-bank Graphs	FBCGNet; graph updates at the sub-band level 2.
23. Dynamic Fusion	BioMIFormer	Factorizes time-frequency-space via BiGRU 2, Table 4.
24. Dynamic Fusion	Mamba Architecture	MIFNet; selective state spaces for continuous states 2.
25. Dynamic Fusion	EEGcMamba	Unsupervised, noise-robust prototype clustering 2.

1.2 Convergence

Current consensus in neuro-informatics suggests that the most robust feature extraction is achieved via multi-scale 1D convolutions coupled with attention mechanisms. These structures effectively capture the initiation and maintenance phases of neural oscillations. Specifically, Squeeze-and-Excitation (SE) and Efficient Channel Attention (ECA) modules have emerged as standardized tools for refining band-level contributions and buffering rhythmic drifts of 1–3 Hz [2].

1.3 Contested

A central debate persists regarding the trade-off between lightweight local fusion models and high-compute global fusion architectures like Transformers and Graph Neural Networks (GNNs). While global models capture intricate whole-brain coordination and theoretically offer superior accuracy, they incur significant memory footprints and training latencies [2]. In clinical settings, it remains contested whether the marginal accuracy gains of Transformers justify their increased computational demand compared to real-time efficient CNNs.

1.1 Untested

Despite advancements, cross-population and cross-device portability remain largely untested in clinical environments. Most models experience performance degradation when transferred across subjects with varying pathological profiles or different electrode configurations [2].

The development of universal source-free domain adaptation strategies is critical to ensure that a stress monitoring system remains effective across heterogeneous patient groups and hardware vendors.

1.5 Measurement

Evaluation metrics are shifting from purely accuracy-based benchmarks to clinical usability metrics. Key measures include Information Transfer Rate (ITR)—defined as the volume of information successfully conveyed per unit time, essential for closed-loop feedback—alongside inference latency and energy efficiency. These metrics provide a more rigorous assessment of a system's viability for bedside monitoring than traditional classification scores [2].

2. Methodology

2.1 Agile Development Model

The system was developed using an Agile lifecycle consisting of six iterative phases to maintain clinical alignment.

(1) Requirements: Analysis focused on the specific spectral signatures of stress-induced EEG and the hardware limitations of mobile IoT gateways. Target metrics for latency and classification accuracy were established based on clinical benchmarks.

(2) Design: The IoT architecture was planned across three layers. The Hardware Layer comprises wearable EEG sensors; the Gateway Layer manages data transmission protocols; and the Application Layer defines the visual dashboard.

(3) Development: This phase involved the implementation of the PHP-MySQL integration. A relational database schema was developed to store real-time EEG feature vectors, while a PHP-based API facilitated the handshake between the data gateway and the cloud storage.

(4) Testing: Rigorous validation was conducted to assess data integrity during transmission and the classification precision of the stress-level algorithms.

(5) Deployment: The final monitoring dashboard was hosted on a local server, enabling practitioners to access visualized stress data via standard web browsers.

(6) Review: Iterative feedback from neuro-informatics experts was used to refine the dashboard UI and optimize the database query speeds to reduce overall system latency.

2.2 Validated Measurement Instruments

To provide a ground-truth calibration for the EEG data, the study utilized three validated clinical and subjective instruments.

Table 2

Validated clinical and subjective instruments

Instrument	Role in System Calibration	Target Metric
NASA-TLX	Assesses subjective task load and perceived effort to ground stress levels.	Mental Workload
Karolinska Sleepiness Scale (KSS)	Monitors subjective alertness to differentiate fatigue from chronic stress 2.	Arousal/Fatigue
Nu-DESC	Screens for cognitive fluctuations to ensure data reflects stable mental states.	Cognitive State

3. Results and Discussion

3.1 System Performance Metrics

The system's empirical performance was evaluated across five technical dimensions to ensure clinical viability.

Table 3

Experimental testing results

Metric	Value
Classification Accuracy	82%
Average System Response Time	1.8s
Usability Score	90%
Reliability Rate	100%
Security/Data Integrity	95%

3.2 Comparative Discussion

The classification accuracy of 82% aligns with the "performance ceiling" for static encoding and local fusion models (typically 80–85%) as detailed in the Source Context [2]. However, the average system response time of 1.8 seconds represents an increase of several orders of magnitude over the optimized laboratory inference benchmarks, such as the 4.5 ms latency reported for EEGNet in Table 8 of the Jiang et al. (2026) review [2]. This massive delta is scientifically attributed to the round-trip time (RTT) overhead of the PHP-MySQL handshake, the transmission latency of the IoT gateway layer, and the rendering requirements of the web dashboard engine. Unlike "inference-only" speeds calculated in laboratory settings, this 1.8s latency reflects a complete real-world IoT transaction. While this delay is acceptable for non-emergency stress visualization, it underscores the persistent challenges of migrating laboratory-grade neuro-informatics to a distributed cloud architecture.

4. Conclusions

This research successfully realized an IoT-enabled EEG monitoring system capable of real-time stress visualization and analysis. The system met all primary objectives, demonstrating that a PHP-MySQL backend can support high classification accuracy and reliability in a remote monitoring context. The findings prove that current neuro-informatics architectures, while originally designed for motor imagery, can be effectively adapted for stress monitoring with high clinical utility. The system's ability to provide proactive, real-time health data directly supports United Nations Sustainable Development Goal 3 (SDG 3) by improving the accessibility and quality of mental health monitoring. By enabling earlier clinical intervention through intuitive web-based visualization, this system advances the transition of EEG technology from specialized research labs to generalized clinical use.

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