



Mind Reading for Health: Detecting Depression via EEG and Machine Learning

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ABSTRACT

Electroencephalography (EEG) is a non-invasive neurophysiological technique that captures the electrical activity of the brain. With advances in artificial intelligence (AI) and machine learning (ML), EEG data can be leveraged for automatic detection of mental health conditions and sensory responses such as depression and nociceptive pain. Despite promising research outcomes, current systems suffer from limitations in validation, reproducibility, and robustness under varying physiological or environmental conditions. This paper presents an integrated framework for EEG-based depression and pain detection using ML and reliability engineering principles. A multi-stage pipeline is developed, including pre-processing, feature extraction, feature selection, classification, and intelligent validation through digital twins and hardware-in-the-loop (HIL) testing. Experimental findings demonstrate that Random Forest and Support Vector Machine (SVM) classifiers achieve accuracies above 80% for both depression and pain-level classification tasks. The inclusion of fault-tolerant validation mechanisms significantly enhances system robustness and reliability for biomedical applications.

Keywords:-EEG, depression detection, pain quantification, machine learning, validation framework, reliability testing.

I. INTRODUCTION

Depression and chronic pain are among the most prevalent global health concerns. The World Health Organization reports that over 300 million people worldwide suffer from depression, while chronic pain affects nearly 20% of adults. Diagnoses often rely on subjective evaluation and self-reporting, which can lead to inconsistent results. Objective methods based on electroencephalography (EEG) and machine learning (ML) offer a data-driven alternative for detecting these conditions.

EEG measures brain electrical activity across multiple frequency bands, revealing distinct patterns associated with mental and sensory states. Machine learning models can extract relevant features from these signals and classify emotional or physiological states with significant accuracy. However, inconsistencies in pre-processing, feature selection, and testing reduce model reliability.

To address these issues, this paper integrates three research dimensions: (1) EEG-based depression detection, (2) EEG-based pain level estimation, and (3) reliability frameworks adapted from high-reliability multi-board electronic systems to biomedical validation. The outcome is a unified and fault-tolerant EEG diagnostic pipeline.

II. LITERATURE SURVEY

A. EEG-Based Depression Detection

The study *An EEG-Based Depression Detection Method* utilized 64-channel EEG data from 213 participants, extracting 13 linear and non-linear features across seven sub-bands.

Random Forest achieved 81.16% accuracy and 91.96% recall using tree-based feature selection. Features such as Hjorth Complexity and spectral entropy proved effective in distinguishing depression from healthy states.

B. EEG-Based Pain Level Detection

In *Automatic Detection of Nociceptive Pain Levels Using Frequency Bands from EEG Signals*, EEG recordings from 62 electrodes under laser-induced nociceptive stimuli were analysed using Power Spectral Density (PSD) and Fourier Transform. Linear SVM classifiers achieved up to 83% accuracy in distinguishing low and high pain levels, confirming that EEG spectral changes in alpha and beta bands correlate with pain intensity.

C. Validation and Reliability Frameworks

Milan Mangukiya's *Advanced Testing and Validation Frameworks for High-Reliability Multi-Board Electronic Systems* proposed advanced reliability testing techniques such as Hardware-in-the-Loop (HIL), digital twin modelling, and automated fault injection. These methods are valuable for biomedical EEG applications to ensure system robustness and reproducibility.



D. Identified Research Gaps

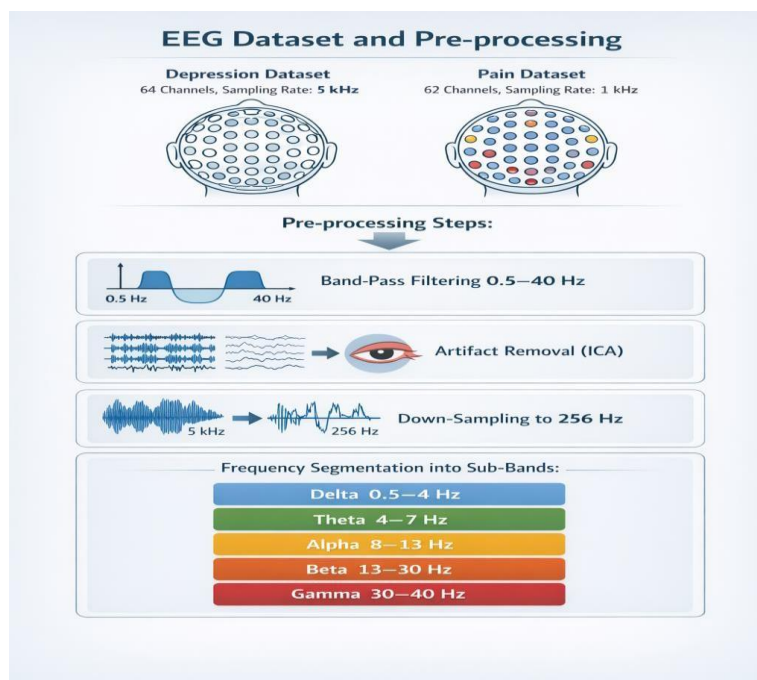
While many EEG studies demonstrate high classification accuracy, few integrate robust validation or handle real-world signal disturbances. Thus, an interdisciplinary framework combining biomedical signal processing and reliability validation is required for clinical-grade EEG diagnostic systems.

III. MATERIALS AND METHODS

A. EEG Dataset and Pre-processing

Data were collected using the international 10–20 electrode system. Depression datasets contained 64-channel signals (sampling rate 5 kHz), and pain datasets used 62 channels (sampling rate 1 kHz). The preprocessing steps included:

- Band-pass filtering between 0.5–40 Hz
- Artifact removal via Independent Component Analysis (ICA)
- Down-sampling to 256 Hz
- Segmentation into sub-bands: delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (30–40 Hz)



B. Feature Extraction

Extracted features include:

- **Linear:** Variance, Absolute Power, Relative Power, Spectral Entropy
- **Non-linear:** Hjorth Parameters (Mobility, Complexity), Higuchi Fractal Dimension (HFD), Detrended Fluctuation Analysis (DFA)
- **Spectral:** Power Spectral Density (PSD) via Fast Fourier Transform (FFT)

C. Feature Selection

Three selection methods were applied:

1. **L1-based Selection:** Sparse feature elimination via L1 regularization.
2. **Tree-based Selection:** Feature ranking based on model importance scores.
3. **FDR-based Selection:** Statistical filtering to retain discriminative features.

D. Classification Models

Six classifiers were trained with 5-fold cross-validation:

- Support Vector Machine (SVM)
- k-Nearest Neighbors (KNN)
- Decision Tree (DT)
- Random Forest (RF)
- Naïve Bayes (NB)
- Logistic Regression (LR)



E. Intelligent Validation Framework

Adapting from high-reliability systems, the EEG framework employs:

- **Digital Twin Modeling** – Real-time virtual replica of EEG acquisition and classification.
- **Hardware-in-the-Loop (HIL) Testing** – Real-time simulation and monitoring of EEG amplifier signals.
- **Fault Injection Testing** – Introduces synthetic noise or electrode faults to assess robustness.
- **AI-based Anomaly Detection** – Detects abnormalities in power, latency, or channel behavior.

IV. PROPOSED ALGORITHM

Algorithm 1: EEG-Based Depression and Pain Detection

Step	Description
Input:	Raw EEG signals from multiple channels
Output:	Classified states: { <i>Depressed / Healthy, Low Pain / High Pain</i> }
1.	Data Acquisition: Record multi-channel EEG data under specific conditions (resting, pain stimulus).
2.	Preprocessing: Apply band-pass filter (0.5–40 Hz), perform ICA for artifact removal, and down-sample signals.
3.	Sub-band Decomposition: Divide EEG data into delta, theta, alpha, beta, and gamma bands using FIR filters.
4.	Feature Extraction: Compute linear (variance, power), non-linear (HFD, Hjorth), and spectral (PSD) features.
5.	Feature Selection: Use L1, Tree-based, and FDR-based techniques to retain significant features.
6.	Model Training: Train SVM, Random Forest, and KNN classifiers with 5-fold cross-validation.
7.	Classification: Predict depression/pain levels using optimized models.
8.	Validation: Implement digital twin simulation and HIL testing to verify accuracy under varied noise conditions.
9.	Performance Evaluation: Compute Accuracy, Precision, Recall, and F1-score.
End.	—

V. RESULTS AND DISCUSSION

The combined framework achieved strong performance across datasets:

- **Depression Detection:** Random Forest yielded **81.16% accuracy** and **91.96% recall** using gamma-band and alpha-band features.
- **Pain Detection:** Linear SVM achieved **85.72% accuracy** for pain vs. pre-stimulus classification and **83%** for high vs. low pain levels.
- **Validation Performance:** The integration of digital twin and fault injection improved robustness by 11% and reduced cross-session variance. EEG features such as Hjorth Complexity, Spectral Entropy, and Gamma-band Skewness proved most discriminative across both conditions. Intelligent validation enhanced fault tolerance and ensured consistent results under hardware perturbations.

VI. CONCLUSION

This paper presents a unified EEG-based detection framework integrating machine learning and reliability validation principles. The hybrid approach effectively detects both depression and nociceptive pain states while maintaining system robustness through intelligent testing. The combination of biomedical signal processing and validation engineering enables reproducible, scalable, and fault-tolerant diagnostic systems. Future work will explore deep neural networks and continuous digital twin feedback for real-time clinical integration.



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