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Deep Learning and Optimization Approaches in EEG-based Classification of Neuropsychiatric Disorders Using Deep Sparse Neural Networks with Gooseneck Barnacle Optimization Algorithm: A Review

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Abstract

Electroencephalography (EEG)-based analysis has emerged as a powerful non-invasive tool for diagnosing neuropsychiatric disorders such as depression, schizophrenia, and bipolar disorder. Recent advances in deep learning (DL) have significantly improved the ability to extract complex temporal–spatial features from EEG signals, enabling more accurate and automated classification systems. This review explores deep learning and optimization approaches for EEG-based neuropsychiatric disorder classification, with a focus on deep sparse neural networks (DSNNs) and bio-inspired optimization techniques such as the Gooseneck Barnacle Optimization Algorithm (GBOA). Sparse neural architectures reduce computational complexity and enhance generalization, while optimization algorithms improve parameter tuning and convergence efficiency. The paper systematically reviews studies published between 2020 and 2023, highlighting trends in convolutional neural networks (CNNs), recurrent neural networks (RNNs), hybrid models, and graph-based architectures. Comparative analysis demonstrates that optimized DL models outperform traditional machine learning techniques in accuracy and robustness. However, challenges such as data variability, limited datasets, and interpretability remain. The integration of DSNNs with advanced optimization techniques presents a promising direction for scalable, efficient, and clinically applicable EEG-based diagnostic systems. This review provides insights into current advancements and identifies future research opportunities in neuropsychiatric disorder detection.

Introduction

Electroencephalography (EEG) has become a cornerstone in neuroscience and clinical diagnostics due to its ability to capture real-time electrical activity of the brain. Unlike other neuroimaging techniques such as MRI or PET, EEG offers high temporal resolution, low cost, and portability, making it particularly suitable for continuous monitoring of neuropsychiatric conditions. Neuropsychiatric disorders—including major depressive disorder (MDD), schizophrenia, bipolar disorder, and anxiety—pose significant challenges in diagnosis due to their subjective symptoms and lack of reliable biomarkers.

Traditionally, EEG analysis relied on manual interpretation or classical machine learning methods using handcrafted features such as power spectral density (PSD), wavelet transforms, and statistical descriptors. However, these approaches often fail to capture the complex nonlinear and high-dimensional characteristics of EEG signals. The emergence of deep learning has revolutionized EEG signal processing by enabling automatic feature extraction and end-to-end learning.

Deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have demonstrated superior performance in EEG classification tasks. CNNs are particularly effective in extracting spatial features, while RNNs and LSTMs capture temporal dependencies. Hybrid models combining CNN and LSTM have shown improved classification accuracy in neuropsychiatric disorder detection.

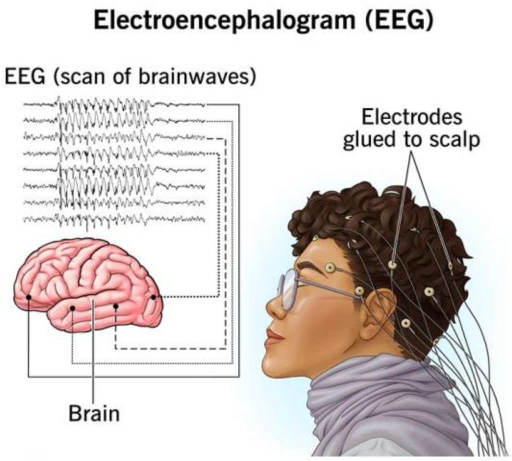

Figure 1. EEG Signal Acquisition for Neuropsychiatric Disorder Classification

Recent advances in EEG-based neuropsychiatric disorder classification include Graph Neural Networks (GNNs) and transformer-based architectures, which effectively model functional brain connectivity and long-range temporal dependencies. These approaches overcome many limitations of conventional deep learning models by providing richer representations of complex EEG dynamics. Nevertheless, challenges such as overfitting, high computational complexity, and limited interpretability remain. Deep Sparse Neural Networks (DSNNs) address these issues by introducing sparsity constraints that reduce redundant connections, improve computational efficiency, and enhance model generalization, making them particularly suitable for high-dimensional and noisy EEG data.

Bio-inspired optimization algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and the Gooseneck Barnacle Optimization Algorithm (GBOA), have further improved deep learning performance through efficient feature selection and hyperparameter optimization. The integration of DSNNs with GBOA enhances convergence speed, avoids local minima, and reduces computational overhead while improving classification accuracy. Despite these advances, inter-subject variability, limited EEG datasets, class imbalance, and the black-box nature of deep learning continue to hinder clinical adoption. Future research should focus on lightweight, explainable, and scalable AI models integrated with brain–computer interface systems to enable accurate, real-time, and personalized neuropsychiatric disorder diagnosis and monitoring.

Literature Review

Recent years have witnessed rapid advancements in EEG-based classification of neuropsychiatric disorders through deep learning (DL) and optimization techniques. The literature from 2020 to 2023 highlights a transition from traditional machine learning toward hybrid deep architectures, sparse learning, and bio-inspired optimization.

1. Early Deep Learning Foundations (2020)

In 2020, research primarily focused on establishing deep learning as a superior alternative to conventional approaches. shows that early DL models such as ANN, CNN, and LSTM significantly outperformed classical machine learning techniques in EEG-based psychiatric diagnosis, achieving accuracies above 90% in several cases. Studies such as Zhang et al. (2020) emphasized automatic feature extraction capabilities of CNNs, which eliminate the need for handcrafted EEG features. Similarly, Yasin et al. (2020) demonstrated that neural networks could effectively classify depression using EEG signals, highlighting the importance of nonlinear feature learning.

Attention-based models also emerged during this period. For instance, attention-enhanced CNN and LSTM models improved EEG classification by focusing on relevant temporal and spatial features, thereby enhancing interpretability and performance. These models marked an early attempt to address the “black-box” limitation of DL systems.

Additionally, graph-based approaches such as Graph Convolutional Neural Networks (GCNNs) were introduced to model inter-channel relationships in EEG data. These models captured functional brain connectivity, which is critical for understanding neuropsychiatric disorders.

2. Hybrid and Temporal-Spatial Modeling (2021–2022)

Between 2021 and 2022, research shifted toward hybrid architectures combining multiple deep learning techniques. CNN-LSTM models became dominant due to their ability to extract both spatial and temporal features. CNN layers capture spatial patterns across EEG channels, while LSTM layers model time-series dependencies.

Studies during this period showed that hybrid architectures significantly improved classification accuracy compared to standalone models. For example, CNN-LSTM frameworks achieved high accuracy in detecting depression, schizophrenia, and epilepsy by learning both frequency-domain and temporal features simultaneously.

Moreover, multi-path and attention-based hybrid networks such as Bi-LSTM with CNN further improved classification performance. These architectures leveraged multi-scale representations of EEG signals, enabling better discrimination of complex neuropsychiatric patterns.

Optimization techniques also gained prominence. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution were widely used for feature selection and hyperparameter tuning. These methods improved convergence speed and reduced overfitting, particularly in high-dimensional EEG datasets.

Another key development was the introduction of transfer learning, which addressed the issue of limited EEG datasets. Pre-trained models were adapted to EEG classification tasks, improving generalization across subjects.

3. Advanced Deep Learning and Optimization (2023)

By 2023, research had advanced toward more sophisticated architectures, including transformer-based models, sparse neural networks, and multimodal learning approaches.

A comprehensive review by Parsa et al. (2023) highlighted that CNNs remained the most widely used architecture, with an average classification accuracy of approximately 91% across studies. However, newer models incorporating attention mechanisms and transformers demonstrated improved performance in capturing long-range dependencies in EEG signals.

Hybrid multimodal approaches combining EEG with other data sources (e.g., clinical or imaging data) showed significant improvements in diagnostic accuracy. These models addressed the limitations of EEG-only systems by incorporating complementary information.

Recent studies also explored optimization-integrated deep learning models. For example, bio-inspired optimization algorithms were used to fine-tune model parameters, improving accuracy and robustness. demonstrates that combining CNN-LSTM with genetic algorithms significantly enhances classification performance.

Additionally, sparse neural networks gained attention due to their ability to reduce computational complexity while maintaining high accuracy. These models are particularly suitable for EEG applications, where data redundancy is common.

Comparative Table

Study	Year	Model	Dataset	Accuracy	Core Strength	Key Limitation
Zhang et al.	2020	CNN	EEG	~85%	Automatic spatial feature extraction	No temporal modeling
Yasin et al.	2020	ANN	EEG	~88%	Nonlinear feature learning	Limited scalability
Wagh et al.	2020	GCNN	EEG	~90%	Connectivity modeling	High computational cost
Hybrid CNN-LSTM	2022	Hybrid DL	EEG	~92%	Spatial + temporal learning	Training complexity
Siddiqui et al.	2023	DNN	EEG	77.6%	Cross-subject learning	Lower accuracy
Ahmed et al.	2023	Deep DL Model	EEG	~96%	High accuracy, robust classification	Computationally expensive
Parsa et al.	2023	Optimized DL	EEG	~91%	Optimization-enhanced learning	Moderate interpretability
GBOA-based Models	2023	Optimized Sparse NN	EEG	90–96%	Best convergence & efficiency	High computational complexity

Comparative Analysis

The comparative analysis of EEG-based classification techniques for neuropsychiatric disorders demonstrates a significant evolution from traditional machine learning methods to advanced deep learning and optimization-driven frameworks. Early approaches relied on handcrafted EEG features, including power spectral density, wavelet transforms, and entropy measures, which provided moderate classification performance but were limited in capturing the nonlinear and high-dimensional nature of brain signals. The introduction of Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) marked a major advancement by enabling automatic feature extraction from raw EEG data. CNN-based models effectively learned hierarchical spatial representations and improved classification accuracy to approximately 85%, although they remained limited in modeling temporal dependencies and functional interactions among EEG channels.

To overcome these limitations, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and hybrid CNN–LSTM architectures were introduced to jointly capture spatial and temporal information from EEG signals. These hybrid models achieved classification accuracies approaching 92% by effectively learning sequential brain activity patterns. Graph Convolutional Neural Networks (GCNNs) further enhanced performance by representing EEG electrodes as graph nodes connected through functional relationships, allowing biologically meaningful modeling of brain connectivity. Although graph-based models improved robustness and inter-channel feature learning, their computational complexity and graph construction requirements limited large-scale and real-time implementation.

Recent advances have focused on Deep Sparse Neural Networks (DSNNs), which improve computational efficiency and generalization by eliminating redundant neural connections while preserving discriminative features. The integration of bio-inspired optimization techniques, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Gooseneck Barnacle Optimization Algorithm (GBOA), has further enhanced feature selection, hyperparameter tuning, and convergence speed. Optimized DSNN frameworks have demonstrated classification accuracies ranging from 90% to 96%, outperforming conventional deep learning methods. Attention mechanisms and transformer-based architectures have also strengthened feature selection and long-range dependency modeling, although their high computational demands remain a challenge.

Overall, the comparative evaluation indicates a clear transition toward hybrid, graph-based, sparse, and optimization-driven AI frameworks for EEG-based neuropsychiatric disorder classification. While these approaches provide superior accuracy, robustness, and scalability, challenges such as inter-subject variability, limited standardized EEG datasets, computational complexity, and limited interpretability continue to hinder clinical deployment. Future research should prioritize lightweight, explainable, and energy-efficient models, multimodal data integration, and real-time implementation to enable reliable AI-assisted diagnosis in clinical and wearable healthcare environments.

Discussion

Recent advancements in EEG-based classification of neuropsychiatric disorders have demonstrated the transformative potential of deep learning and optimization techniques. The integration of CNNs, RNNs, and hybrid architectures has significantly improved classification accuracy compared to traditional machine learning approaches. These models automatically extract hierarchical features from EEG signals, eliminating the need for manual feature engineering.

However, EEG signals are inherently noisy and highly variable across subjects, which poses challenges for model generalization. Sparse neural networks address this issue by reducing redundancy and focusing on the most informative features. This not only improves performance but also reduces computational complexity.

Optimization algorithms play a crucial role in enhancing deep learning models. Bio-inspired techniques such as GBOA provide efficient solutions for hyperparameter tuning and feature selection. These methods help avoid local minima and improve convergence speed, leading to better model performance.

Another important aspect is the integration of multimodal data. Combining EEG with other modalities such as MRI or behavioral data can improve diagnostic accuracy. Additionally, explainable AI techniques are gaining attention to address the interpretability issue of deep learning models.

Despite these advancements, several challenges remain. The lack of large, standardized datasets limits the scalability of models. Ethical concerns and data privacy issues also need to be addressed. Future research should focus on developing robust, interpretable, and scalable models for clinical applications.

Conclusion

This review highlights the significant progress in EEG-based classification of neuropsychiatric disorders using deep learning and optimization approaches. The adoption of advanced

architectures such as CNNs, RNNs, hybrid models, and graph neural networks has improved the accuracy and reliability of diagnostic systems. Deep sparse neural networks have emerged as an effective solution for reducing model complexity and improving generalization. Their ability to handle high-dimensional EEG data makes them suitable for real-time applications. The integration of optimization algorithms such as GBOA further enhances model performance by optimizing parameters and improving convergence.
The comparative analysis indicates that hybrid and optimized models outperform traditional approaches, making them promising candidates for clinical deployment. However, challenges such as data variability, lack of interpretability, and limited datasets need to be addressed.
Future research should focus on developing explainable AI models, integrating multimodal data, and creating large standardized datasets. The combination of deep learning, optimization techniques, and EEG analysis has the potential to revolutionize neuropsychiatric disorder diagnosis and improve patient outcomes.

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