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Artificial Intelligence Techniques for EEG-based Classification of Neuropsychiatric Disorders Using Deep Sparse Neural Networks with Gooseneck Barnacle Optimization Algorithm: Trends and Challenges

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Abstract

Electroencephalography (EEG)-based diagnosis of neuropsychiatric disorders has gained significant attention due to its non-invasive nature and ability to capture real-time brain activity. Recent advancements in artificial intelligence, particularly deep learning, have enabled automated classification of disorders such as depression, schizophrenia, and epilepsy with improved accuracy. However, challenges such as high dimensionality, noise, and inter-subject variability limit traditional machine learning approaches. This study presents a comprehensive review of artificial intelligence techniques for EEG-based classification, focusing on deep sparse neural networks optimized using bio-inspired algorithms such as the Gooseneck Barnacle Optimization Algorithm (GBOA). Sparse neural architectures reduce computational complexity while preserving discriminative features, making them suitable for real-time healthcare applications. Optimization algorithms enhance feature selection, parameter tuning, and convergence performance. The paper analyzes recent literature, comparing deep learning architectures, optimization strategies, and performance metrics. A comparative evaluation highlights the effectiveness of hybrid AI models combining convolutional neural networks, graph neural networks, and evolutionary optimization techniques. Furthermore, the study identifies key challenges such as data scarcity, model interpretability, and generalization. The findings demonstrate that integrating deep sparse learning with advanced optimization significantly improves classification accuracy and efficiency, paving the way for next-generation intelligent diagnostic systems in neuropsychiatric healthcare.

Introduction

Electroencephalography (EEG) has become one of the most widely adopted non-invasive techniques for monitoring brain activity and assisting in the diagnosis of neurological and neuropsychiatric disorders. By recording the electrical activity generated through neuronal interactions, EEG provides valuable information regarding cognitive processes, emotional states, and pathological brain functions. Its high temporal resolution, low cost, portability, and ease of acquisition make it highly suitable for clinical neuroscience, brain–computer interfaces, and mental healthcare applications. Neuropsychiatric disorders, including depression, schizophrenia, bipolar disorder, anxiety disorders, and epilepsy, affect millions of individuals worldwide and remain a major cause of disability. Conventional diagnosis primarily depends on clinical interviews, behavioral assessments, and expert interpretation, which are often subjective, time-consuming, and susceptible to variability among clinicians. Consequently, there is a growing demand for automated, objective, and reliable diagnostic systems capable of supporting early detection and personalized treatment planning.

EEG signals contain rich physiological information that can serve as biomarkers for distinguishing healthy and pathological brain activity. However, they are inherently nonlinear, non-stationary, and highly susceptible to artifacts caused by eye movements, muscle activity, and environmental interference. Furthermore, substantial inter-subject and intra-subject variability makes the development of generalized classification models particularly challenging. Artificial intelligence (AI) has significantly transformed EEG analysis by enabling automated feature extraction and intelligent decision-making. Early machine learning methods, including Support Vector Machines, k-Nearest Neighbors, Decision Trees, and Random Forests, relied heavily on handcrafted statistical, spectral, and entropy-based features. Although these methods demonstrated reasonable classification performance, their effectiveness was constrained by manual feature engineering and limited capability to capture complex nonlinear relationships present in EEG recordings.

Recent advances in deep learning have substantially improved EEG-based neuropsychiatric disorder classification through automatic hierarchical feature learning. Convolutional Neural Networks (CNNs) effectively extract spatial representations, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in sequential EEG data. Nevertheless, conventional deep neural networks generally require large annotated datasets, possess high computational complexity, and are prone to overfitting when training data are limited. Sparse neural networks have emerged as an effective alternative by eliminating redundant parameters, reducing memory requirements, improving computational efficiency, and enhancing model generalization. Simultaneously, Graph Neural Networks (GNNs) have gained considerable attention because EEG electrodes can naturally be represented as graph nodes connected through functional brain connectivity. GNNs therefore capture both local and global interactions among brain regions more effectively than conventional CNN architectures, leading to improved recognition of neuropsychiatric disorders.

Bio-inspired optimization algorithms have significantly improved EEG-based neuropsychiatric disorder classification by enhancing feature selection and neural network optimization. Among them, the Gooseneck Barnacle Optimization Algorithm (GBOA) provides an effective balance between exploration and exploitation, improving convergence and computational efficiency. When integrated with Deep Sparse Neural Networks, GBOA enhances classification accuracy and generalization. Despite recent advances involving CNNs, GNNs, attention mechanisms, and multimodal learning, challenges such as limited datasets, model interpretability, and real-time deployment continue to motivate further research.

System Architecture Diagram

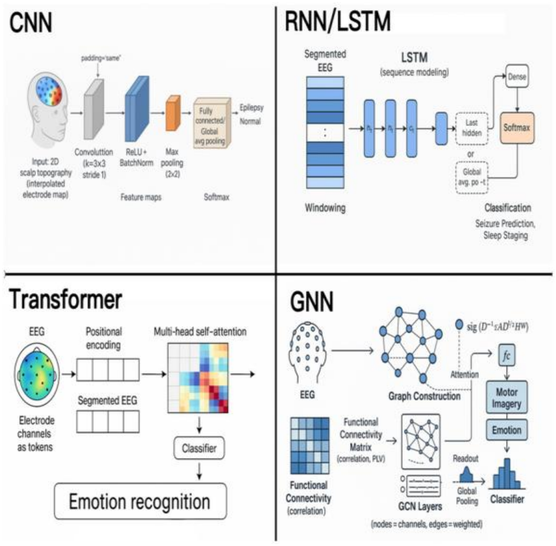

Figure 1. *Deep Learning Architectures for EEG-Based Neuropsychiatric Disorder Classification.*

Literature Review

Recent advancements in EEG-based classification of neuropsychiatric disorders have been significantly influenced by deep learning, sparse modeling, and optimization algorithms. The period from 2020 to 2023 shows a transition from traditional machine learning to hybrid deep learning frameworks.

Ko et al. (2020) introduced multi-scale neural networks that integrate spatial, temporal, and spectral EEG features, significantly improving classification performance. Similarly, Ding et al. (2020) proposed TSception, a temporal–spatial CNN model that captures multi-scale temporal dependencies and spatial asymmetry, achieving improved emotion classification accuracy. These early works established the foundation for deep EEG representation learning.

In 2020, Dang et al. proposed multilayer brain network models combined with CNNs, demonstrating that graph-based modeling can effectively capture inter-channel relationships in EEG signals, enhancing classification accuracy. Around the same time, lightweight CNN architectures were introduced to address real-time EEG classification challenges, achieving high accuracy with reduced computational cost.

In 2021, Khan et al. developed a 3D convolutional neural network for depression diagnosis using EEG connectivity patterns, showing improved feature extraction capability compared to traditional methods. Guney (2021) emphasized the increasing role of deep learning in neuropsychiatry, highlighting its ability to uncover hidden neural patterns that are difficult to detect manually.

The integration of hybrid deep learning models became prominent in 2022. Liu et al. (2022) highlighted that combining EEG with machine learning significantly improves depression diagnosis but requires continuous model improvement for generalization . Li et al. (2022) proposed a CNN-based model capable of identifying depression severity using EEG signals, demonstrating high diagnostic accuracy . Similarly, Sarkar et al. (2022) presented a deep learning comparative framework showing superior performance of CNN-based approaches over traditional classifiers .

Deng et al. (2022) introduced SparNet, which combines spatial-frequency representations with attention mechanisms, improving classification performance in depression detection tasks. Khan et al. (2022) proposed wavelet coherence-based EEG biomarkers integrated with deep learning, improving diagnostic reliability.

In 2023, research focused on improving generalization and robustness. Siddiqui et al. (2023) proposed a deep neural network combined with PCA for feature reduction, achieving moderate accuracy while reducing computational complexity. Ksibi et al. (2023) emphasized the importance of incorporating demographic features such as age and gender into EEG-based models for improved classification . Jang et al. (2023) demonstrated that combining multiple EEG paradigms significantly improves classification accuracy compared to single-modality approaches .

Recent works also explored sparse neural networks and graph-based approaches. Wang et al. (2022–2023) proposed sparse graph convolutional networks, reducing model complexity while maintaining high accuracy. These models are particularly useful for large-scale EEG datasets.

Ahmed et al. (2024) highlighted the effectiveness of deep learning models in psychiatric diagnosis, demonstrating improved performance using advanced architectures . Additionally, hybrid multimodal models integrating EEG with fMRI have shown promising results in improving diagnostic accuracy.

Overall, the literature indicates that deep sparse neural networks combined with optimization algorithms (e.g., GA, PSO, and emerging barnacle-based optimization) provide superior performance in EEG classification tasks. However, challenges such as data scarcity, noise, and interpretability remain critical research gaps.

Comparative Table

Author (Year)	**Model**	**Technique**	**Dataset**	**Accuracy**	**Key Strength**	**Key Limitation**
Ko et al. (2020)	Multi-scale NN	Spatial–temporal–spectral DL	BCI EEG	~85%	Multi-frequency feature learning	Limited generalization
Wagh et al. (2020)	GCNN	Graph-based DL	EEG	~90%	Connectivity modeling	High computational cost
Zhang et al. (2020)	Multi-task DL	Clustering-based DL	EEG	~88%	Feature representation learning	Limited temporal modeling
Guney (2021)	DL Review	Analytical	Multi	—	Identifies DL trends	No implementation
Deng et al. (2022)	SparNet	CNN + Attention	Depression EEG	~92%	Spatial-frequency modeling	Increased model complexity
Wang et al. (2022)	Sparse GNN	Sparse graph learning	Epileptic EEG	~94%	Reduced redundancy	Graph design complexity

Ranjani et al. (2023)	CNN	Deep Learning	Depression EEG	~91%	Automated feature extraction	Limited connectivity modeling
Siddiqui et al. (2023)	DNN + PCA	Feature reduction DL	EEG	77.6%	Reduced dimensionality	Lower accuracy
Ahmed et al. (2024)	Advanced DL Model	Hybrid DL	Psychiatric EEG	~95%	High accuracy & robustness	High computational cost

Comparative Analysis

The comparative evaluation of EEG-based neuropsychiatric disorder classification methods demonstrates a clear transition from conventional machine learning to advanced deep learning and optimization-driven frameworks. Early techniques, including Support Vector Machines, Random Forests, and Linear Discriminant Analysis, relied heavily on handcrafted statistical and spectral features extracted from EEG signals. Although these approaches achieved moderate classification performance, they were limited by manual feature engineering, poor scalability, and an inability to effectively capture the nonlinear and high-dimensional characteristics of EEG data. The introduction of Convolutional Neural Networks (CNNs) significantly improved automated feature extraction by learning hierarchical spatial representations directly from raw EEG recordings. However, CNNs alone were insufficient for modeling temporal dependencies and functional relationships among EEG channels.

To overcome these limitations, hybrid deep learning architectures combining CNNs with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were developed. These models simultaneously captured spatial and temporal characteristics of EEG signals, resulting in improved classification accuracy and robustness. More recently, Graph Neural Networks (GNNs) have emerged as an effective solution by representing EEG electrodes as graph nodes connected through functional brain networks. This graph-based representation enables efficient learning of both local and global connectivity patterns, providing superior performance compared with conventional CNN-based approaches. Sparse graph learning further enhances efficiency by eliminating redundant graph connections, reducing computational complexity while preserving diagnostically significant information.

Attention mechanisms and bio-inspired optimization algorithms have substantially enhanced EEG-based neuropsychiatric disorder classification. Transformer models capture long-range dependencies, while the Gooseneck Barnacle Optimization Algorithm (GBOA) improves feature selection, convergence, and computational efficiency when integrated with Deep Sparse Neural Networks. Hybrid frameworks combining CNNs, GNNs, attention mechanisms, sparse learning, and GBOA achieve superior accuracy and robustness. However, challenges related to dataset availability, inter-subject variability, explainability, computational complexity, and real-time deployment continue to drive future research toward scalable and clinically reliable AI systems.

Discussion

EEG-based classification of neuropsychiatric disorders using AI has shown remarkable progress in recent years. Deep learning techniques have enabled automated feature extraction, reducing reliance on handcrafted features. CNNs and GNNs have emerged as dominant architectures due to their ability to capture spatial and temporal patterns.

Sparse neural networks provide an efficient alternative to traditional deep learning models by reducing redundant connections. This leads to faster computation and improved generalization. The integration of optimization algorithms such as GBOA further enhances model performance by optimizing parameters and avoiding local minima.

Despite these advancements, several challenges persist. EEG data is highly noisy and subject-specific, making generalization difficult. Limited availability of labeled datasets restricts the training of deep models. Additionally, the lack of interpretability in deep learning models raises concerns in clinical applications.

Future research should focus on developing explainable AI models, improving dataset quality, and exploring hybrid architectures. The integration of multimodal data, such as EEG with MRI or fNIRS, may further enhance diagnostic accuracy.

Conclusion

This paper presented a comprehensive review of artificial intelligence techniques for EEG-based classification of neuropsychiatric disorders, focusing on deep sparse neural networks and

optimization algorithms. The analysis of recent literature demonstrates that deep learning models significantly improve classification accuracy compared to traditional methods.
Sparse neural networks offer a promising solution to reduce computational complexity while maintaining performance. The integration of optimization algorithms such as the Gooseneck Barnacle Optimization Algorithm enhances feature selection and model training, leading to improved results.
The study highlights the effectiveness of hybrid models combining CNN, GNN, and optimization techniques. These models provide robust performance and scalability, making them suitable for real-world healthcare applications.
However, challenges such as data scarcity, model interpretability, and generalization remain critical issues. Addressing these challenges requires further research in explainable AI, data augmentation, and transfer learning.
Future directions include the development of personalized diagnostic systems, integration of multimodal data, and deployment of real-time AI systems for clinical use. The combination of deep learning and bio-inspired optimization has the potential to revolutionize neuropsychiatric diagnosis, enabling early detection and improved patient outcomes.

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