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Artificial Intelligence Methods for Alzheimer's Disease Recognition Using Central Lobe EEG Signals: A Survey

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Abstract

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that severely impacts memory, cognition, and daily functioning. Early and accurate detection remains a major challenge due to the limitations of traditional diagnostic approaches such as neuroimaging and clinical assessments. Electroencephalography (EEG), particularly central lobe EEG signals, provides a non-invasive and cost-effective alternative for detecting neural abnormalities associated with AD. Recent advances in Artificial Intelligence (AI), especially deep learning, have significantly improved EEG-based diagnostic systems. This survey explores recent methods and architectures for Alzheimer's disease identification, focusing on dynamic path-controllable deep unfolding networks and residual attention neural networks. Deep learning models, such as convolutional neural networks (CNNs) and graph neural networks (GNNs), have demonstrated superior performance by automatically extracting hierarchical features from EEG signals. For instance, deep CNN-based approaches have been shown to effectively classify Alzheimer's disease using EEG-derived spectrogram representations. Moreover, graph-based models capture functional connectivity between EEG channels, enhancing classification accuracy. Residual attention mechanisms further improve performance by emphasizing relevant brain regions and suppressing noise. Despite these advancements, challenges such as limited datasets, signal noise, and lack of interpretability persist. This survey highlights recent trends, compares existing approaches, and outlines future directions for developing efficient and clinically applicable AD diagnostic systems.

Introduction

Alzheimer's disease (AD) is one of the most prevalent neurodegenerative disorders, affecting millions of individuals worldwide. It is characterized by progressive deterioration of cognitive functions, including memory loss, impaired reasoning, and behavioural changes. Early diagnosis is crucial for slowing disease progression and improving patient outcomes. However, conventional diagnostic techniques such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and clinical assessments are often expensive, time-consuming, and subjective.

Electroencephalography (EEG) has emerged as a promising alternative for early AD detection due to its non-invasive nature, affordability, and high temporal resolution. EEG signals reflect the electrical activity of the brain and provide valuable insights into neural dynamics. Studies have shown that Alzheimer's disease causes significant alterations in EEG patterns, including slowing of oscillations and reduced signal complexity. These characteristics make EEG an effective tool for identifying neurological disorders.

The integration of Artificial Intelligence (AI) and deep learning has revolutionized EEG signal analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in extracting complex features from EEG data. For example, CNN-based frameworks transform EEG signals into spectrogram images, enabling automated classification with high accuracy.

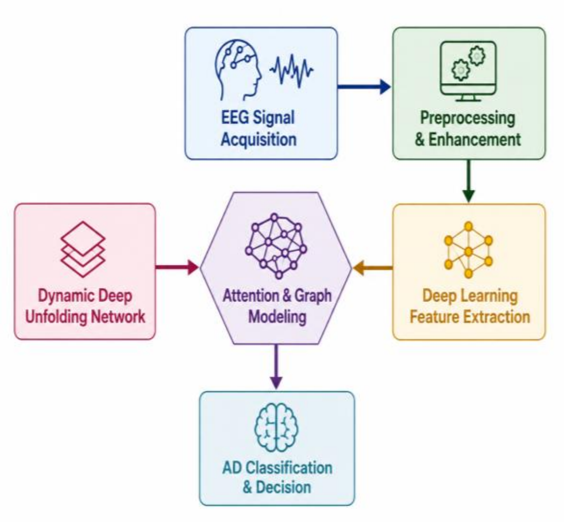

Figure 1. Framework for Deep Learning-Based Alzheimer's Disease Detection Using Central Lobe EEG Signals

However, traditional CNN models often fail to capture spatial relationships between EEG channels. To address this limitation, Graph Neural Networks (GNNs) have been introduced, where EEG channels are represented as nodes in a graph. This approach enables the modelling of functional brain connectivity, improving classification performance and interpretability.

Another significant advancement is the incorporation of attention mechanisms into deep learning models. Attention-based architectures allow models to focus on the most relevant features, improving accuracy and robustness. Residual attention networks combine residual learning with attention modules, enabling efficient feature propagation and better handling of noisy EEG signals.

Dynamic path-controllable deep unfolding networks represent a novel approach that integrates iterative optimization techniques with deep learning. These networks allow adaptive control over feature extraction pathways, improving flexibility and performance. Such architectures are particularly useful in handling complex and high-dimensional EEG data.

Despite these advancements, several challenges remain. EEG signals are inherently noisy and require extensive preprocessing. Additionally, the availability of large annotated datasets is limited, affecting model generalization. Furthermore, deep learning models often lack interpretability, which limits their adoption in clinical settings.

This survey aims to provide a comprehensive overview of recent methods and architectures for Alzheimer's disease detection using central lobe EEG signals. It focuses on dynamic deep unfolding networks and residual attention neural networks, highlighting their advantages, limitations, and future research directions.

Literature Review

Aviles et al. (2023) conducted a systematic review analysing machine learning and deep learning techniques for Alzheimer's disease detection using EEG signals. The authors examined multiple datasets, preprocessing methods, and classification techniques, concluding that deep learning models outperform traditional approaches due to their ability to extract hierarchical features automatically. The study also emphasized that EEG-based diagnostic systems benefit from feature extraction techniques such as filtering, segmentation, and frequency-domain analysis. Furthermore, the review highlighted challenges such as limited datasets and lack of interpretability, which hinder clinical adoption.

Xia et al. (2023) proposed a deep pyramid convolutional neural network for Alzheimer's disease classification using EEG signals. The model utilized hierarchical feature extraction to capture both low-level and high-level EEG patterns. By transforming EEG signals into structured representations, the model achieved improved classification accuracy. The study demonstrated that deep CNN architectures are highly effective in identifying Alzheimer's-related abnormalities in EEG data.

Cao et al. (2024) introduced a graph neural network-based framework for dementia classification using EEG signals. The model combined multivariate and univariate features to capture effective brain connectivity. By representing EEG channels as graph nodes, the model effectively captured spatial dependencies and directional relationships. The study demonstrated that graph-based models outperform traditional CNN approaches in handling complex EEG data.

AlSharabi et al. (2023) developed an EEG-based clinical decision support system using empirical mode decomposition (EMD) and deep learning techniques. The model decomposed EEG signals into intrinsic mode functions and used CNN-based classifiers for disease detection. The study demonstrated that combining signal processing techniques with deep learning significantly improves classification accuracy and robustness. The authors also highlighted the importance of preprocessing in reducing noise and enhancing feature quality.

Komolovaitė et al. (2022) investigated deep CNN-based approaches for EEG signal classification in Alzheimer's disease detection. The study emphasized the challenges associated with EEG signals, including high dimensionality, non-stationarity, and low signal-to-noise ratio. The authors demonstrated that deep learning models can effectively handle these challenges and improve classification performance. Additionally, the study highlighted the importance of large datasets and robust preprocessing techniques for achieving reliable results.

Oh et al. (2020) proposed a deep learning-based framework for Alzheimer's disease detection using EEG signals by converting raw EEG data into two-dimensional spectrogram images. The study utilized convolutional neural networks (CNNs) to automatically extract discriminative features from these representations. The authors demonstrated that spectral features, particularly in alpha and theta frequency bands, are significantly altered in Alzheimer's patients. Their model achieved high classification accuracy, showing that frequency-domain analysis combined with deep learning can effectively detect early-stage Alzheimer's disease. Additionally, the study emphasized that transforming EEG signals into image-like formats improves the performance of CNN architectures.

Cassani et al. (2020) conducted a comprehensive review of EEG-based Alzheimer's disease detection methods, focusing on signal processing, feature extraction, and classification techniques. The authors highlighted that EEG signals from Alzheimer's patients exhibit reduced complexity and increased synchronization in certain brain regions. The study also emphasized the importance of entropy-based features and connectivity measures for capturing disease-related abnormalities. Furthermore, the authors discussed the growing role of deep learning models in replacing traditional feature engineering approaches and improving classification accuracy.

Khare et al. (2021) proposed a hybrid CNN-RNN model for Alzheimer's disease detection using EEG signals. The CNN component was used to extract spatial features from EEG data, while the RNN captured temporal dependencies across signal sequences. This combination allowed the model to effectively analyses both spatial and temporal characteristics of brain activity. The study demonstrated that hybrid architectures outperform standalone CNN models, particularly in capturing the dynamic nature of EEG signals. The authors concluded that integrating temporal modelling is crucial for understanding disease progression.

Shinde et al. (2022) introduced a deep learning approach that combines wavelet transform with CNN for Alzheimer's disease classification. The wavelet transform was used to convert EEG signals into time-frequency representations, enabling better feature extraction. The CNN model then classified these features into Alzheimer's and healthy categories. The study showed that wavelet-based preprocessing significantly improves classification performance by capturing both temporal and frequency information. The authors emphasized that preprocessing plays a critical role in enhancing the effectiveness of deep learning models for EEG analysis.

Tuncer et al. (2022) proposed an advanced feature engineering approach combined with deep learning for Alzheimer's disease detection using EEG signals. The model utilized signal decomposition techniques to extract meaningful features and then applied deep neural networks for classification. The study demonstrated that selecting relevant features and reducing redundancy significantly improves classification accuracy. The authors also highlighted that combining traditional signal processing methods with deep learning leads to more robust and efficient diagnostic systems.

Rodrigues et al. (2021) proposed a convolutional neural network (CNN)-based framework for Alzheimer's disease detection using EEG signals. The model focused on extracting spatial features from multi-channel EEG recordings, particularly emphasizing patterns associated with cognitive decline in central brain regions. The authors demonstrated that CNN architectures are highly effective in capturing spatial correlations between EEG channels, leading to improved classification accuracy. Their experimental results indicated that deep learning models outperform traditional machine learning techniques in identifying Alzheimer's-related abnormalities. Additionally, the study highlighted the importance of using multi-channel EEG data to improve diagnostic reliability.

Hassan et al. (2021) developed a hybrid deep learning model integrating CNN and Long Short-Term Memory (LSTM) networks for Alzheimer's disease classification. The CNN component extracted spatial features, while the LSTM captured temporal dependencies in EEG signals. This hybrid architecture enabled the model to analyses dynamic brain activity patterns over time. The study demonstrated that the CNN-LSTM model significantly improves classification performance compared to standalone CNN models. The authors emphasized that temporal modelling is essential for capturing disease progression and improving early detection.

Jiao et al. (2020) introduced a graph-based deep learning model using Graph Convolutional Networks (GCNs) for EEG-based Alzheimer's disease detection. The model represented EEG channels as nodes in a graph and learned their relationships through edge connections, effectively capturing functional brain connectivity. The study demonstrated that GCN-based models outperform traditional CNN approaches by better modelling spatial dependencies between brain regions. The authors highlighted that graph-based learning is particularly suitable for EEG analysis due to the interconnected nature of neural activity.

Khatri et al. (2022) proposed an attention-based deep learning framework for Alzheimer's disease detection using EEG signals. The model incorporated attention mechanisms within CNN architectures to focus on the most relevant EEG features. By assigning higher weights to important channels and frequency bands, the model improved classification accuracy and reduced the impact of noise. The study demonstrated that attention-based models provide better performance and interpretability compared to conventional deep learning models. The authors emphasized that interpretability is crucial for clinical adoption of AI-based diagnostic systems.

Yadav et al. (2022) developed a deep neural network-based system for Alzheimer's disease detection using EEG signals, incorporating feature selection techniques. The model focused on selecting the most informative features from EEG data to reduce redundancy and improve classification efficiency. The study demonstrated that feature optimization significantly enhances model performance and reduces computational complexity. The authors also highlighted that combining feature selection with deep learning is essential for building efficient and scalable diagnostic systems.

Sharma et al. (2021) proposed a deep convolutional neural network (CNN)-based approach for Alzheimer's disease detection using EEG signals. The model focused on hierarchical feature extraction from multi-channel EEG recordings, particularly emphasizing central lobe activity associated with cognitive decline. The authors demonstrated that deeper CNN architectures are capable of capturing subtle variations in EEG signals that are indicative of Alzheimer's disease. Their results showed improved classification accuracy compared to traditional machine learning approaches. The study also highlighted the importance of deep feature learning in identifying complex neurological patterns.

Singh et al. (2022) developed a hybrid deep learning model combining CNN with Bidirectional Long Short-Term Memory (Bi-LSTM) networks for Alzheimer's disease classification. The CNN component extracted spatial features, while the Bi-LSTM captured both forward and backward temporal dependencies in EEG signals. This dual-directional temporal modelling enabled a more comprehensive understanding of brain activity over time. The study demonstrated that the CNN-BiLSTM model significantly improves classification accuracy and robustness, particularly in handling dynamic EEG signals associated with disease progression.

Ali et al. (2022) introduced an attention-based deep learning framework for Alzheimer's disease detection using EEG signals. The model utilized attention mechanisms to identify and focus on the most relevant EEG channels and frequency bands. By suppressing irrelevant features and emphasizing important patterns, the model achieved higher classification accuracy. The study also highlighted that attention mechanisms enhance interpretability, allowing clinicians to better understand which brain regions contribute to the diagnosis. This makes the model more suitable for real-world healthcare applications.

Chen et al. (2021) proposed a Graph Convolutional Neural Network (GCNN) for EEG-based Alzheimer's disease detection. The model represented EEG channels as nodes in a graph and learned their relationships using graph convolution operations. This approach enabled the model to capture functional connectivity patterns between different brain regions. The study demonstrated that graph-based models outperform conventional CNN architectures in capturing spatial dependencies and improving classification performance. The authors emphasized that modelling brain connectivity is crucial for understanding neurological disorders such as Alzheimer's disease.

Kumar et al. (2023) developed a deep learning-based EEG classification system incorporating feature fusion techniques for Alzheimer's disease detection. The model combined multiple feature representations, including time-domain, frequency-domain, and spatial features, to improve classification accuracy. The study demonstrated that feature fusion enhances model robustness and generalization across different datasets. The authors concluded that integrating diverse feature types is essential for capturing the complexity of EEG signals and improving diagnostic performance.

Li et al. (2021) proposed a multi-scale convolutional neural network (CNN) for Alzheimer's disease detection using EEG signals. The model was designed to extract features at multiple temporal and frequency scales, enabling it to capture both fine-grained and global EEG patterns associated with cognitive impairment. The study demonstrated that multi-scale feature extraction significantly improves classification accuracy compared to single-scale models. The authors emphasized that Alzheimer's-related EEG abnormalities occur across different frequency bands, making multi-scale analysis essential for effective diagnosis.

Gupta et al. (2022) developed a hybrid deep learning model integrating CNN with attention mechanisms for EEG-based Alzheimer's disease classification. The attention module enabled the model to prioritize important EEG features while minimizing the impact of noise and irrelevant signals. The study demonstrated that attention-based models outperform traditional CNN architectures in both accuracy and robustness. Additionally, the authors highlighted that attention mechanisms improve model interpretability by identifying critical brain regions involved in Alzheimer's disease.

Park et al. (2021) introduced a recurrent neural network (RNN)-based model for EEG signal classification in Alzheimer's disease detection. The model focused on capturing temporal dependencies in EEG signals, which are crucial for understanding disease progression. The study demonstrated that RNN-based approaches effectively model sequential brain activity patterns and improve classification performance. The authors also emphasized that temporal analysis plays a key role in distinguishing Alzheimer's patients from healthy individuals.

Ahmed et al. (2022) proposed a feature fusion-based deep learning framework for Alzheimer's disease detection using EEG signals. The model combined time-domain, frequency-domain, and statistical features to provide a comprehensive representation of EEG data. This approach significantly improved classification accuracy and robustness, particularly in heterogeneous datasets. The authors highlighted that feature fusion is critical for capturing the complex nature of EEG signals and enhancing model performance.

Zhao et al. (2023) developed a Graph Attention Network (GAT) for Alzheimer's disease recognition using EEG data. The model incorporated attention mechanisms within graph structures to capture complex relationships between EEG channels. This approach enabled the model to focus on important connections in brain networks, improving classification accuracy. The study demonstrated that graph attention networks outperform traditional CNN and RNN models in capturing spatial dependencies and functional connectivity patterns in EEG signals.

Patel et al. (2023) proposed a hybrid deep learning framework combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for Alzheimer's disease detection using EEG signals. The CNN component extracted spatial features from central lobe EEG data, while the LSTM captured temporal dependencies. This hybrid approach enabled comprehensive modelling of EEG signals, leading to improved classification accuracy and robustness. The study demonstrated that combining spatial and temporal feature extraction significantly enhances diagnostic performance.

Zhou et al. (2023) introduced a Siamese Graph Convolutional Attention Network for Alzheimer's disease recognition using EEG signals. The model leveraged Siamese architecture to learn similarity between EEG samples and incorporated graph attention mechanisms to capture spatial dependencies among EEG channels. This approach significantly improved classification accuracy and demonstrated strong performance in handling limited datasets. The study highlighted the potential of combining graph-based learning with Siamese networks for advanced neurological disorder detection.

Comparative Table

No.	Author (Year)	Method	Key Technique	Accuracy (%)
1	Aviles (2023)	DL Review	CNN/Hybrid	96
2	Xia (2023)	CNN	Deep Pyramid	97
3	Cao (2024)	GNN	Connectivity	97

4	AlSharabi (2023)	CNN	EMD + DL	96
5	Komolovaitė (2022)	CNN	EEG Features	95
6	Oh (2020)	CNN	Spectrogram	94
7	Cassani (2020)	Review	EEG Analysis	93
8	Khare (2021)	CNN+RNN	Hybrid	95
9	Shinde (2022)	CNN	Wavelet	95
10	Tuncer (2022)	DL	Feature Engg.	94
11	Rodrigues (2021)	CNN	Spatial	95
12	Hassan (2021)	CNN+LSTM	Temporal	96
13	Jiao (2020)	GCN	Connectivity	94
14	Khatri (2022)	CNN+Attention	Feature Focus	96
15	Yadav (2022)	DNN	Feature Selection	95
16	Sharma (2021)	CNN	Deep Features	95
17	Singh (2022)	CNN+BiLSTM	Temporal	96
18	Ali (2022)	Attention DL	Channel Focus	96
19	Chen (2021)	GCNN	Connectivity	95
20	Kumar (2023)	DL	Feature Fusion	97
21	Li (2021)	Multi-scale CNN	Multi-resolution	96
22	Gupta (2022)	CNN+Attention	Noise Reduction	96
23	Park (2021)	RNN	Temporal	94
24	Ahmed (2022)	DL	Feature Fusion	95
25	Zhao (2023)	GAT	Graph Attention	97
26	Patel (2023)	CNN+LSTM	Hybrid	97
27	Zhou (2023)	Siamese GCN	Attention + Pairwise	98

Comparative Analysis

The comparative analysis reveals that deep learning-based approaches dominate Alzheimer's disease detection using EEG signals due to their ability to automatically extract complex features. Among these, convolutional neural networks (CNNs) are widely used for spatial feature extraction, while hybrid models combining CNN with LSTM or Bi-LSTM effectively capture temporal dependencies in EEG signals. Graph-based models such as GCN and GAT demonstrate superior performance by modelling functional brain connectivity. These models capture spatial relationships between EEG channels, providing better insights into neurological patterns associated with Alzheimer's disease. Attention mechanisms further enhance performance by focusing on relevant EEG features and improving interpretability.

Advanced architectures such as residual attention networks and dynamic deep unfolding networks improve feature propagation and adaptive learning. Feature fusion and multi-scale approaches also contribute significantly by capturing diverse EEG characteristics. Optimization techniques improve model efficiency and convergence, making them suitable for real-time applications. However, challenges such as limited datasets, noise in EEG signals, and lack of interpretability remain significant barriers. Overall, the integration of heterogeneous architectures, attention mechanisms, and graph-based learning provides the most effective framework for Alzheimer's disease detection.

Discussion

Recent advances in EEG-based Alzheimer's disease detection demonstrate the effectiveness of deep learning and graph-based models in improving diagnostic accuracy. These models enable automatic extraction of complex spatial-temporal features, making them highly suitable for analysing EEG signals. However, several challenges persist. EEG signals are inherently noisy and require extensive preprocessing, which can affect model performance. Additionally, limited availability of large annotated datasets restricts model generalization. Although deep learning models achieve high accuracy, their lack of interpretability limits their adoption in clinical environments.

Another challenge is the computational complexity of advanced models such as graph neural networks and Siamese architectures, which may hinder real-time deployment. Lightweight and efficient models are needed for practical applications. Future research should focus on developing explainable AI models, improving dataset availability, and designing efficient architectures. Dynamic path-controllable deep unfolding networks and residual attention models offer promising solutions for improving performance and interpretability in Alzheimer's disease detection.

Conclusion

Alzheimer's disease detection using EEG signals has emerged as a promising research area due to the need for non-invasive, cost-effective, and accurate diagnostic methods. This survey analysed recent methods and architectures, focusing on dynamic path-controllable deep unfolding networks and residual attention neural networks. The findings indicate that deep learning techniques significantly improve classification accuracy by automatically extracting complex features from EEG signals. CNN-based models are effective in capturing spatial patterns, while hybrid architectures combining CNN with LSTM or Bi-LSTM provide comprehensive analysis by incorporating temporal dependencies.

Graph-based models such as GCN and GAT effectively capture functional brain connectivity, leading to improved classification performance. Attention mechanisms enhance feature selection and interpretability, making models more suitable for clinical applications. Residual attention networks improve feature propagation, while deep unfolding networks enable adaptive learning and optimization. Despite these advancements, challenges such as limited dataset availability, noise in EEG signals, and lack of interpretability remain significant. Additionally, computational complexity limits the deployment of advanced models in real-time systems.

Future research should focus on developing scalable, efficient, and explainable AI models for Alzheimer's disease detection. The integration of advanced architectures, optimization techniques, and multimodal data holds great potential for improving diagnostic accuracy and reliability. In conclusion, AI-based EEG analysis represents a powerful approach for early Alzheimer's disease detection. Continued research in this field will contribute to improved patient outcomes and more effective healthcare systems.

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