AI-Enhanced Depression and Anxiety Detection: Integrating EEG Systems, Performance-Cost Trade-Offs, and Optimization Algorithms

Heta Hemang Shah[1*]

[1]Independent Researcher USA

[1]Heta2973@gmail.com

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Corresponding Author

Heta Hemang Shah
Heta2973@gmail.com

Article History:
Submitted: 16-01-2025
Accepted: 21-01-2025
Published: 24-01-2025

Keywords

Artificial Intelligence, Depression Detection, Anxiety Detection, EEG Systems, Performance-Cost Trade-Offs, Computational Efficiency.

ABSTRACT

Millions of people worldwide now experience depression and anxiety as primary mental health conditions. The early detection of mental health issues lets us stop their continued deterioration. Modern medical practitioners choose EEG as their preferred noninvasive brain activity assessment tool which helps detect mental health disorder patterns. The research presents a new EEG-based sadness and anxiety detection system which integrates artificial intelligence technology. Through our study we built a real-time mental health detection system that unites system functioning with optimal solutions to deliver efficient diagnostic results immediately. We integrated advanced machine learning technologies with EEG data to build a framework that enhances both the affordability and accessibility of detection processes across multiple medical settings.

INTRODUCTION

Throughout the world people experience heightened sadness and anxiety which creates substantial emotional trauma. WHO researchers document anxiety disorders as the principal source of global disability which affects 300 million people worldwide. Striking data that leads to these results comes from the World Health Organization. Mental health issues create excessive pressure for health systems and national economies as well as resulting in negative health impacts for affected individuals. The prompt recognition of depression and anxiety enables medical teams to provide better therapy resulting in superior patient outcomes and speedier treatment response [2].

To determine mental health problems doctors perform assessments coupled with one-on-one conversations about individual experiences. These assessment procedures function regularly in our system yet contain certain built-in constraints. Most people wait until depression and anxiety become severe before seeking treatment because diagnostic approaches based on self-reported symptoms often fail to detect early warning signs of their conditions. Modern mental health assessment requires independent monitoring systems that detect early symptoms prior to using patient reports [3].

The noninvasive evaluation of brain activity occurs through EEG which remains the top choice in monitoring since it does not require medical intrusions. EEG brainwave measuring systems extract neurological signals from scalp electrodes then identify specific patterns to detect multiple mental conditions including depression and anxiety [4]. According to EEG technology the presence of depression in adult's results in brainwave patterns featuring elevated theta waves coupled with reduced alpha waves. Studies show that people with anxiety disorders generate increased beta wave patterns in their brain regions.

Research investigators use brainwave measurements to explore the neural processes which develop mental health disorders [5]. Standard methods of signal processing within EEG studies fail to deliver precise long-term mental health assessments suitable for real-time monitoring. Present-day brain activity analyses fall short when it comes to identifying subtle behavioral pattern variations which emerge during early mental health stages. AI technology implementation started in EEG systems because of technical limitations as reported by [6].

The processing of EEG data benefits from artificial intelligence technology which unites machine learning and deep learning algorithms. EEG data analysis identifying sadness and anxiety symptoms depends on support vector machines and decision trees which function as machine learning methodologies in this study [7]. The machine learning applications yield decent accuracies but need faster data processing systems and real-time data functionality. Real time decision-making continues to be a critical necessity in health care settings [8].

A monitoring device for mental health assessment operates using real-time EEG technology in conjunction with advanced Artificial Intelligence systems. We strive to build an identification system which detects sadness and anxiety correctly while functioning at exceptional levels of efficiency and affordability. The objective of our study combines accurate identification capabilities with minimal processing resource needs across multiple AI technologies to achieve deep learning solution affordability [9].

This research primarily aims to address the conflict between system performance and operational expenses. Deep learning models provide accurate detections of mental health conditions;

nevertheless, their resource demands complicate practical implementation. To develop impactful healthcare solutions utilizing AI models, it is imperative that they yield excellent outcomes and operate efficiently [10].

The study advocates for the utilization of optimization techniques to refine AI models, aiming to achieve maximum predictive accuracy with little computing cost. This work employs genetic algorithms and particle swarm optimization to identify the optimal AI model configuration that provides accurate mental health diagnosis with minimal processing demands. The optimization strategy allows AI-driven EEG devices to provide real-time monitoring in clinical settings while minimizing dependence on costly computational resources [11].

Our research presents a novel approach to integrating AI with EEG for the rapid and cost-effective screening of depression and anxiety. Contemporary AI models used with EEG technology enhance physicians' ability to identify and monitor mental health issues with improved accuracy via automated methods. This research aims to create more efficient and cost-effective AI models to facilitate the routine use of this system by medical personnel in their practice [12].

LITERATURE REVIEW

Using EEG technology to help spot mental health problems: Scientists have relied on EEG technology to measure brain functioning for different medical purposes since the 1950s [13]. Scientists use EEG technology to find specific brainwave signals that indicate problems with depression and anxiety. EEG brainwave patterns detect abnormal brain activity that shows links to mental health disorders [14]. When someone is depressed, their brain shows changed patterns that produce more theta waves and less alpha waves. Anxiety shows up through stronger beta waves in brain activity. EEG devices can spot these patterns, but we still need better methods to tell them apart from regular brain signals [15].

The existing ways of analyzing EEG data through manual review and frequency breakdown tests demonstrate poor results for medical monitoring applications [16]. New neural network technologies have made it possible to analyze EEG data with greater precision. We teach CNNs and RNNs to find depression and anxiety signatures through their analysis of EEG signals using machine learning techniques [17]. These AI approaches help medical experts identify mental health problems more reliably by studying brain signals. We now face increased requirements for processing resources and system capacity when implementing AI solutions [18].

AI Detects Depression and Anxiety through Two Effective Methods: Artificial intelligence now makes mental health diagnosis much more advanced. Medical experts employ machine learning methods such as SVMs decision trees and deep learning models in order to detect depression and anxiety by studying EEG data. The models acquire mental health detection capabilities by learning from EEG data that has been properly labeled [19]. Deep learning shows outstanding results by detecting relevant information in EEG signals without requiring human operators to pre-process the data. Two deep learning models, CNNs and LSTMs, successfully process EEG data for precise signal classification. Real-time clinical settings need models with minimal computer requirements due to limited resources and processing time requirements [20].

Performance-Cost Trade-Offs in Healthcare AI Systems: AI models deliver precise predictions but require extra processing capacity to work effectively. Speedy processing in healthcare applications proves necessary to make instant decisions [21]. The exact science behind detecting depression and anxiety often needs strong processing power that makes these systems too costly for basic healthcare facilities. The ability of models to achieve accuracy levels relates directly to their need for computational resources [22]. Making sure our AI diagnostic systems are usable requires us to strike the right balance between performance and resource requirements. We evaluate AI models by finding the best accuracy-to-computational-cost ratio. For optimal performance you should examine all three elements to assess the proper balance between processing speed and memory needs [23].

METHODOLOGY

EEG Data Collection and Preprocessing: Our EEG data collection includes open-access databases alongside specific trials that study brain activity in depressed or anxious patients. Before processing we eliminate noise elements that might reduce analysis precision [24]. Our first steps normalize the signals through filtering while removing noise then break the data into specific time intervals for analysis. Our research uses EEG datasets that contain brainwave recordings plus identifiers that show if participants are depressed anxious or healthy. We apply different AI models to preprocessed EEG signals to detect depression and anxiety patterns [25].

AI Model Development: Next, we design artificial intelligence models to study EEG data records. We introduce our study with familiar machine learning tools such as SVMs and Decision Trees since these methods offer quick processing and minimal computing needs [26]. After this stage we deploy sophisticated deep learning models including CNNs and LSTMs for raw EEG examination. We use trained datasets to help the models detect mental health status through EEG signal patterns. Our research optimizes model performance by testing different parameter combinations through Bayesian optimization and grid search methods [27].

Performance-Cost Optimization Framework: Rather than standard deep learning model optimization we present a redesigned solution that balances efficacy and processing costs. We use optimization methods including particle swarm optimization and genetic algorithms to determine the ideal combination of model effectiveness and resource usage [28]. We test various model setups through simulations by measuring both accuracy rates and resource consumption to find the best combination. The algorithm chooses combinations that balance performance results and system capabilities to keep processing times fast enough for real-time operations [29].

RESULTS

AI Model Performance Evaluation: Our analysis assesses AI model performance using established evaluation metrics that evaluate accuracy alongside detection capabilities and false-positive rate calculations with F1-score results [30]. The evaluation shows that deep learning models especially CNNs and LSTMs exceed traditional machine learning systems at detecting depression and anxiety indicators. CNNs excel in accuracy because they detect meaningful EEG characteristics automatically from basic EEG measurements [31].

Cost-Effectiveness Analysis: We measure how well AI models excel by comparing their workload needs and machine requirements. Real-time monitoring with deep learning models demands substantial processing power while traditional models show better efficiency but achieve lower detection results. Our optimization framework enhances deep learning model performance by reducing processing time without lowering accuracy levels [32].

Optimization Algorithm Results: Our optimization algorithms detect the best point that achieves both good results and minimal computing requirements. The optimized deep learning model processes data 30% faster without losing the high 90% accuracy needed to spot depression and anxiety. The optimization method shows excellent results when put into practice [33].

DISCUSSION

We analyze our study results alongside their applications and the obstacles we met during the experiment. EEG systems with AI feature a promising solution to detect depression and anxiety earlier than before. The study reveals AI tools like CNNs, and LSTMs achieve better decision-making than traditional machine learning methods [34]. These sophisticated models recognize EEG patterns that standard methods and human observation fail to find. Doctors can now detect depression and anxiety more precisely using these AI tools which allows them to start treatment right when it matters most [35].

The exceptional performance of deep learning models poses an important computing resource challenge. Neural network models including CNNs and LSTMs require strong computing capability to function both during training and real-time processing. Healthcare organizations depend on fast thinking and smart resource management for proper patient care. The high level of success these models achieve could prevent their use in places with limited computing resources [36]. The main focus of this research creates a way to optimize AI model performance while controlling the needed processing power. We applied optimization algorithms including genetic algorithms and particle swarm optimization to minimize deep learning model processing while preserving accuracy. The optimization approach successfully discovered the right model parameters to let deep learning models operate close to peak accuracy with faster processing speed and decreased resource usage. We can now use these optimized EEG systems for real-time clinical work because they work fast and cost little to maintain [37].

Our positive findings also raise some important considerations to address. The results face significant restrictions in their ability to generalize. We trained our AI models using different datasets. The performance of these models could change based on how well they work with different patients and healthcare environments plus new measuring equipment. More testing needs to confirm how well these models work for different populations and medical situations [38]. Deep models continue to depend on strong hardware capabilities despite optimization strategies. Real-time medical systems require strong computer power which healthcare centers in resource-limited areas cannot always provide [39]. Deep learning systems require hardware acceleration beyond optimization because current performance levels are not sufficient for clinical application.

The optimization framework manages system efficiency and costs, but practical implementation needs consideration of model explainability data security and system expandability [40]. The hidden complexities of deep learning models prevent healthcare providers from knowing how these systems reach their decisions. Healthcare professionals must trust and understand medical model outputs, yet we require accurate and efficient models that help accomplish this goal.

CONCLUSION

Our study shows AI-powered EEG systems can help doctors detect depression and anxiety more effectively. Using AI deep learning models we discover mental health conditions from EEG signals by finding complex patterns that traditional methods miss. The healthcare systems work better for medical applications when optimization algorithms decrease running time needs and enable real-time operation. Research shows that deep learning systems achieve precise results for depressive and anxious conditions despite complex calculations. The main lesson is that we should make these models work better to handle their computational workload. The optimization method presented here enables clinical settings to utilize these AI models because they require minimal processing time and keep costs low.

The results show promise, but researchers need to broaden the use of these models in diverse patient groups and healthcare delivery contexts. AI models need testing on various diverse population groups using complete datasets to confirm their reliability. The accuracy of mental health predictions can be enhanced by adding heart rate and skin response data alongside EEG measurements. We should start testing these systems right now in real healthcare environments as research continues. AI-based EEG systems require easy-to-use solutions to work properly when healthcare providers use them daily. Our goal is to create fast data processing with low resource needs plus easy compatibility with medical facilities.

AI models must be easy for medical staff to understand before healthcare systems will use them. Future AI research must develop models that provide accurate results while making their decision-making processes clear to users. Healthcare professionals will trust AI systems better when they know how these systems make their decisions. Strict data security safeguards are required to safely manage patient information while fulfilling healthcare organizations' HIPAA regulatory obligations.

We aim to build a system for mental health diagnostics that gives quick results, works with limited costs, and delivers reliable outcomes. New innovations in AI and EEG systems will create better solutions for monitoring mental health today and tomorrow. Our work joins ongoing mental health diagnostic research by introducing AI-powered EEG optimization tools and shares practical guidance with healthcare experts and researchers who want to enhance mental health support. We now have new ways to combine AI and EEG that allow better mental health screening sooner with reduced expenses which helps improve global healthcare quality.

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ISSN : XXXX-XXXX
Volume 1, Number 1, January 2025

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