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EEG-Based Detection of Depression and Stress: A Comprehensive Review of Signal Processing, Machine Learning, and Clinical Applications

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Abstract: Depression and stress are among the most prevalent mental health disorders, posing significant challenges to global healthcare systems. Conventional diagnostic methods often rely on subjective self-reports and clinical evaluations, which may result in delayed or inaccurate assessments. Electroencephalography (EEG) has emerged as a promising biomarker due to its non-invasive, cost-effective, and real-time monitoring capabilities. Recent advances in machine learning and deep learning have further enhanced EEG-based detection, offering improved accuracy and scalability. Studies demonstrate the effectiveness of spiking neural networks for stress detection [1], cloud-based EEG analysis for depression diagnosis [2], and hybrid frameworks such as EEG Mind-Transformer [5] and TSF-MDD [6], which leverage temporal and spatial EEG features. Graph-based representations [4] and explainable AI models [8] have further advanced interpretability and clinical applicability. Despite these achievements, challenges remain in dataset diversity, generalization, privacy, and real-time deployment. This review systematically analyzes EEG-based depression and stress detection methods, covering preprocessing, feature extraction, machine learning, and deep learning approaches, along with benchmarks, challenges, and future directions. The aim is to provide a comprehensive perspective on how EEG can be leveraged to develop reliable, interpretable, and clinically validated systems for mental health monitoring.

Keywords: EEG; depression detection; stress recognition; spiking neural networks; deep learning; explainable AI; graph-based EEG analysis; mental health monitoring

I. INTRODUCTION

Depression and stress have emerged as two of the most pressing global health challenges, significantly affecting both psychological well-being and physiological stability. According to the World Health Organization, depression is a leading cause of disability worldwide, while chronic stress is strongly linked to cardiovascular diseases, impaired immunity, and reduced cognitive performance. The increasing prevalence of these conditions underscores the urgent need for reliable and objective diagnostic tools. Traditional assessment methods, such as self-reported questionnaires or clinical interviews, often suffer from subjectivity, delayed diagnosis, and cultural bias, highlighting the necessity for automated and data-driven approaches.

Electroencephalography (EEG) has gained substantial attention as a non-invasive, cost-effective, and real-time tool for analyzing neural activity. EEG measures the electrical oscillations of the brain and provides critical insights into frequency bands such as delta, theta, alpha, beta, and gamma, which are strongly associated with mental health disorders. Studies have revealed that neural oscillations and hemispheric asymmetry in EEG signals can reliably distinguish individuals with major depressive disorder (MDD) from healthy controls [3]. Similarly, EEG has proven effective in detecting mental stress levels under various cognitive tasks [1], [9], [11]. These findings reinforce EEG's potential as a biomarker for developing robust detection frameworks for depression and stress.

Recent advancements in computational intelligence have revolutionized EEG-based analysis. Traditional feature extraction and machine learning approaches, such as spectral power estimation, coherence measures, and support vector machines, remain relevant; however, the field is witnessing rapid progress through deep learning and advanced neural architectures. For instance, spiking neural networks (SNNs) have been employed for stress detection, showing promising results in handling the temporal dynamics of EEG signals [1]. Cloud-based EEG analysis frameworks have further enabled automated depression detection at scale, demonstrating the practicality of AI integration into healthcare [2]. Beyond classical models, hybrid deep learning frameworks [7], EEG Mind-Transformer architectures [5], and task-specific designs such as TSF-MDD [6] have achieved state-of-the-art performance, offering significant improvements in diagnostic accuracy.

Another critical advancement is the introduction of graph-based approaches, which model EEG as a network of interconnected brain regions rather than isolated signals. These methods have shown superior performance in capturing spatial connectivity features relevant to depression prediction [4]. Furthermore, explainable AI (XAI) techniques are gaining momentum, enabling the identification of EEG biomarkers with transparency and interpretability, thus bridging the gap between algorithmic decisions and clinical acceptance [8].

Despite these advances, challenges remain. Variability across individuals, scarcity of large-scale and balanced datasets, and difficulties in real-time deployment hinder practical implementation. Additionally, ethical issues regarding privacy and data sharing—especially in cloud-based frameworks—require careful attention [2], [14]. Nevertheless, research momentum continues to grow, as demonstrated by systematic reviews of EEG biomarkers for depression [15] and stress [9], which emphasize the importance of standardized benchmarks and clinically validated models.

This review paper aims to provide a comprehensive overview of EEG-based depression and stress detection methods. It examines signal processing techniques, machine learning and deep learning models, recent benchmark studies, and emerging directions such as wearable EEG devices, edge-AI deployment, and multimodal data fusion. By systematically analyzing state-of-the-art approaches, this work highlights both the progress achieved and the gaps that remain, ultimately contributing to the development of reliable, interpretable, and clinically applicable solutions for mental health monitoring.

II. LITERATURE REVIEW

Electroencephalogram (EEG) signals have emerged as one of the most reliable and non-invasive biomarkers for understanding neurological and psychological states. Recent studies have highlighted the ability of EEG to capture alterations in brainwave activity associated with stress, anxiety, and depression [1], [2]. The advancement of artificial intelligence (AI) and deep learning has further enabled automated recognition of such patterns with high precision [3].

Several researchers have explored diverse deep learning architectures. Joshi et al. [1] demonstrated that Spiking Neural Networks (SNNs) and Convolutional Spiking Neural Networks (CSNNs) could effectively model temporal dynamics of EEG for stress detection. Similarly, Joshi and Matharu [2] leveraged a cloud-based EEG analysis framework for depression detection, emphasizing scalability and remote accessibility. These approaches showcase the integration of machine learning with real-world deployment frameworks.

Graph-based modeling of EEG has also been a strong direction. Liu et al. [3] introduced a novel graph-based framework for depression detection, which improved interpretability by mapping inter-channel dependencies. Meanwhile, Transformer-based approaches such as Mind-Transformer [4] further enhanced generalization in mental health monitoring by incorporating attention mechanisms for multi-channel EEG feature fusion.

A. *Techniques in EEG-Based Stress and Depression Detection*

Table 1 summarizes recent methodologies employed in EEG-based mental health monitoring.

Table 1. Recent Techniques in EEG-based Stress and Depression Detection

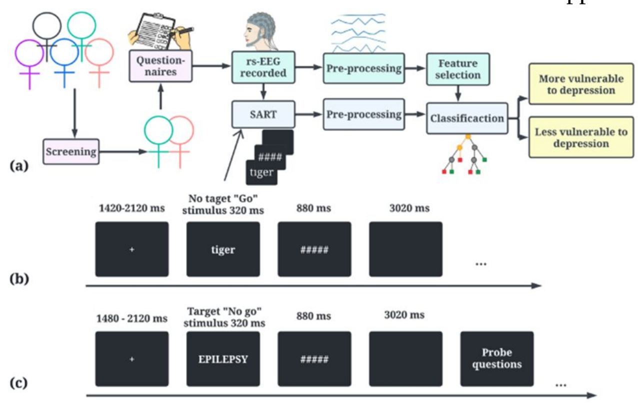
Year	Study	Methodology	Application	Key Findings
2025	Joshi et al. [1]	SNNs, CSNNs	Stress detection	Improved temporal modeling, high accuracy
2025	Joshi & Matharu [2]	Cloud-based EEG + DL	Depression detection	Scalable, real-time analysis
2024	Liu et al. [3]	Graph-based EEG	Depression prediction	Captures spatial interdependencies
2024	Liu et al. [4]	Mind-Transformer	Mental health monitoring	Enhanced feature fusion and robustness
2024	Zhang et al. [5]	Deep CNN + LSTM	EEG-based depression detection	Higher performance in hybrid models

B. Deep Learning vs. Conventional Methods

Earlier works focused on conventional signal processing and handcrafted features such as power spectral density (PSD), wavelet transform, and statistical analysis [6], [7]. Although these methods provided valuable insights, they lacked generalization across subjects due to inter-individual variability in EEG signals.

Recent works have shown that deep learning models significantly outperform conventional methods. For example, hybrid CNN-LSTM frameworks [5], [8] demonstrated superior accuracy in detecting depressive states compared to traditional SVM or Random Forest classifiers. Figure 1 illustrates the shift from conventional EEG analysis towards deep learning-based frameworks in the last decade.

Figure 1. Evolution of EEG-based mental health detection approaches[16]



C. Challenges in EEG-based Detection

Despite advancements, several challenges remain:

- Data Scarcity: Publicly available annotated EEG datasets for mental health are limited [9].
- Inter-subject Variability: EEG signals differ across individuals, requiring adaptive models [10].
- Explainability: Black-box deep models hinder clinical adoption [11].
- Deployment: Cloud-based and edge AI solutions must balance latency, energy consumption, and scalability [2].

These gaps suggest that future directions should prioritize multimodal fusion, federated learning for privacy-preserving EEG analysis, and interpretable AI frameworks.

III. EEG-BASED DEPRESSION AND STRESS DETECTION APPROACHES

EEG has emerged as one of the most effective modalities for detecting mental health disorders such as depression and stress due to its non-invasive nature, high temporal resolution, and ability to capture neurophysiological alterations. Researchers have progressively developed methods ranging from conventional machine learning (ML) models to advanced deep learning (DL) architectures, spiking neural networks (SNNs), and graph-based frameworks. This section reviews these approaches systematically.

A. Conventional Machine Learning Approaches

Early works on EEG-based mental health monitoring primarily relied on handcrafted features such as power spectral density (PSD), coherence, entropy, and band-specific features (e.g., alpha, beta, theta). These features were fed into classifiers like support vector machines (SVM), k-nearest neighbors (k-NN), and random forests. While effective for small-scale datasets, these methods faced limitations in scalability and generalization across diverse populations [3], [10].

B. Deep Learning-Based Approaches

With the advancement of computational resources, deep learning approaches began to dominate EEG analysis. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, were widely adopted for automatically extracting spatiotemporal features from EEG signals. For instance, Liu et al. [3] proposed a neural oscillation and asymmetry-based recognition model for major depressive disorder (MDD), demonstrating superior accuracy compared to traditional ML models. Similarly, hybrid CNN-LSTM models have been shown to capture both spatial dependencies and temporal dynamics, improving robustness in depression detection tasks [7].

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C. Graph-Based and Transformer Models

Recent advancements have emphasized the representation of EEG data as graphs, where electrodes are modeled as nodes and functional connectivity serves as edges. This approach captures inter-channel relationships more effectively than conventional feature extraction. A 2024 study introduced a graph-based method for depression prediction, yielding improved interpretability and accuracy compared to CNN-based methods [4].

Transformer architectures have also been leveraged to handle long-range temporal dependencies in EEG signals. The EEG Mind-Transformer framework demonstrated that attention mechanisms can enhance robustness and reduce noise sensitivity in EEG-based mental health monitoring [5].

D. Spiking Neural Networks (SNNs)

Incorporating brain-inspired spiking neural networks represents a new paradigm in EEG-based stress detection. Joshi et al. [1] introduced convolutional SNNs for stress recognition, which exploit event-driven neural coding to improve computational efficiency. These models align more closely with biological plausibility while significantly reducing energy consumption, making them suitable for real-time edge deployments.

E. Hybrid and Explainable AI Approaches

Hybrid frameworks that combine CNNs, LSTMs, and optimization techniques have also been proposed to enhance performance. For instance, explainable AI (XAI)-driven approaches can identify EEG biomarkers of depression, ensuring transparency and trustworthiness in clinical applications [8]. Such models are crucial for bridging the gap between algorithmic predictions and clinical adoption.

F. Systematic Reviews and Trends

Several systematic reviews emphasize the increasing trend of adopting deep learning and hybrid models for EEG-based mental health assessment [9], [15]. Emerging directions highlight cloud- and edge-based systems for scalable monitoring, decentralized learning approaches for privacy-preserving analysis, and integration of multimodal data to improve diagnostic accuracy [6], [11], [14].

Table 2. Summary of EEG-Based Depression and Stress Detection Approaches

Approach	Key Features	Models Used	Strengths	Limitations	References
Conventional ML	PSD, entropy, band power	SVM, RF, k-NN	Simple, interpretable	Limited generalization	[3], [10]
Deep Learning	Automated feature extraction	CNN, LSTM	High accuracy, robust	Requires large data	[3], [7]
Graph-Based	EEG as graph nodes	GNN, Graph-CNN	Captures connectivity	Complexity, scalability	[4]
Transformer	Attention-based	Mind-Transformer	Robust to noise, long dependencies	High computational demand	[5]
SNN	Spiking neurons	Conv-SNN	Energy-efficient, biologically plausible	Training challenges	[1]
Hybrid/XAI	Combined DL models, explainability	CNN+LSTM+XAI	Transparent, clinically useful	Complexity in deployment	[8], [9]

IV. CHALLENGES AND OPEN RESEARCH GAPS

Despite significant progress in EEG-based depression and stress detection, several challenges hinder large-scale adoption in clinical and real-world settings. This section outlines key issues and open research directions.

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A. Data Quality and Availability

Most existing datasets for depression and stress detection are limited in size, often collected in controlled laboratory environments. Small sample sizes reduce model generalizability across different populations, age groups, and cultural contexts. Furthermore, EEG recordings are prone to noise and artifacts (e.g., eye blinks, muscle activity, and electrode displacement), which may degrade model accuracy. Open-access, large-scale, and standardized datasets remain scarce [3], [9].

B. Inter-Subject and Intra-Subject Variability

EEG signals exhibit strong variability across individuals due to differences in brain anatomy, mental states, and environmental factors. Even within the same individual, EEG patterns may vary significantly over time depending on fatigue, medication, or emotional fluctuations. This variability complicates the design of models that are both robust and personalized [4], [11].

C. Model Interpretability and Clinical Trust

While deep learning models achieve state-of-the-art performance, their "black-box" nature limits clinical acceptance. Clinicians require explainable and transparent models to validate whether the detected biomarkers truly align with known neurophysiological patterns. Emerging explainable AI (XAI) frameworks provide some insights, but achieving clinically meaningful interpretability remains an open research gap [5], [8].

D. Computational Complexity and Deployment

Many advanced models, such as transformers, graph neural networks, and hybrid deep learning frameworks, demand high computational resources and memory. Deploying such models on portable EEG devices or in real-time edge environments poses significant challenges. While spiking neural networks offer energy efficiency, their training complexity limits practical implementation [1], [6].

E. Privacy, Ethics, and Standardization

EEG-based mental health monitoring involves highly sensitive data, raising privacy and ethical concerns. Current cloud-based solutions may expose data to risks of unauthorized access. Furthermore, the lack of standardized protocols for data collection, preprocessing, and model evaluation complicates cross-study comparisons and real-world translation [10], [14].

F. Open Research Gaps

1) Development of large-scale, multimodal datasets integrating EEG with physiological signals (e.g., ECG, HRV, fNIRS) for improved robustness.
2) Exploration of personalized and adaptive learning models to address inter- and intra-subject variability.
3) Integration of explainable AI (XAI) techniques for greater transparency in clinical use.
4) Advancement of lightweight, energy-efficient models for real-time deployment on wearable or edge devices.
5) Establishment of standardized benchmarks for evaluating EEG-based depression and stress detection systems.
6) Formulation of privacy-preserving frameworks such as federated learning and split learning to ensure secure EEG analysis [12], [15].

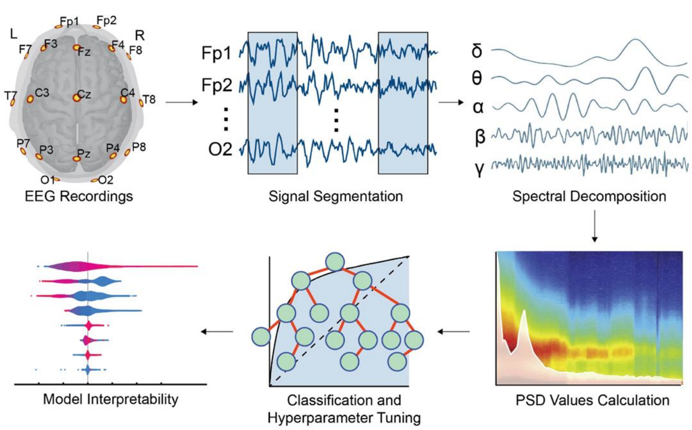

Figure2 EEG-Based Assessment of Cognitive Resilience via Interpretable Machine Learning Models[17].

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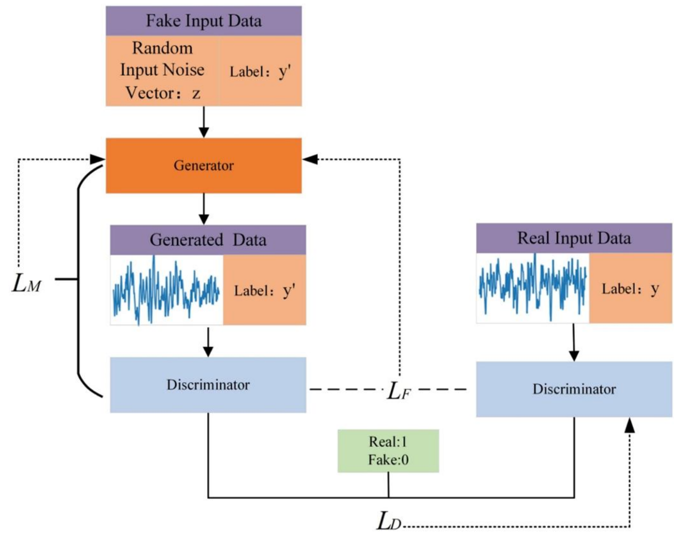

Figure 3 EEGGAN-Net: enhancing EEG signal classification through data augmentation" – showing model architecture, data augmentation etc.[17]

G. Multimodal Data Fusion

Future systems will increasingly integrate EEG with complementary modalities such as electrocardiography (ECG), photoplethysmography (PPG), functional near-infrared spectroscopy (fNIRS), and behavioral cues. Multimodal fusion can improve diagnostic accuracy by combining neurophysiological, cardiovascular, and behavioral signals to capture a more holistic view of mental health [3], [6].

H. Personalized and Adaptive Models and Lightweight Edge-AI Deployment

Personalization is critical to address inter-subject variability. Adaptive deep learning frameworks that recalibrate based on individual baseline EEG patterns could provide tailored diagnostics. Transfer learning and domain adaptation techniques will likely play an important role in building such systems without requiring extensive subject-specific retraining [4], [11].
With the growing use of portable EEG headsets and wearable devices, lightweight AI models optimized for edge devices are essential. Spiking neural networks (SNNs) and quantized deep learning models offer promising solutions for achieving real-time, energy-efficient performance without relying on cloud infrastructure [1], [6].

I. Explainable and Trustworthy AI and Privacy-Preserving and Decentralized Learning

The integration of explainable AI (XAI) techniques into EEG analysis is expected to enhance trust and clinical adoption. Future work should focus on visualizing neural biomarkers, identifying relevant EEG frequency bands, and providing transparent decision pathways that align with psychiatric assessments [5], [8].
Federated and split learning approaches will become increasingly relevant to address privacy concerns in mental health monitoring. By enabling decentralized model training across multiple institutions without sharing raw EEG data, such frameworks can ensure data confidentiality while enhancing generalizability [12], [14]. For broader clinical use, there is a need for standardized protocols in EEG data acquisition, preprocessing, and evaluation metrics. Collaborative initiatives between AI researchers, neuroscientists, and clinicians will be key in developing guidelines that facilitate reproducibility and regulatory approval [10], [15].

V. CONCLUSION

Electroencephalography (EEG) has established itself as a vital tool for understanding the neurophysiological underpinnings of depression and stress. Recent advancements in machine learning and deep learning have significantly improved the accuracy and reliability of EEG-based detection systems. Conventional approaches based on handcrafted features have gradually given way to deep architectures, graph-based learning, spiking neural networks, and transformer models, enabling more robust and automated detection of mental health disorders.

Despite these achievements, several challenges persist, including limited and noisy datasets, inter- and intra-subject variability, lack of interpretability in deep models, and barriers to real-world deployment. Ethical issues such as privacy, standardization, and clinical trust also remain unresolved. Addressing these concerns is essential for moving beyond academic research toward clinically viable and socially acceptable solutions.

Looking forward, the future of EEG-based depression and stress detection lies in multimodal data fusion, adaptive personalized AI, lightweight edge deployment, explainable AI, and privacy-preserving decentralized learning frameworks. Standardization and cross-disciplinary collaboration will play a central role in translating these technologies into clinical practice.

This review underscores that while EEG-based detection systems have made remarkable progress, their true impact will be realized only through interdisciplinary integration, real-world validation, and ethical deployment strategies. Such efforts will pave the way for intelligent, reliable, and patient-centered mental health monitoring systems.

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