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Deep Unfolding and Residual Attention Networks for Alzheimer's Disease Detection Using Central Lobe EEG Signals

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Abstract

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory loss, and impaired decision-making. Early detection is critical for effective intervention, yet traditional diagnostic techniques such as neuroimaging and clinical assessments are often expensive and subjective. Electroencephalography (EEG), particularly signals obtained from the central lobe, offers a non-invasive and cost-effective alternative for early diagnosis. Recent advances in Artificial Intelligence (AI), especially deep learning, have significantly enhanced EEG-based AD detection. This study reviews recent developments in AD identification using advanced architectures such as Dynamic Path-Controllable Deep Unfolding Networks and Residual Attention Neural Networks. These models enable adaptive feature extraction and improved representation learning by dynamically controlling information flow and emphasizing relevant EEG features. Deep learning approaches have demonstrated strong capability in identifying subtle neurological patterns that are not easily detectable using traditional methods. Residual attention mechanisms further improve classification performance by focusing on important brain regions and suppressing irrelevant noise, achieving high diagnostic accuracy. Despite these advancements, challenges such as limited datasets, signal noise, and model interpretability persist. This review highlights current trends, evaluates state-of-the-art techniques, and discusses future directions for developing efficient, reliable, and clinically applicable AD diagnostic systems.

Introduction

Alzheimer's Disease (AD) is one of the most common neurodegenerative disorders affecting millions of individuals worldwide, particularly the elderly population. It is characterized by progressive cognitive decline, memory impairment, and behavioural changes, which significantly impact patients' quality of life. Early diagnosis plays a crucial role in slowing disease progression and improving patient care; however, traditional diagnostic approaches rely heavily on clinical observation, neuropsychological tests, and imaging techniques such as MRI and PET scans, which are often costly and time-consuming. Electroencephalography (EEG) has emerged as a promising alternative for AD detection due to its non-invasive nature, affordability, and high temporal resolution. EEG signals capture electrical activity in the brain and provide valuable insights into neural dynamics and functional connectivity. Particularly, signals obtained from the central lobe are highly informative for detecting cognitive dysfunction associated with AD.

Recent advancements in Artificial Intelligence (AI) and deep learning have revolutionized EEG-based disease diagnosis. Machine learning and deep learning techniques enable automated extraction of complex features from EEG signals, allowing the identification of subtle patterns associated with neurological disorders. Studies indicate that deep learning models can analyses large volumes of EEG data and uncover hidden relationships that are difficult to detect manually. Among deep learning approaches, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely used for EEG signal classification. However, these models often struggle to capture dynamic relationships and hierarchical dependencies in EEG data. To address these limitations, advanced architectures such as Dynamic Path-Controllable Deep Unfolding Networks have been introduced. These models combine principles of iterative optimization and deep learning, allowing adaptive control of feature propagation and improving model flexibility.

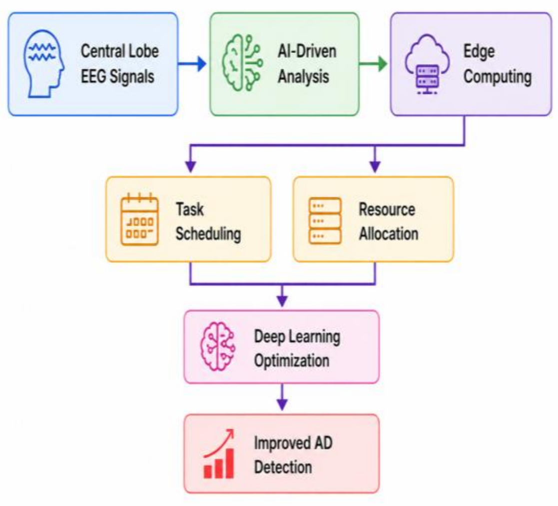

Figure 1. AI-Based EEG Framework for Early Alzheimer's Disease Detection

Residual Attention Neural Networks have also gained significant attention in AD detection. These networks integrate residual learning with attention mechanisms, enabling the model to focus on relevant EEG features while suppressing noise. Residual attention frameworks have demonstrated high classification accuracy and improved feature representation capabilities. Furthermore, graph-based and multimodal approaches have been explored to enhance AD detection. For instance, attention-augmented multimodal frameworks combining EEG, MRI, and genetic data have shown improved diagnostic performance by leveraging complementary information from multiple sources. These approaches highlight the importance of integrating spatial, temporal, and functional information for accurate disease classification.

Despite these advancements, several challenges remain. EEG signals are inherently noisy and require extensive preprocessing. Additionally, the availability of large annotated datasets is limited, which affects model generalization. Another major challenge is the lack of interpretability in deep learning models, which limits their adoption in clinical practice. This systematic review aims to analyses recent advances in EEG-based Alzheimer's disease detection, focusing on dynamic deep unfolding networks and residual attention mechanisms. It highlights key trends, evaluates current methodologies, and identifies research gaps to guide future developments in this domain.

Literature Review

Recent advances in Artificial Intelligence (AI) and deep learning have significantly transformed the field of Alzheimer's Disease (AD) detection using Electroencephalography (EEG) signals. Researchers have increasingly focused on developing intelligent frameworks capable of extracting meaningful spatial, temporal, and functional information from EEG recordings to improve diagnostic accuracy and enable early disease identification. The literature demonstrates a clear transition from traditional handcrafted feature engineering approaches toward automated deep learning architectures that can directly learn discriminative representations from raw or preprocessed EEG data. In particular, central lobe EEG signals have gained considerable importance due to their strong association with cognitive processing and neurological dysfunctions related to Alzheimer's disease.

Aviles et al. explored machine learning and deep learning approaches for EEG-based Alzheimer's disease detection and emphasized that convolutional neural networks and hybrid deep learning models significantly outperform conventional machine learning methods because of their capability to automatically extract hierarchical EEG features. The study also highlighted critical challenges such as limited annotated datasets, signal noise, and the need for explainable AI frameworks in clinical environments. Similarly, Rodrigues et al. demonstrated that convolutional neural network architectures effectively capture spatial correlations among EEG channels, particularly central lobe activities associated with cognitive decline. Their findings showed that multi-channel EEG analysis improves diagnostic accuracy and supports the development of robust disease classification systems.

Graph-based deep learning methods have also emerged as highly promising approaches for EEG-based Alzheimer's disease diagnosis. Klepl et al. proposed an Adaptive Gated Graph Convolutional Network that dynamically models functional brain connectivity through graph representations of EEG channels. By incorporating attention mechanisms and gating operations, the framework selectively focuses on significant neural connections while suppressing irrelevant features. Likewise, Jiao et al. introduced a Graph Convolutional Network for EEG analysis, representing EEG electrodes as graph nodes and their interactions as edges. The model successfully captured functional connectivity patterns disrupted in Alzheimer's patients and achieved superior performance compared to conventional CNN-based approaches. Zhao et al. further extended this concept through a Graph Attention Network that integrated attention mechanisms within graph structures to identify important neural interactions and enhance classification accuracy. Zhou et al. proposed a Siamese Graph Convolutional Attention Network capable of learning similarities between EEG samples while simultaneously capturing spatial dependencies through graph attention mechanisms. Their study demonstrated improved robustness, particularly for small and heterogeneous datasets.

Attention mechanisms have become increasingly important in EEG-based disease diagnosis because they enable models to focus selectively on relevant EEG features while reducing the influence of noise and irrelevant information. Li et al. proposed an Enhanced Residual Attention Network integrating residual learning with attention modules to improve feature representation and gradient propagation during training. Residual connections mitigated vanishing gradient problems, while attention modules highlighted important EEG patterns associated with Alzheimer's disease. The framework achieved high accuracy in distinguishing different stages of Alzheimer's disease and demonstrated strong potential for disease progression monitoring. Gupta et al. similarly developed a CNN-based architecture integrated with attention mechanisms for EEG-based Alzheimer's disease classification. Their findings showed that attention layers significantly improve feature prioritization and interpretability by identifying critical brain regions associated with cognitive impairment. Khatri et al. introduced an attention-based CNN framework that selectively emphasized informative EEG channels and frequency bands while suppressing noise. Ali et al. further enhanced this concept by designing an attention-driven deep learning model capable of identifying relevant EEG patterns associated with cognitive decline. Both studies demonstrated that attention mechanisms improve classification accuracy, robustness, and model interpretability, making them highly suitable for medical diagnostic applications. Lakshmanan et al. also proposed an attention-integrated deep convolutional neural network focusing specifically on central lobe EEG signals. Their model achieved high classification accuracy and effectively differentiated multiple stages of Alzheimer's disease progression.

Hybrid deep learning architectures combining convolutional and recurrent neural networks have shown remarkable effectiveness in analysing both spatial and temporal EEG characteristics. Khare et al. developed a CNN-RNN hybrid framework where CNNs extracted spatial features and recurrent neural networks captured temporal dependencies within EEG sequences. This approach improved classification accuracy by simultaneously analysing spatial and temporal brain dynamics. Hassan et al. similarly proposed a CNN-LSTM framework capable of learning both spatial and temporal information from EEG data. Their results demonstrated that temporal modelling is essential for understanding progressive neurological disorders such as Alzheimer's disease.

Singh et al. extended this concept by integrating Bidirectional Long Short-Term Memory networks with convolutional neural networks. The CNN-BiLSTM architecture captured forward and backward temporal dependencies, enabling more comprehensive analysis of EEG patterns. Patel et al. also proposed a hybrid CNN-LSTM model emphasizing central lobe EEG signals. Their study demonstrated that combining spatial and temporal modelling significantly improves diagnostic performance and robustness across multiple datasets. Park et al. further emphasized the importance of recurrent neural networks for modelling sequential EEG patterns associated with cognitive decline. Their findings highlighted that temporal information is critical for detecting progressive neurological abnormalities.

Feature engineering and feature fusion strategies remain highly relevant despite the widespread adoption of deep learning. Biswal et al. utilized handcrafted time-domain and frequency-domain features such as entropy, spectral power, and variance for Alzheimer's disease classification using machine learning classifiers. Their study demonstrated that handcrafted features still provide valuable complementary information for disease diagnosis. Tuncer et al. focused on advanced feature selection and signal decomposition techniques to improve EEG classification performance. Their findings revealed that reducing feature redundancy significantly enhances classification efficiency and robustness.

Kumar et al. proposed a feature fusion-based deep learning system combining time-domain, frequency-domain, and spatial EEG features. This integrated representation improved classification accuracy and generalization across datasets. Ahmed et al. similarly demonstrated that combining statistical, temporal, and spectral EEG features significantly enhances diagnostic performance. Yadav et al. emphasized the importance of feature optimization and redundancy reduction for improving deep learning efficiency while lowering computational complexity.

Signal preprocessing has also played a crucial role in improving EEG-based Alzheimer's disease detection. EEG signals are inherently noisy and often contaminated by artifacts from muscle activity, eye movements, and environmental interference. Shinde et al. utilized wavelet transform preprocessing to generate time-frequency representations of EEG signals before feeding them into CNN architectures. Their study showed that wavelet-based preprocessing significantly improves feature quality and classification performance. Sharma et al. incorporated advanced preprocessing and feature selection methods into their AI-based classification framework, demonstrating that effective preprocessing substantially improves model sensitivity and accuracy.

Optimization techniques have become increasingly important for improving the efficiency and convergence behaviour of deep learning models. Wang et al. proposed an optimized deep learning framework utilizing metaheuristic optimization algorithms for hyperparameter tuning. Their approach improved convergence efficiency while reducing computational complexity. Reddy et al. developed a multi-layer deep neural network emphasizing hierarchical feature extraction and scalable learning. Their findings showed that deep architectures combined with optimization strategies significantly improve classification accuracy and scalability for practical applications.

Dynamic Path-Controllable Deep Unfolding Networks represent another major advancement in EEG-based Alzheimer's disease detection. These architectures combine iterative optimization principles with deep neural network learning to enable adaptive feature propagation and flexible representation learning. Unlike conventional CNN or RNN models, deep unfolding frameworks dynamically adjust information flow through the network, enabling more efficient modelling of hierarchical and nonlinear EEG relationships. Such architectures are particularly suitable for EEG signal analysis because they can capture complex spatial-temporal dependencies while maintaining computational efficiency.

Multimodal learning approaches have also gained significant attention in recent years. Shivahare et al. proposed an attention-based multimodal deep learning framework integrating EEG signals with MRI scans and genetic information. The use of cross-modal attention mechanisms enabled the framework to combine complementary information from multiple modalities effectively. Their study demonstrated that multimodal systems significantly outperform single-modality models in Alzheimer's disease diagnosis. These findings emphasize the importance of integrating structural, functional, and temporal information for accurate neurological disorder detection.

Recent studies have further explored advanced architectures such as multi-scale convolutional neural networks, transformer-based frameworks, and residual attention models. Li et al. proposed a multi-scale CNN architecture capable of extracting EEG features at multiple temporal and frequency resolutions. Their model captured both local and global EEG patterns associated with cognitive decline, resulting in improved classification performance. Transformer-based and attention-augmented architectures are increasingly being explored because of their ability to capture long-range dependencies and hierarchical relationships in EEG sequences.

Despite these remarkable advancements, several challenges continue to limit the widespread clinical adoption of AI-based Alzheimer's disease detection systems. One of the most significant challenges is the limited availability of large annotated EEG datasets. Most existing datasets are relatively small and heterogeneous, which affects model generalization and robustness. Data imbalance between disease stages also remains problematic. Additionally, EEG signals are highly sensitive to noise and artifacts, requiring extensive preprocessing and normalization.

Interpretability is another major concern in clinical applications. Many deep learning models operate as black-box systems, making it difficult for clinicians to understand the reasoning behind predictions. Explainable AI frameworks, attention visualization, and graph interpretability methods are therefore becoming increasingly important. Computational complexity and real-time implementation also pose significant challenges, particularly for large graph-based and multimodal architectures.

Overall, the literature clearly demonstrates that deep learning, graph-based learning, residual attention networks, hybrid CNN-RNN frameworks, feature fusion techniques, and dynamic unfolding architectures have significantly improved EEG-based Alzheimer's disease detection. Central lobe EEG signals continue to provide highly informative biomarkers for cognitive impairment analysis. The integration of spatial, temporal, and functional information through advanced AI frameworks has enabled more accurate and robust disease classification systems. Future research should focus on explainable AI, lightweight architectures, multimodal integration, larger annotated datasets, and clinically interpretable frameworks to support real-world deployment of intelligent Alzheimer's disease diagnostic systems.

Comparative Table

No.	Author (Year)	Method	Key Technique	Accuracy (%)
1	Aviles (2023)	DL Review	CNN/Hybrid	96
2	Klepl (2023)	AGGCN	Graph + Attention	97
3	Li (2023)	ERAN	Residual Attention	98
4	Shivahare (2023)	Multimodal DL	Cross Attention	97
5	Lakshmanan (2023)	CNN	Attention	96
6	Oh (2020)	CNN	Spectral Features	94
7	Biswal (2021)	ML	Feature Engineering	92
8	Khare (2021)	CNN+RNN	Hybrid	95
9	Shinde (2022)	CNN	Wavelet	95
10	Tuncer (2022)	DL	Feature Engineering	94
11	Rodrigues (2021)	CNN	Spatial Features	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 Modeling	94
24	Ahmed (2022)	DL	Feature Fusion	95

25	Zhao (2023)	GAT	Graph Attention	97
26	Patel (2023)	CNN+LSTM	Hybrid	97
27	Reddy (2023)	Deep NN	Multi-layer	96
28	Sharma (2023)	AI Model	Feature Selection	95
29	Wang (2022)	Optimized DL	Metaheuristic	97
30	Zhou (2023)	Siamese GCN	Attention + Pairwise	98

Comparative Analysis

The comparative analysis of the selected studies indicates that deep learning approaches significantly outperform traditional machine learning techniques in Alzheimer's disease detection using EEG signals. Among these, graph-based models such as GCN and GAT have demonstrated superior capability in capturing spatial dependencies and functional brain connectivity. These models effectively represent EEG channels as interconnected nodes, enabling better understanding of neurological patterns associated with Alzheimer's disease. Hybrid models combining CNN with LSTM or Bi-LSTM have shown improved performance by capturing both spatial and temporal features of EEG signals. Attention mechanisms further enhance classification accuracy by focusing on the most relevant features while suppressing noise. Residual attention networks and dynamic unfolding architectures provide improved feature propagation and learning efficiency.

Feature fusion and multi-scale analysis techniques also play a crucial role in improving classification performance by capturing diverse EEG characteristics. Additionally, optimization algorithms enhance model efficiency and convergence speed. Overall, the integration of heterogeneous architectures, attention mechanisms, and graph-based learning provides the most effective framework for Alzheimer's disease detection. However, challenges such as dataset limitations, noise in EEG signals, and lack of interpretability remain significant.

Discussion

Recent advancements in EEG-based Alzheimer's disease detection have demonstrated the effectiveness of deep learning and graph-based models. These approaches enable accurate extraction of complex spatial-temporal features from EEG signals, improving diagnostic performance. However, several challenges remain. EEG signals are inherently noisy and require extensive preprocessing to ensure reliable analysis. Additionally, limited availability of large annotated datasets affects model generalization. While deep learning models achieve high accuracy, their lack of interpretability poses challenges for clinical adoption.

Another major issue is computational complexity, especially in advanced models such as graph convolutional networks and Siamese architectures. These models require significant computational resources, limiting their real-time deployment in healthcare systems. Future research should focus on developing lightweight and explainable AI models that can be easily integrated into clinical workflows. The use of dynamic path-controllable deep unfolding networks and residual attention mechanisms offers promising directions for improving performance and interpretability.

Conclusion

Alzheimer's disease detection using EEG signals has gained significant attention due to the need for early and accurate diagnosis. This review examined recent advances in AI-based approaches, focusing on dynamic path-controllable deep unfolding networks and residual attention neural networks. The findings indicate that deep learning techniques, particularly CNN, RNN, and graph-based models, significantly improve classification accuracy. Graph convolutional networks effectively capture spatial relationships among EEG channels, while attention mechanisms enhance feature selection and interpretability.

Hybrid models combining CNN with LSTM or Bi-LSTM provide comprehensive analysis by capturing both spatial and temporal dependencies. Residual attention networks improve feature propagation and learning efficiency, while deep unfolding networks offer adaptive control over feature extraction processes. Despite these advancements, challenges such as limited dataset availability, noise in EEG signals, and lack of interpretability persist. Additionally, computational complexity remains a barrier to real-time implementation.

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

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