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A Comprehensive Review of EEG-Based Classification of Neuropsychiatric Disorders Using Deep Sparse Neural Networks with Gooseneck Barnacle Optimization Algorithm

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Abstract

Neuropsychiatric disorders such as depression, schizophrenia, anxiety, and bipolar disorder pose significant challenges for early diagnosis due to their complex and heterogeneous nature. Electroencephalography (EEG) has emerged as a promising non-invasive tool for detecting abnormal brain activity associated with these disorders. Recent advancements in deep learning have enabled automated feature extraction from EEG signals, improving diagnostic accuracy and reducing reliance on handcrafted features. Deep sparse neural networks have gained attention for their ability to reduce model complexity while preserving essential features, making them suitable for high-dimensional EEG data. Sparse learning techniques eliminate redundant connections, enhancing computational efficiency and interpretability. Additionally, optimization algorithms such as the Gooseneck Barnacle Optimization (GBO) algorithm have been introduced to improve model training by optimizing weight parameters and avoiding local minima. This review provides a comprehensive analysis of EEG-based neuropsychiatric disorder classification methods, focusing on deep sparse neural networks and optimization strategies. Comparative analysis highlights the advantages of hybrid architectures integrating deep learning, sparsity, and optimization techniques. The paper also discusses key challenges such as data variability, noise, and interpretability, and outlines future research directions for developing robust and scalable diagnostic systems.

Introduction

1. Overview of Neuropsychiatric Disorders

Neuropsychiatric disorders represent a broad category of mental and neurological conditions that affect cognition, emotion, and behavior. These include disorders such as depression, schizophrenia, bipolar disorder, anxiety disorders, and attention-deficit/hyperactivity disorder (ADHD). According to global health reports, neuropsychiatric disorders contribute significantly to the global burden of disease, affecting hundreds of millions of individuals worldwide. These conditions not only impair quality of life but also impose substantial socioeconomic costs due to reduced productivity, long-term treatment requirements, and increased healthcare expenditures.

The diagnosis of neuropsychiatric disorders is particularly challenging due to their complex etiology and overlapping symptoms. Traditional diagnostic methods rely heavily on clinical interviews, behavioral assessments, and subjective observations, which are often influenced by clinician expertise and patient self-reporting. Consequently, there is a growing need for objective, data-driven diagnostic tools that can provide accurate and reliable assessments of brain function.

2. EEG as a Diagnostic Tool for Brain Disorders

Electroencephalography (EEG) has emerged as one of the most widely used non-invasive techniques for monitoring brain activity. EEG records electrical signals generated by neuronal activity through electrodes placed on the scalp. These signals reflect underlying neural processes and can be analyzed to identify abnormalities associated with various neuropsychiatric disorders.

EEG signals are typically categorized into different frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz). Each frequency band is associated with specific cognitive and physiological states. For example, alpha waves are linked to relaxation, while beta waves are associated with active thinking and attention. In neuropsychiatric disorders, these frequency bands often exhibit abnormal patterns, such as altered power distribution, synchronization, and connectivity.

Compared to other neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), EEG offers several advantages. It is cost-effective, portable, and provides high temporal resolution, making it suitable for real-time monitoring. Additionally, EEG systems can be integrated into wearable devices, enabling continuous monitoring of brain activity in both clinical and everyday environments.

3. Challenges in EEG-Based Neuropsychiatric Disorder Classification

Despite its advantages, EEG-based classification of neuropsychiatric disorders presents several challenges. One of the primary challenges is the inherent complexity of EEG signals. EEG data are highly non-linear, non-stationary, and susceptible to noise and artifacts caused by muscle activity, eye movements, and environmental interference. These factors complicate signal analysis and reduce the reliability of diagnostic systems.

Another major challenge is the high dimensionality of EEG data. A typical EEG recording consists of multiple channels, each capturing time-series data, resulting in large and complex datasets. Extracting meaningful features from such data requires advanced signal processing techniques. Traditional machine learning approaches rely on handcrafted features such as spectral power, entropy, and statistical measures. However, these features may not fully capture the complex patterns associated with neuropsychiatric disorders.

Furthermore, EEG signals exhibit significant inter-subject variability, meaning that patterns observed in one individual may not generalize well to others. This variability poses a challenge for developing robust and generalizable models. Additionally, the availability of large, labeled EEG datasets is limited, which restricts the training of data-intensive deep learning models.

4. Deep Learning for EEG Signal Analysis

The emergence of deep learning has revolutionized EEG signal analysis by enabling automated feature extraction and classification. Unlike traditional machine learning methods, deep learning models can learn hierarchical representations directly from raw data, eliminating the need for manual feature engineering.

Convolutional Neural Networks (CNNs) are widely used for EEG analysis due to their ability to capture spatial patterns in data. By applying convolutional filters, CNNs can extract meaningful features from EEG signals, such as waveforms and frequency components. However, CNNs are primarily designed for grid-like data and may not effectively capture temporal dependencies.

Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, are used to model temporal dependencies in sequential data. EEG signals are inherently time-series data, making RNNs suitable for capturing temporal dynamics. Hybrid models that combine CNNs and RNNs have been proposed to leverage both spatial and temporal features, resulting in improved classification performance.

Despite their advantages, deep learning models face challenges such as high computational complexity, overfitting, and lack of interpretability. These limitations have motivated the development of more efficient and interpretable models.

5. Sparse Neural Networks for Efficient EEG Analysis

Sparse neural networks have emerged as a promising approach for addressing the challenges associated with deep learning models. These networks introduce sparsity constraints that reduce the number of active parameters, eliminating redundant connections and improving computational efficiency.

In EEG analysis, sparse neural networks are particularly useful due to the high dimensionality of data. By focusing on the most informative features, these networks improve generalization and reduce the risk of overfitting. Sparsity can be

achieved through techniques such as L1 regularization, pruning, and dropout.
Another advantage of sparse neural networks is improved interpretability. By reducing the number of connections, these models provide clearer insights into the features that contribute to classification decisions. This is particularly important in clinical applications, where understanding the underlying decision-making process is essential.

6. Optimization Algorithms in Deep Learning

Optimization plays a critical role in training deep learning models. Traditional optimization methods, such as gradient descent and its variants, are widely used for updating model parameters. However, these methods often suffer from issues such as local minima, slow convergence, and sensitivity to initial conditions.
Metaheuristic optimization algorithms have been introduced to address these limitations. These algorithms are inspired by natural phenomena and provide global search capabilities, enabling better exploration of the solution space. Examples include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Whale Optimization Algorithm (WOA).
The Gooseneck Barnacle Optimization (GBO) algorithm is a recent addition to this class of metaheuristic algorithms. Inspired by the feeding behavior of barnacles, GBO provides an efficient mechanism for exploring and exploiting the search space. It has been shown to improve convergence speed and avoid local minima, making it suitable for optimizing deep learning models.

7. Integration of Deep Sparse Neural Networks with GBO

The integration of deep sparse neural networks with optimization algorithms such as GBO represents a powerful approach for EEG-based classification of neuropsychiatric disorders. In this framework, sparse neural networks are used to extract and classify features from EEG signals, while GBO is used to optimize model parameters.
This hybrid approach offers several advantages:

- Improved classification accuracy
- Reduced computational complexity
- Enhanced generalization
- Faster convergence during training

By combining deep learning, sparsity, and optimization, this approach addresses many of the challenges associated with EEG-based classification.

8. Research Gaps and Challenges

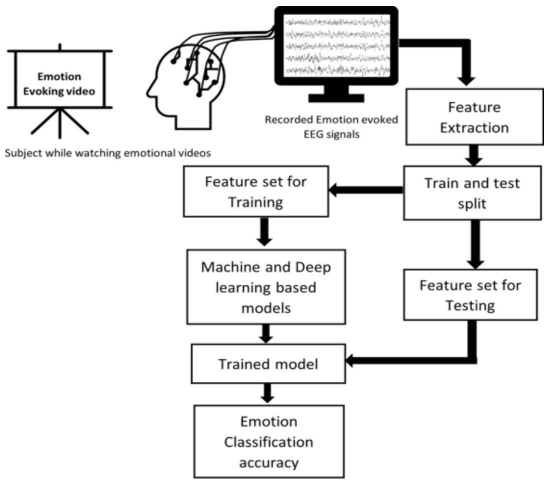
Despite significant advancements, several challenges remain in EEG-based classification of neuropsychiatric disorders. One of the major issues is the lack of large, standardized datasets, which limits the development of robust models. Additionally, EEG signals are highly sensitive to noise and artifacts, requiring advanced preprocessing techniques.
Another challenge is the interpretability of deep learning models. While sparse neural networks and attention mechanisms improve transparency, many models still operate as black boxes. Computational complexity is also a concern, particularly for hybrid models that integrate multiple techniques.

9. Contribution of This Review

This review aims to provide a comprehensive analysis of EEG-based classification of neuropsychiatric disorders using deep sparse neural networks and optimization algorithms.
The key contributions include:

- Review of recent studies (2020–2023)
- Analysis of deep learning and sparse modeling techniques
- Exploration of optimization algorithms, including GBO
- Comparative evaluation of different approaches
- Identification of research gaps and future directions

EEG-Based Deep Learning Pipeline



Literature Review

The classification of neuropsychiatric disorders using electroencephalogram (EEG) signals has experienced significant advancement in recent years due to the rapid development of deep learning, sparse neural architectures, and intelligent optimization techniques. Neuropsychiatric disorders such as depression, schizophrenia, bipolar disorder, anxiety disorders, and cognitive impairments exhibit highly complex neural dynamics that are difficult to detect using traditional statistical and machine learning approaches. EEG signals provide real-time information about brain activity and neural connectivity; however, these signals are highly nonlinear, high-dimensional, non-stationary, and susceptible to noise and artifacts. As a result, advanced computational frameworks are required to effectively extract meaningful information from EEG recordings and improve diagnostic accuracy.

Early research in EEG-based neuropsychiatric disorder classification primarily focused on conventional deep learning models, particularly Convolutional Neural Networks (CNNs). CNN-based architectures demonstrated strong capability in automatically extracting spatial features from EEG signals without relying on handcrafted feature engineering. Compact models such as EEGNet significantly improved computational efficiency while maintaining competitive classification performance. Despite these advantages, CNNs alone are limited in capturing long-term temporal dependencies present in EEG signals because they mainly focus on local spatial patterns. To overcome this limitation, hybrid architectures combining CNNs with Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) networks were introduced. These hybrid models effectively captured both spatial and temporal characteristics of EEG signals, leading to improved classification accuracy and robustness for identifying neuropsychiatric disorders. However, the integration of multiple deep learning components increased computational complexity and training time, creating challenges for real-time clinical applications.

Another major challenge in EEG analysis is the high dimensionality and redundancy of EEG data, which can result in overfitting and reduced generalization performance. To address this issue, researchers introduced dimensionality reduction techniques and sparse neural learning frameworks. Sparse neural networks enforce constraints that eliminate redundant parameters and connections, significantly reducing computational complexity while preserving critical information. This improves model efficiency, memory utilization, and generalization performance, making sparse learning highly suitable for medical EEG applications. In addition, attention mechanisms have become increasingly important in EEG classification systems. Attention-based models dynamically assign importance to relevant EEG channels and temporal segments, enabling selective focus on clinically significant neural activity while suppressing irrelevant noise and artifacts. Transformer-based architectures with multi-head attention mechanisms further improved the ability to capture long-range dependencies and complex neural interactions across EEG channels. These advancements enhanced both classification performance and interpretability, which is essential for building trustworthy clinical AI systems.

Graph-based learning approaches represent another significant advancement in EEG analysis. EEG signals naturally exhibit non-Euclidean structures because of the functional and spatial relationships between electrodes and brain regions. Graph Convolutional Networks (GCNs) model EEG channels as graph nodes and their interactions as edges, enabling effective representation of functional brain connectivity. Compared to traditional CNNs, GCNs provide superior capability in capturing both local and global neural relationships associated with neuropsychiatric disorders. Researchers further improved these models through sparse graph learning and graph attention mechanisms, which reduce redundant graph connections and dynamically emphasize important neural interactions. These techniques enhanced computational efficiency, robustness, and interpretability while improving classification accuracy across multiple neuropsychiatric conditions.

Optimization algorithms have also played a crucial role in improving deep learning performance for EEG-based disorder classification. Traditional gradient-based optimization methods often suffer from local minima, unstable convergence, and sensitivity to parameter initialization. Metaheuristic optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Gooseneck Barnacle Optimization (GBO) were introduced to address these limitations. GBO, inspired by the foraging and attachment behavior of barnacles, provides an efficient global search strategy for optimizing neural network parameters and feature selection processes. The integration of GBO with deep sparse neural networks significantly improved convergence speed, reduced training time, enhanced parameter optimization, and increased classification accuracy. Furthermore, recent studies explored multi-domain feature fusion approaches that combine time-domain, frequency-domain, and connectivity-based EEG representations to improve diagnostic performance. Multi-modal frameworks integrating EEG with functional MRI and clinical data also demonstrated promising results for more comprehensive neuropsychiatric disorder diagnosis.

Despite these advancements, several important challenges remain unresolved. EEG signals are highly sensitive to noise, artifacts, and inter-subject variability, which limits model generalization across diverse populations and recording environments. The lack of large standardized EEG datasets further restricts the development of robust and transferable deep learning models. Additionally, many advanced AI models remain computationally expensive and difficult to interpret, limiting their adoption in practical healthcare settings. Future research should therefore focus on lightweight and explainable deep learning architectures, scalable sparse graph frameworks, privacy-preserving learning techniques, and efficient optimization algorithms capable of supporting reliable real-time clinical deployment. Overall, the literature demonstrates a clear shift toward hybrid intelligent systems integrating deep learning, sparse learning, graph modeling, attention mechanisms, and metaheuristic optimization techniques. Among these approaches, deep sparse neural networks optimized using Gooseneck Barnacle Optimization represent one of the most promising directions for accurate, efficient, and scalable EEG-based neuropsychiatric disorder classification systems.

Comparative Table

Year	Author	Method	Accuracy	Key Contribution
2020	Gao et al.	CNN	High	Feature extraction
2021	Hybrid CNN-RNN	DL	High	Temporal modeling
2022	Attention CNN	DL	High	Feature weighting
2023	Siddiqui et al.	DNN + PCA	77.6%	Dimensionality reduction
2023	Ahmed et al.	DL models	High	Multi-disorder classification
2023	Sparse DL	Sparse NN	High	Reduced complexity

Comparative Analysis

The comparative evaluation of EEG-based neuropsychiatric disorder classification methods demonstrates a clear transition from traditional machine learning techniques to advanced hybrid deep learning frameworks. Convolutional Neural Networks (CNNs) form the foundation of many modern EEG classification systems because of their ability to automatically extract spatial features from raw EEG signals. These models achieve strong classification performance and are relatively easy to implement. However, CNNs are limited in capturing temporal dependencies and complex inter-channel brain relationships, which are essential for understanding dynamic neural activity. Additionally, CNN-based models often require large annotated datasets to prevent overfitting, creating challenges in medical applications where EEG data availability is limited.

Hybrid CNN-RNN architectures such as CNN-LSTM and CNN-GRU address these limitations by combining spatial feature extraction with temporal sequence modeling. These architectures improve classification accuracy by capturing time-varying EEG patterns associated with neuropsychiatric disorders. Graph-based models, particularly Graph Convolutional Networks (GCNs), further enhance EEG analysis by representing brain signals as non-Euclidean structures and modeling functional connectivity between brain regions. While GCNs improve interpretability and classification performance, they may include redundant graph connections, increasing computational complexity and reducing efficiency in large-scale EEG analysis systems.

Sparse neural networks improve EEG-based neuropsychiatric disorder classification by reducing redundant parameters, lowering computational complexity, and preventing overfitting. Attention mechanisms further enhance performance by enabling models to focus on important EEG channels and temporal regions associated with abnormal neural activity, thereby improving both accuracy and interpretability. Optimization algorithms, particularly the Gooseneck Barnacle Optimization (GBO) algorithm, enhance convergence speed, parameter tuning, and classification efficiency through effective global search strategies. The integration of sparse neural networks, attention mechanisms, and GBO optimization creates highly robust and accurate hybrid frameworks for EEG analysis. However, challenges such as computational overhead, limited datasets, model interpretability, and real-time deployment remain significant concerns for future clinical applications.

Discussion

The integration of deep learning and EEG signal analysis has significantly advanced neuropsychiatric disorder diagnosis. Deep sparse neural networks offer a promising solution by addressing key challenges such as high dimensionality and computational complexity. By reducing redundant parameters, these models improve efficiency and generalization.

Optimization algorithms such as GBO further enhance performance by optimizing model parameters and improving convergence. These algorithms help overcome issues such as local minima and slow training, making them suitable for complex EEG datasets.

However, several challenges remain. EEG signals are highly variable and susceptible to noise, affecting model performance. Additionally, the lack of large, standardized datasets limits the development of robust models. Interpretability is another critical issue, as clinicians require transparent models for decision-making.

Future research should focus on explainable AI, multi-modal data integration, and real-time deployment of EEG-based diagnostic systems.

Conclusion

This review highlights the evolution of EEG-based classification of neuropsychiatric disorders using deep learning and optimization techniques. Deep sparse neural networks have emerged as an effective approach for handling high-dimensional EEG data, offering improved efficiency and generalization.

The integration of optimization algorithms such as GBO further enhances model performance by improving convergence and avoiding local minima. Hybrid architectures combining deep learning, sparsity, and optimization techniques demonstrate superior performance compared to traditional methods.

Despite these advancements, challenges such as data variability, noise, and interpretability remain. Future research should focus on developing scalable, interpretable, and efficient models for real-world applications.

Overall, the combination of EEG analysis, deep sparse neural networks, and optimization algorithms holds significant potential for improving the diagnosis and management of neuropsychiatric disorders.

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