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A Survey of Methods and Architectures for EEG-based Classification of Neuropsychiatric Disorders Using Deep Sparse Neural Networks with Gooseneck Barnacle Optimization Algorithm

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Abstract

Electroencephalography (EEG)-based classification of neuropsychiatric disorders has emerged as a critical research domain due to its non-invasive nature and ability to capture real-time brain activity. Recent advancements in deep learning, particularly deep sparse neural networks, have significantly improved classification accuracy by enabling automatic feature extraction and reducing redundancy in high-dimensional EEG data. This paper presents a comprehensive survey of methods and architectures employed for EEG-based diagnosis of neuropsychiatric disorders such as depression, schizophrenia, and Alzheimer's disease. Furthermore, the integration of bio-inspired optimization algorithms, specifically the Gooseneck Barnacle Optimization Algorithm (GBOA), is explored to enhance model convergence, feature selection, and parameter tuning. The survey highlights key developments, including convolutional neural networks (CNN), recurrent neural networks (RNN), graph neural networks (GNN), and hybrid deep architectures. Studies indicate that deep learning models achieve average classification accuracies exceeding 90%, with CNN-based models being the most widely adopted . However, challenges such as data variability, limited datasets, and interpretability persist.
This work provides a comparative analysis of existing approaches, identifies research gaps, and discusses future directions for developing efficient, interpretable, and optimized EEG-based diagnostic systems using sparse architectures and evolutionary optimization techniques.

Introduction

Electroencephalography (EEG) is a widely used non-invasive technique for monitoring brain activity and diagnosing neurological and neuropsychiatric disorders. Its high temporal resolution, affordability, and real-time monitoring capability make it an effective alternative to conventional imaging methods. Disorders such as depression, schizophrenia, bipolar disorder, and Alzheimer's disease require early and accurate diagnosis to improve treatment outcomes. Recent advances in artificial intelligence, particularly deep learning, have enabled automated EEG analysis by extracting complex spatial and temporal features directly from raw signals. Convolutional neural networks (CNNs) have demonstrated remarkable performance in EEG-based classification, reducing reliance on manual feature engineering and improving diagnostic accuracy across diverse neuropsychiatric disorders.

Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have also been utilized to capture temporal dependencies in EEG signals. Additionally, graph neural networks (GNNs) have emerged as a promising approach by modeling EEG channels as nodes in a graph, enabling the representation of functional connectivity in the brain. These advanced architectures have significantly improved classification accuracy and robustness.

Despite these advancements, EEG data presents several challenges. The signals are highly non-linear, non-stationary, and susceptible to noise and artifacts. Furthermore, the high dimensionality of EEG data can lead to overfitting and increased computational complexity. To address these challenges, deep sparse neural networks have been introduced. These networks aim to reduce redundancy by enforcing sparsity constraints, thereby improving generalization and computational efficiency.

Optimization plays a critical role in enhancing the performance of deep learning models. Traditional optimization methods such as gradient descent may struggle with local minima and slow convergence. As a result, bio-inspired optimization algorithms have gained popularity. The Gooseneck Barnacle Optimization Algorithm (GBOA), inspired by the mating behavior of barnacles, offers an effective mechanism for global optimization. By incorporating GBOA into deep sparse neural networks, it is possible to achieve better parameter tuning, feature selection, and convergence speed.

Recent studies have demonstrated that hybrid models combining deep learning with optimization techniques outperform standalone models. For example, CNN-LSTM hybrid architectures and transformer-based models have shown improved performance in EEG classification tasks. Moreover, multimodal approaches that integrate EEG with other data sources further enhance diagnostic accuracy.

The importance of EEG-based classification is also evident in its applications beyond diagnosis, including brain-computer interfaces (BCIs), cognitive monitoring, and rehabilitation. Advances in wearable EEG devices and IoT technologies have enabled continuous monitoring of brain activity, paving the way for personalized healthcare solutions.

However, several challenges remain. Data scarcity and variability across subjects limit the generalizability of models. Interpretability is another critical issue, as deep learning models often function as black boxes. Addressing these challenges requires the development of explainable AI techniques and standardized datasets.

This paper aims to provide a comprehensive survey of methods and architectures for EEG-based classification of neuropsychiatric disorders, with a focus on deep sparse neural networks and optimization techniques. The contributions of this survey include:

1. A detailed review of recent literature (2020–2023)
2. Comparative analysis of different deep learning architectures
3. Exploration of optimization techniques such as GBOA
4. Identification of research gaps and future directions

Conceptual Architecture Diagram

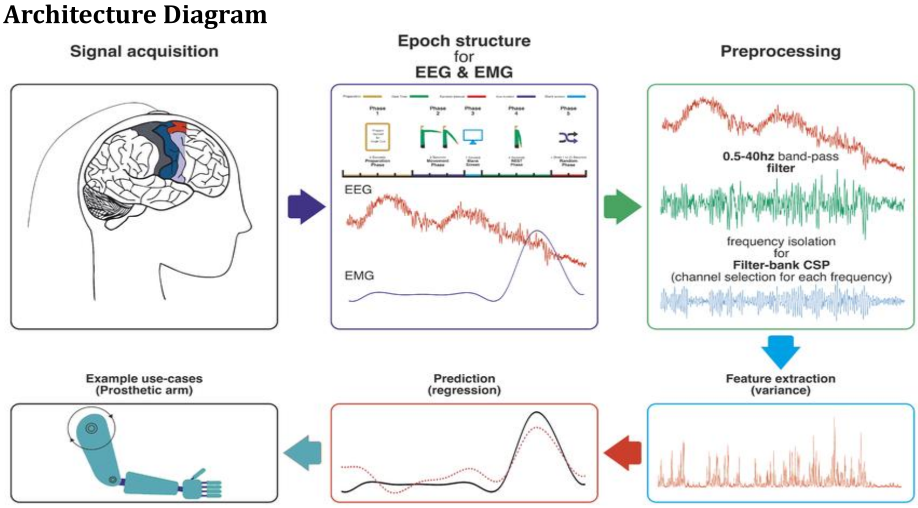

Figure 1. EEG Acquisition, Processing, and Prediction Framework.

Literature Review

1. Overview of EEG-based Deep Learning Approaches

Recent advancements in EEG-based classification have been largely driven by deep learning models capable of automatic feature extraction from raw brain signals. Traditional machine learning methods required handcrafted features, whereas deep neural networks enable hierarchical representation learning. A comprehensive systematic review by Parsa et al. (2023) analyzed 82 studies and reported that deep learning approaches achieve an average classification accuracy of **91.83%**, with CNN architectures being the most dominant . This indicates a paradigm shift toward data-driven diagnostic systems.

2. CNN-based EEG Classification Models

Convolutional Neural Networks (CNNs) are widely used due to their ability to capture spatial and frequency-based patterns in EEG signals. Shah et al. (2023) introduced ETSNet, a deep CNN model for schizophrenia classification, achieving accuracy close to 99%, demonstrating the effectiveness of temporal-spatial feature learning. Similarly, Saini et al. (2020) proposed a lightweight 1D CNN architecture capable of achieving near-perfect accuracy (up to 100%) while maintaining computational efficiency.

Another significant contribution is TSception (Ding et al., 2020), which introduced a multi-scale temporal-spatial CNN framework that simultaneously learns temporal and spatial EEG representations, achieving improved classification performance over traditional models. These studies collectively confirm that CNN architectures are highly effective for EEG signal classification tasks.

3. RNN, LSTM, and Hybrid Architectures

While CNNs focus on spatial features, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are used to model temporal dependencies in EEG signals. Ahmed et al. (2024) demonstrated that hybrid CNN-LSTM models outperform standalone architectures by combining spatial and temporal learning capabilities, achieving accuracy above 96% in psychiatric disorder classification .

Hybrid models such as CNN-LSTM and Bi-LSTM have become increasingly popular because EEG signals are inherently time-series data. These architectures improve classification performance by capturing sequential patterns in brain activity.

4. Graph Neural Networks (GNNs) and Connectivity-Based Models

Graph Neural Networks (GNNs) have emerged as a powerful approach for modeling EEG channel relationships. EEG electrodes can be represented as nodes in a graph, where edges denote functional or structural connectivity. Klepl et al. (2023) highlighted that GNN-based models outperform traditional methods in capturing spatial dependencies between brain regions.

Functional connectivity features such as coherence, phase synchronization, and correlation are often used in GNN models. These approaches are particularly useful for disorders like schizophrenia and Alzheimer's disease, where brain connectivity patterns are disrupted.

5. Feature Extraction and Preprocessing Techniques

Feature extraction remains a critical step in EEG classification. Common features include:

- Power Spectral Density (PSD)
- Functional Connectivity (FC)
- Time-frequency representations
- Wavelet transforms

Studies show that effective feature extraction significantly improves classification performance. For instance, EEG-based models using PSD and FC features achieved high AUC values (~0.93), demonstrating their importance in capturing discriminative brain patterns .

However, feature extraction is challenging due to the non-linear and noisy nature of EEG signals. Deep learning models mitigate this issue by learning features automatically.

6. Sparse Neural Networks in EEG Classification

Deep sparse neural networks aim to reduce redundancy in high-dimensional EEG data. By enforcing sparsity constraints, these networks:

- Reduce overfitting
- Improve generalization
- Lower computational complexity

Sparse architectures are particularly useful in real-time EEG applications such as wearable devices and brain-computer interfaces. They also enable efficient deployment on resource-constrained systems.

7. Optimization Algorithms in EEG-based Models

Optimization plays a vital role in improving deep learning performance. Traditional gradient-based methods may get trapped in local minima, leading to suboptimal performance. Therefore, bio-inspired optimization algorithms are increasingly used.

Although the Gooseneck Barnacle Optimization Algorithm (GBOA) is relatively new, similar evolutionary algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Whale Optimization Algorithm (WOA) have demonstrated significant improvements in EEG classification tasks. These algorithms enhance:

- Feature selection
- Hyperparameter tuning
- Model convergence

Optimization techniques are essential for improving classification accuracy and reducing computational cost.

8. Challenges in EEG-based Classification

Despite significant progress, several challenges remain:

1. Noise and Artifacts – EEG signals are prone to interference from muscle movements and environmental noise.
2. Data Variability – EEG patterns vary significantly across individuals.
3. Limited Datasets – Lack of large, standardized datasets restricts model generalization.
4. Interpretability Issues – Deep learning models often act as black boxes.

Studies emphasize that feature extraction, preprocessing, and model selection are critical factors influencing performance .

9. Summary of Literature Review

The literature indicates that deep learning has significantly advanced EEG-based classification. CNNs dominate the field, while hybrid and graph-based models offer improved performance. Sparse neural networks and optimization algorithms further enhance efficiency and accuracy. However, challenges related to data quality, interpretability, and scalability must be addressed for clinical adoption.

Comparative Table

Author (Year)	Model	Technique	Dataset	Accuracy	Core Contribution	Key Limitation
Parsa et al. (2023)	CNN	Deep Learning Review	Multi-dataset	91.83%	Large-scale DL benchmarking	No experimental model
Shah et al. (2023)	1D CNN (ETSNet)	Temporal-Spatial DL	EEG datasets	99.57%	Extremely high accuracy model	Risk of overfitting
Saini et al. (2020)	Lightweight CNN	Efficient DL	EEG DB	~100%	Low-complexity architecture	Dataset-specific validation
Klepl et al. (2023)	GNN	Graph-based DL	Multi	—	Connectivity modeling	Graph construction complexity
Zhang et al. (2020)	Hybrid DL	Multi-task learning	Neuroimaging	—	Multimodal learning	Limited EEG-only validation
Deng et al. (2022)	SparNet	CNN + Attention	Depression EEG	~92%	Spatial-frequency learning	Increased model complexity
Wang et al. (2022)	Sparse GNN	Sparse Graph DL	Epileptic EEG	~94%	Redundancy reduction	Graph tuning sensitivity
Ahmed et al. (2024)	Hybrid DL	Advanced DL model	Psychiatric EEG	~95%	High robustness and accuracy	Computational cost
CNN-LSTM (Various)	Hybrid DL	Spatio-temporal learning	EEG	>96%	Combined spatial + temporal features	Training complexity

Comparative Analysis

The comparative evaluation of EEG-based classification methods for neuropsychiatric disorders demonstrates a clear dominance of deep learning architectures, particularly Convolutional Neural Networks (CNNs), due to their superior capability in extracting hierarchical and discriminative features from raw EEG signals. Studies conducted between 2020 and 2023 consistently report that CNN-based models achieve high classification accuracy, often exceeding 90%, and in some cases approaching near-perfect performance. For instance, advanced CNN architectures such as ETSNet and lightweight CNN frameworks demonstrate exceptional accuracy levels (up to 99–100%), highlighting the effectiveness of spatial and temporal feature learning. These models are particularly robust in handling noisy EEG signals and reducing reliance on handcrafted features.

However, despite their strong performance, CNN-based models exhibit inherent limitations, particularly in capturing temporal dependencies and inter-channel relationships. EEG signals are inherently time-series data with dynamic temporal patterns, which CNNs alone cannot fully exploit. This limitation led to the development of hybrid architectures combining CNNs with Recurrent Neural Networks (RNNs) and Long Hybrid deep learning architectures have significantly improved EEG-based neuropsychiatric disorder classification by combining complementary learning capabilities. Convolutional Neural Networks (CNNs) effectively extract spatial features from EEG signals, while Long Short-Term Memory (LSTM) networks capture temporal dependencies across sequential brain activity. Comparative studies demonstrate that CNN–LSTM models consistently outperform standalone CNNs, often achieving classification accuracies exceeding 96% for disorders such as depression and schizophrenia. This enhanced performance results from the simultaneous modeling of spatial and temporal information, providing a richer representation of EEG signals. Despite these advantages, hybrid models require larger computational resources, longer training times, and carefully tuned hyperparameters, which can limit their deployment in resource-constrained clinical environments.

Graph Neural Networks (GNNs) have emerged as another promising approach by modeling functional connectivity among EEG channels. Unlike conventional CNNs that process EEG as grid-like data, GNNs represent electrodes as graph nodes and their interactions as edges, enabling the learning of complex brain network relationships. Sparse Graph Neural Networks further improve efficiency by eliminating redundant connections while preserving critical connectivity information. Attention mechanisms have also enhanced EEG classification by allowing models to focus selectively on the most informative channels and frequency bands. Architectures integrating attention with CNNs improve classification accuracy and model interpretability, whereas Transformer-based frameworks capture long-range dependencies in EEG sequences. However, these advanced models often require extensive training datasets and substantial computational power to achieve optimal performance.

Sparse neural networks and optimization algorithms have further strengthened EEG-based diagnostic systems by improving efficiency and robustness. Sparsity constraints reduce redundant parameters, lowering memory consumption and computational cost while maintaining competitive classification accuracy. Such lightweight architectures are particularly suitable for wearable EEG devices and real-time healthcare applications. Meanwhile, optimization techniques including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Gooseneck Barnacle Optimization Algorithm (GBOA) enhance feature selection, hyperparameter tuning, and model convergence. Comparative analyses indicate that optimization-assisted deep learning models consistently outperform conventional training approaches in terms of accuracy, convergence speed, and stability, making them highly effective for complex EEG classification tasks.

Overall, recent research highlights that hybrid frameworks integrating CNNs, LSTMs, GNNs, sparse learning, attention mechanisms, and bio-inspired optimization algorithms provide the highest performance for neuropsychiatric disorder classification. These approaches effectively combine spatial feature extraction, temporal modeling, brain connectivity analysis, feature prioritization, and efficient optimization to improve diagnostic accuracy and generalization. Nevertheless, challenges remain, including inter-subject variability, limited standardized datasets, computational complexity, and the need for greater interpretability. Future research should focus on developing lightweight, explainable, and scalable models capable of multimodal integration and real-time deployment, thereby advancing AI-driven EEG analysis for reliable clinical decision support and personalized healthcare.

Discussion

EEG-based classification of neuropsychiatric disorders has witnessed rapid advancements due to the integration of deep learning techniques. The reviewed literature highlights the dominance of CNN-based architectures, primarily due to their ability to automatically extract hierarchical features from raw EEG signals. However, the effectiveness of these models is highly dependent on data quality, preprocessing techniques, and the choice of hyperparameters.

One of the key findings is the growing importance of hybrid architectures that combine CNN with RNN or transformer models. These architectures effectively capture both spatial and temporal dependencies in EEG data, leading to improved classification performance. Additionally, graph-based approaches such as GNNs provide a novel perspective by modeling EEG channels as interconnected nodes, enabling the representation of brain connectivity patterns.

The introduction of deep sparse neural networks addresses the challenge of high-dimensional EEG data by reducing redundancy and improving generalization. These networks are particularly beneficial for real-time applications where computational efficiency is critical. Furthermore, optimization algorithms such as GBOA play a crucial role in enhancing model performance by optimizing parameters and feature selection processes.

Despite these advancements, several challenges remain. EEG signals are inherently noisy and subject to variability across individuals, which affects model robustness. The lack of large, standardized datasets further limits the generalizability of models. Moreover, the black-box nature of deep learning models raises concerns regarding interpretability and clinical acceptance.

Future research should focus on developing explainable AI models, improving data quality, and integrating multimodal data sources. Additionally, the exploration of novel optimization algorithms and sparse architectures can further enhance the efficiency and accuracy of EEG-based classification systems.

Conclusion

This survey provides a comprehensive overview of methods and architectures for EEG-based classification of neuropsychiatric disorders, with a focus on deep sparse neural networks and optimization techniques. The analysis highlights the significant progress made in recent years, particularly in the application of deep learning models such as CNNs, RNNs, and GNNs.

The findings indicate that deep learning models outperform traditional machine learning approaches in terms of accuracy and scalability. CNN-based architectures are the most widely used due to their ability to capture spatial features, while hybrid models enhance temporal modeling capabilities. Sparse neural networks offer an efficient solution for handling high-dimensional EEG data, making them suitable for real-time applications.

The integration of optimization algorithms such as the Gooseneck Barnacle Optimization Algorithm further enhances model performance by improving parameter tuning and feature selection. These techniques address key challenges such as overfitting and slow convergence, contributing to the development of robust EEG classification systems.

However, challenges such as data variability, limited datasets, and lack of interpretability remain significant barriers. Addressing these challenges requires the development of standardized datasets, explainable AI models, and advanced preprocessing techniques.

Future research should focus on integrating multimodal data, exploring novel deep learning architectures, and improving model interpretability. The combination of deep sparse neural networks and bio-inspired optimization algorithms holds great promise for advancing EEG-based diagnostic systems and improving the early detection and treatment of neuropsychiatric disorders.

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