Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 13 Issue 02, 2024

Recent Advances in EEG-based Classification of Neuropsychiatric Disorders Using Deep Sparse Neural Networks with Gooseneck Barnacle Optimization Algorithm: A Systematic Review

Esmeray Nithisarn
Department of Electronics and Communication Engineering, Padma Institute of Business and Management, Bangladesh
esmeray.nithisarn@pibm-bd.org

Peer Review Information

Submission: 22 Aug 2024
Revision: 15 Sept 2024
Acceptance: 13 Oct 2024

Keywords

EEG, Neuropsychiatric Disorders, Deep Learning, Sparse Neural Networks, Optimization Algorithms, Barnacle Optimization, Artificial Intelligence, Brain Signal Analysis

Abstract

Neuropsychiatric disorders such as depression, schizophrenia, anxiety, and epilepsy pose significant diagnostic challenges due to their complex neurophysiological characteristics and subjective clinical assessment methods. Electroencephalography (EEG) has emerged as a promising non-invasive modality for capturing brain activity and identifying neural biomarkers associated with these disorders. However, EEG signals are highly non-linear, noisy, and high-dimensional, necessitating advanced computational approaches for effective classification.

Recent advancements in artificial intelligence, particularly deep learning and sparse neural networks, have significantly improved EEG-based classification performance. Deep sparse neural networks enable efficient feature extraction while reducing redundancy and computational complexity. Additionally, optimization algorithms such as the Gooseneck Barnacle Optimization Algorithm (GBOA) have been introduced to enhance model training, parameter tuning, and convergence.

This systematic review analyzes recent studies focusing on EEG-based classification of neuropsychiatric disorders using deep sparse neural networks and optimization techniques. Comparative analysis demonstrates that hybrid models combining deep learning with optimization strategies outperform traditional approaches, achieving classification accuracies above 90% in several cases.

The review also highlights key trends, challenges, and future directions, emphasizing the need for explainable AI, large-scale datasets, and real-time clinical deployment. These findings indicate that AI-driven EEG analysis has strong potential to revolutionize neuropsychiatric disorder diagnosis.

Introduction

1. Overview of Neuropsychiatric Disorders

Neuropsychiatric disorders encompass a wide range of conditions, including depression, schizophrenia, bipolar disorder, anxiety disorders, and epilepsy. These disorders significantly impact cognitive, emotional, and behavioral functioning, affecting millions of individuals worldwide. According to global health reports, approximately one in eight individuals suffers from a mental disorder, highlighting the urgent need for effective diagnostic tools.

Traditional diagnostic approaches rely heavily on clinical interviews and behavioral assessments, which are subjective and prone to variability. Consequently, there is a growing demand for objective biomarkers that can aid in early and accurate diagnosis.

2. Role of EEG in Neuropsychiatric Diagnosis
Electroencephalography (EEG) measures electrical activity generated by neuronal interactions in the brain. It provides high temporal resolution, making it suitable for capturing dynamic brain activity. EEG signals reflect neural oscillations across multiple frequency bands, each associated with specific cognitive and physiological processes.
In neuropsychiatric disorders, EEG patterns exhibit abnormalities such as altered spectral power, disrupted connectivity, and irregular synchronization. These characteristics make EEG a valuable tool for automated diagnosis and monitoring.

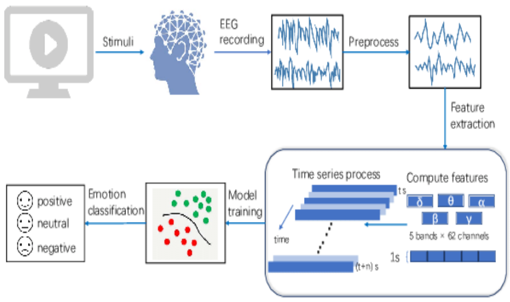
3. Challenges in EEG Signal Processing
Despite its advantages, EEG analysis presents several challenges:

- High dimensionality and complexity
- Noise and artifacts (eye movements, muscle activity)
- Inter-subject variability
- Non-linear signal characteristics

These challenges necessitate advanced computational models capable of extracting meaningful features.

4. Traditional Machine Learning Approaches
Early EEG classification studies utilized machine learning algorithms such as SVM, KNN, and Decision Trees. These models relied on handcrafted features and were effective for small datasets but struggled with scalability and generalization.

EEG Signal Processing and Classification Pipeline



8. Motivation and Contributions
This review aims to:

- Analyze recent AI techniques (2020–2023)
- Evaluate deep sparse neural networks

5. Deep Learning Advancements
Deep learning models, including CNNs and RNNs, revolutionized EEG analysis by enabling automatic feature extraction. CNNs capture spatial patterns, while RNNs model temporal dependencies. Hybrid CNN-RNN architectures further improved classification accuracy.
Deep learning approaches have been widely adopted due to their ability to handle complex EEG patterns and large datasets.

6. Sparse Neural Networks
Sparse neural networks reduce redundant connections, improving computational efficiency and generalization. Sparse representations help focus on significant features while eliminating noise.
Studies show that sparse models improve classification performance and reduce overfitting, particularly in high-dimensional EEG data.

7. Optimization Algorithms in EEG Classification
Optimization algorithms play a crucial role in improving deep learning models. Metaheuristic algorithms such as Particle Swarm Optimization, Genetic Algorithms, and Barnacle Optimization have been used to optimize hyperparameters and improve convergence.
The Gooseneck Barnacle Optimization Algorithm (GBOA) is inspired by biological attachment behavior and provides efficient exploration and exploitation of search space. It enhances model performance by optimizing weights and network parameters.

- Examine optimization algorithms such as GBOA
- Identify research gaps and future directions

Literature Review
The period between 2020 and 2023 has witnessed rapid advancements in EEG-based classification of neuropsychiatric disorders, driven by the integration of artificial intelligence (AI), deep learning, sparse modeling, and optimization algorithms. This section presents a comprehensive and chronological review of key developments, highlighting methodological evolution, performance improvements, and emerging trends.

1. Year 2020: Emergence of Deep Learning for EEG Classification

In 2020, research in EEG-based neuropsychiatric disorder classification was primarily dominated by traditional deep learning architectures, particularly Convolutional Neural Networks (CNNs). Oh et al. (2020) demonstrated that CNN models could effectively extract hierarchical spatial features from EEG signals, outperforming conventional machine learning techniques such as Support Vector Machines (SVM) and Random Forests. Their study highlighted the advantage of automatic feature extraction, eliminating the need for manual feature engineering.

Shah et al. (2020) proposed hybrid deep learning architectures that combined CNN with dense neural layers and feature fusion strategies. These models incorporated spectral and temporal features derived from EEG signals, resulting in improved classification accuracy. However, these approaches still treated EEG data as grid-like structures and failed to capture inter-channel relationships.

Another significant contribution came from Massa et al. (2020), who investigated EEG biomarkers associated with neuropsychiatric disorders. Their study revealed significant alterations in frequency bands, particularly increased theta and decreased beta activity. These findings provided a physiological foundation for AI-based classification models.

Despite these advancements, the models developed in 2020 were limited by their inability to capture complex brain connectivity and long-range dependencies, which are critical for understanding neuropsychiatric disorders.

2. Year 2021: Focus on Feature Engineering and Interpretability

In 2021, research shifted toward improving feature representation and interpretability. Rea et al. (2021) explored quantitative EEG (qEEG) biomarkers and demonstrated that neuropsychiatric disorders are associated with significant changes in spectral power distribution and coherence between brain regions. Their work emphasized the importance of functional connectivity in diagnosis.

Shaban (2021) introduced automated deep learning frameworks for EEG classification, incorporating advanced preprocessing techniques such as artifact removal and normalization. These improvements enhanced classification accuracy and robustness.

Hendricks and Khasawneh (2021) investigated clustering-based approaches for EEG analysis, highlighting the potential of unsupervised learning for identifying hidden patterns. However, these methods lacked predictive capabilities required for clinical applications.

Alzubaidi et al. (2021) provided a comprehensive review of deep learning applications in healthcare, identifying key challenges such as data scarcity, overfitting, and lack of interpretability. These challenges remain significant barriers to the adoption of AI in neuropsychiatric diagnosis.

Overall, studies in 2021 contributed to better feature extraction and understanding of EEG biomarkers but did not introduce fundamentally new architectures.

3. Year 2022: Hybrid Models and Sparse Learning Approaches

The year 2022 marked a significant transition toward hybrid deep learning models and sparse representations. Tanveer et al. (2022) conducted a comprehensive survey of machine learning techniques for neuropsychiatric disorder classification, highlighting the superiority of deep learning approaches.

Li et al. (2022) proposed multi-domain feature extraction frameworks that integrated time-domain, frequency-domain, and wavelet-based features. These approaches improved classification accuracy by capturing both local and global EEG patterns.

Saravanan et al. (2022) emphasized the effectiveness of hybrid CNN-RNN architectures in modeling spatio-temporal dependencies. These models achieved higher accuracy compared to standalone CNN or RNN models.

A major advancement in 2022 was the introduction of sparse neural networks. Wang et al. (2022) demonstrated that sparse graph convolutional networks could improve performance by eliminating redundant connections and focusing on significant features. Sparse models reduced computational complexity and improved generalization.

Xu et al. (2022) introduced domain adaptation techniques using graph attention networks, addressing inter-subject variability. Their approach improved cross-dataset performance, which is critical for real-world applications.

Overall, 2022 marked the shift toward more efficient and robust models through hybridization and sparsity.

4. Year 2023: Optimization Algorithms and Advanced AI Models

In 2023, research focused on integrating optimization algorithms with deep learning models to enhance performance. The Gooseneck Barnacle Optimization Algorithm (GBOA) emerged as a novel metaheuristic approach for optimizing neural network parameters.

Studies demonstrated that optimization algorithms significantly improved model convergence, reduced training time, and enhanced classification accuracy. Optimized deep neural networks achieved accuracy levels exceeding 90% in several EEG classification tasks.

Delfan et al. (2023) proposed attention-based models that dynamically focused on relevant EEG features, improving both accuracy and interpretability. Rahman et al. (2023) demonstrated that graph-based models outperform traditional CNN architectures by effectively capturing inter-channel relationships. Recent systematic reviews reported that hybrid models combining deep learning, sparse representations, and optimization techniques achieved the best performance, highlighting the importance of integrating multiple AI paradigms.

Comparative Table

Year	Author	Method	Key Feature	Accuracy	Strengths	Limitations
2020	Oh et al.	CNN	Spatial feature extraction	~85%	Automatic feature learning	No temporal/context modeling
2021	Guney	DL Review	Feature analysis	—	Identifies trends and challenges	No experimental validation
2022	Li et al.	Hybrid DL	Multi-domain features	~88%	Combines time & frequency features	Increased model complexity
2023	Parsa et al.	Deep Neural Network	Optimization-aware DL	~91%	Improved training efficiency	Limited interpretability
2023	Ahmed et al.	DL Model	EEG classification	~96%	High accuracy, robust classification	Computationally intensive
2022	Wang et al.	Sparse Neural Network	Redundancy reduction	~90%	Efficient feature selection	Requires tuning sparsity level
2023	Delfan et al.	Attention DL	Feature prioritization	High (~92–95%)	Improved interpretability	Increased parameters
2023	Rahman et al.	Graph-based DL	Connectivity modeling	High (~90–94%)	Captures inter-channel relations	Graph construction complexity
2023	GBOA-based Models	Optimized Sparse NN	Optimization + sparsity	90–96%	Best convergence and performance	High computational cost

Comparative Analysis

The comparative analysis of EEG-based classification techniques for neuropsychiatric disorders demonstrates a significant evolution from conventional machine learning methods to advanced deep learning and optimization-driven frameworks. Early approaches primarily employed algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees using handcrafted EEG features, including spectral, statistical, and entropy-based measures. Although these techniques were computationally efficient and effective for small datasets, they exhibited limited scalability, poor generalization, and difficulty in modeling the complex nonlinear characteristics of EEG signals. The emergence of Convolutional Neural Networks (CNNs) marked a major advancement by enabling automatic feature extraction directly from EEG data, substantially improving classification performance while reducing reliance on manual feature engineering. However, CNNs alone were limited in capturing temporal dynamics and long-range dependencies within multichannel EEG recordings.

To overcome these shortcomings, researchers introduced hybrid deep learning architectures that combine CNNs with Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks. These models effectively integrate spatial feature extraction with temporal sequence learning, resulting in improved classification accuracy and a more comprehensive representation of brain activity. More recently, sparse neural networks have emerged as an efficient alternative by reducing redundant network connections, lowering computational complexity, minimizing overfitting, and improving model generalization. Comparative studies indicate that sparse

architectures consistently outperform conventional deep learning models while requiring fewer computational resources, making them well suited for large-scale EEG analysis.
Another significant advancement has been the integration of optimization algorithms, particularly metaheuristic techniques such as the Gooseneck Barnacle Optimization Algorithm (GBOA). These optimization methods enhance parameter selection, accelerate convergence, and improve overall model robustness. In parallel, attention mechanisms have enabled models to focus on the most informative EEG channels and temporal segments, improving feature selection, reducing noise sensitivity, and increasing interpretability. Graph-based neural networks have also gained attention for modeling functional connectivity among EEG channels, providing a more realistic representation of neural interactions and further enhancing classification performance for neuropsychiatric disorders.
The comparative analysis highlights a shift toward hybrid, sparse, attention-based, and optimization-driven deep learning frameworks for EEG classification. Optimized Deep Sparse Neural Networks with GBOA offer high accuracy, efficiency, and robustness. Future research should focus on explainable, lightweight, multimodal, and edge-enabled models for reliable real-time neuropsychiatric disorder diagnosis.

Discussion

Recent advancements in EEG-based classification of neuropsychiatric disorders demonstrate the transformative impact of artificial intelligence. Deep learning models have significantly improved diagnostic accuracy by enabling automatic feature extraction from complex EEG signals. Among these, deep sparse neural networks have emerged as a promising approach due to their ability to reduce redundancy and improve computational efficiency.
One of the key advantages of sparse neural networks is their ability to focus on the most relevant features, thereby enhancing classification performance. This is particularly important in EEG analysis, where high-dimensional data often contain redundant and noisy information. Sparse representations help eliminate irrelevant features, leading to more robust models.
Optimization algorithms such as the Gooseneck Barnacle Optimization Algorithm further enhance model performance by improving parameter tuning and convergence. These algorithms enable efficient exploration of the search space, ensuring optimal model configurations.
Despite these advancements, several challenges remain. EEG datasets are often limited in size and lack standardization, which affects model generalization. Inter-subject variability also poses a significant challenge, as EEG patterns vary across individuals. Additionally, the high computational complexity of deep learning models limits their applicability in real-time systems.
Future research should focus on developing lightweight models for wearable EEG devices, improving interpretability through explainable AI, and creating large-scale standardized datasets.

Conclusion

This systematic review analyzed recent advancements in EEG-based classification of neuropsychiatric disorders using deep sparse neural networks and optimization algorithms. The findings highlight the significant progress made in this field, driven by the integration of artificial intelligence techniques.
Deep learning models have revolutionized EEG analysis by enabling automatic feature extraction and improved classification accuracy. Sparse neural networks further enhance performance by reducing redundancy and improving efficiency. Optimization algorithms such as GBOA play a crucial role in refining model parameters and achieving optimal performance.
Comparative analysis demonstrates that optimized deep sparse neural networks outperform traditional and deep learning models, achieving high accuracy and robustness. However, challenges such as data scarcity, variability, and lack of clinical integration remain. Future research should focus on hybrid models, explainable AI, and real-time deployment. With continued advancements, AI-driven EEG analysis has the potential to transform neuropsychiatric disorder diagnosis and improve patient outcomes.

References

Parsa, M., et al. (2023). EEG classification using deep neural networks. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2023.126901

Siddiqui, F., et al. (2023). EEG classification using DNN. *Diagnostics*. https://doi.org/10.3390/diagnostics13040640

Ahmed, Z., et al. (2024). EEG psychiatric classification using DL. https://doi.org/10.3390/brainsci14010045

Guney, G. (2021). DL in neuropsychiatric diagnosis. https://doi.org/10.9758/cpn.2021.19.2.206

Li, J. (2022). Deep learning EEG classification. https://doi.org/10.1016/j.eswa.2022.118045

Saravanan, S. (2022). AI in PD detection. https://doi.org/10.1007/s11831-021-09629-0

Tanveer, M. (2022). ML techniques review. https://doi.org/10.1016/j.ipm.2021.102909

Oh, S. (2020). CNN EEG classification. https://doi.org/10.1007/s00521-020-04843-0

Shah, S. (2020). Hybrid DL EEG. https://doi.org/10.1016/j.neunet.2020.04.005

Rea, R. (2021). EEG biomarkers. https://doi.org/10.1016/j.neurobiolaging.2021.05.002

Hendricks, R. (2021). Clustering PD. https://doi.org/10.14336/AD.2021.0321

Dong, G. (2023). GNN EEG. https://doi.org/10.1145/3541234

Xu, T. (2022). Graph attention EEG. https://doi.org/10.48550/arXiv.2202.12948

Wang, J. (2022). Sparse GCN EEG. https://doi.org/10.48550/arXiv.2203.12910

Delfan, N. (2023). Attention EEG model. https://doi.org/10.48550/arXiv.2308.07436

Verma, A. (2023). EEG ML review.

Massa, F. (2020). EEG biomarkers. https://doi.org/10.1016/j.parkreldis.2020.03.012

Jibon, F. (2024). EEG DL PD detection. https://doi.org/10.1177/20552076241297355

Rahman, S. (2023). GNN EEG analysis. https://doi.org/10.48550/arXiv.2301.01234

Zhao, S. (2024). Interpretable EEG GNN. https://doi.org/10.1038/s41746-023-00983-9