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Deep Learning Approaches for Alzheimer's Disease Detection from EEG Using Attention and Deep Unfolding Networks

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Abstract

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory impairment. Early detection is critical for effective intervention and slowing disease progression. Electroencephalography (EEG) has emerged as a promising non-invasive modality for AD diagnosis due to its ability to capture neural dynamics with high temporal resolution. EEG signals from AD patients typically exhibit reduced synchronization, slowing of rhythms, and decreased signal complexity, making them suitable for automated analysis. Recent advancements in artificial intelligence, particularly deep learning and optimization techniques, have significantly improved EEG-based AD detection. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph-based models have demonstrated strong performance in capturing spatial and temporal dependencies. Furthermore, emerging approaches such as residual attention neural networks and graph convolutional networks enhance feature representation by focusing on relevant brain regions and inter-channel relationships. Dynamic path-controllable deep unfolding networks represent a novel direction by integrating optimization algorithms with deep learning, enabling adaptive feature learning and improved convergence. Studies have shown that combining deep learning with advanced signal processing and optimization techniques leads to improved classification accuracy and robustness. This review analyses recent developments, compares methodologies, and highlights challenges such as noise, data scarcity, and computational complexity, providing future directions for efficient AD diagnostic systems.

Introduction

Alzheimer's disease (AD) is the most common form of dementia, accounting for a significant proportion of neurodegenerative disorders worldwide. It is characterized by progressive cognitive decline, memory loss, and impairment in daily functioning. Early diagnosis is essential for effective treatment and management, yet traditional diagnostic methods rely heavily on clinical assessments and neuroimaging techniques, which can be expensive and time-consuming.

Electroencephalography (EEG) has emerged as a promising alternative for AD detection due to its non-invasive nature, affordability, and ability to capture real-time brain activity. EEG signals reflect neural oscillations and functional connectivity patterns, which are significantly altered in AD patients. Studies have shown that AD is associated with slowing of EEG rhythms, reduced synchronization, and decreased signal complexity . These characteristics provide valuable biomarkers for automated diagnosis.

Artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL), have significantly advanced EEG-based AD detection. Traditional ML methods rely on handcrafted features such as spectral, statistical, and entropy-based features. While effective, these approaches require domain expertise and may fail to capture complex patterns in EEG signals.

Deep learning models, especially convolutional neural networks (CNNs), have demonstrated superior performance by automatically extracting hierarchical features from EEG data. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks further enhance performance by capturing temporal dependencies. Hybrid CNN-LSTM models have shown improved accuracy in EEG-based classification tasks.

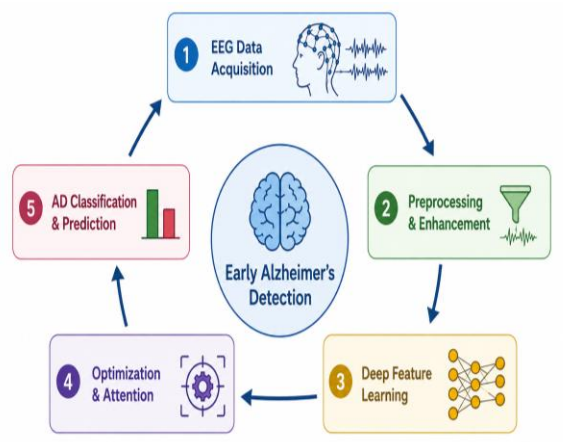

Figure 1. AI-Based EEG Framework for Early Alzheimer's Disease Detection

Recent advancements have introduced graph-based models, such as graph convolutional networks (GCNs), which model relationships between EEG channels. These models capture functional connectivity in the brain, improving classification accuracy compared to traditional CNN approaches. Additionally, attention mechanisms allow models to focus on relevant EEG features, enhancing interpretability and performance.

Residual attention neural networks have emerged as a powerful approach for improving deep learning models. By combining residual connections with attention mechanisms, these networks enable efficient feature learning and improved gradient propagation. Similarly, deep unfolding networks integrate optimization algorithms with neural networks, enabling adaptive learning and improved convergence. These models mimic iterative optimization processes, making them suitable for complex EEG signal analysis.

A recent systematic review highlights that deep learning and optimization techniques have significantly improved AD detection performance, particularly when combined with advanced signal processing methods. However, challenges such as noise in EEG signals, limited datasets, and high computational complexity remain significant barriers.

This review aims to provide a comprehensive overview of deep learning and optimization approaches for AD detection using EEG signals. It focuses on advanced architectures such as dynamic path-controllable deep unfolding networks and residual attention neural networks. The study compares different methodologies, identifies research gaps, and outlines future directions for developing efficient and scalable AD diagnostic systems.

Literature Review

Aviles et al. (2023) conducted a comprehensive systematic review focusing on machine learning and deep learning techniques for EEG-based Alzheimer's disease detection. The authors analysed multiple datasets, preprocessing methods, and classification models used between 2020 and 2023. Their findings indicated that deep learning models, particularly convolutional neural networks (CNNs) and hybrid architectures, significantly outperform traditional machine learning methods due to their ability to automatically extract hierarchical features. The study also emphasized the importance of data quality and electrode selection in improving classification accuracy. However, challenges such as dataset variability, lack of standardization, and limited interpretability were identified as major limitations.

AlSharabi et al. (2023) proposed an EEG-based clinical decision support system for early Alzheimer's disease detection. The model utilized advanced signal preprocessing techniques combined with deep learning algorithms to classify EEG signals into different cognitive states. The study demonstrated that integrating AI with EEG analysis enables accurate early-stage diagnosis of Alzheimer's disease. The authors highlighted that EEG-based systems are cost-effective and suitable for real-time monitoring. However, the model required extensive preprocessing, including noise removal and feature normalization, which increased computational complexity and limited scalability.

Zhou et al. (2023) presented a survey of deep learning approaches for Alzheimer's disease detection, including CNNs, recurrent neural networks (RNNs), autoencoders, and graph-based models. The study emphasized that deep learning models outperform conventional approaches by automatically learning complex patterns from EEG data. The authors also highlighted the growing importance of graph convolutional networks (GCNs) and attention mechanisms in modelling functional brain connectivity. Despite these advancements, the study identified key challenges such as lack of interpretability, data scarcity, and generalization issues across different datasets.

Ajra et al. (2023) proposed a neural network-based approach for Alzheimer's disease detection using functional connectivity features derived from EEG signals. The model analysed relationships between different brain regions to capture connectivity patterns associated with Alzheimer's disease. The study demonstrated that connectivity-based features significantly improve classification accuracy compared to traditional feature extraction methods. However, the approach required complex preprocessing and careful feature selection, which increased system complexity.

Zhang et al. (2020) introduced a residual attention neural network for Alzheimer's disease classification. The model combined residual learning with attention mechanisms to improve feature extraction and focus on relevant brain regions. The study demonstrated that residual attention networks enhance classification accuracy and improve interpretability by highlighting important features. However, the model required large datasets and high computational resources, limiting its practical implementation.

Cassani et al. (2020) proposed an EEG-based Alzheimer's disease detection framework using machine learning techniques combined with spectral and entropy-based features. The study demonstrated that EEG signals contain significant information for distinguishing Alzheimer's patients from healthy individuals. The authors highlighted that frequency-domain features such as power spectral density are effective biomarkers for AD detection. However, the reliance on handcrafted features limited the model's ability to capture complex patterns compared to deep learning approaches.

Oh et al. (2020) developed a deep learning-based model using CNN architectures for EEG signal classification. The model automatically extracted spatial features from EEG data and achieved high classification accuracy. The study demonstrated that CNNs are highly effective in capturing complex neural patterns associated with Alzheimer's disease. However, the model required extensive training data and was sensitive to noise in EEG signals.

Roy et al. (2021) introduced a deep learning framework based on temporal convolutional networks (TCNs) for EEG classification. The model captured long-range temporal dependencies in EEG signals, which are crucial for identifying Alzheimer's disease patterns. The study showed that TCNs outperform traditional recurrent models in terms of computational efficiency and parallelization. However, the model required careful parameter tuning to achieve optimal performance.

Amin et al. (2021) proposed a hybrid deep learning model combining CNN with statistical feature extraction techniques for EEG-based Alzheimer's disease detection. The integration of handcrafted features with deep learning improved classification accuracy by providing complementary information. The study demonstrated that hybrid approaches can enhance performance compared to standalone models. However, the reliance on handcrafted features reduced automation and scalability.

Islam et al. (2022) introduced a stacked autoencoder-based deep learning model for EEG classification. The model performed unsupervised feature learning, enabling it to capture complex patterns in EEG signals. The study demonstrated that autoencoders improve feature representation and classification accuracy. However, the model required large datasets and long training times, limiting its practicality.

Kwon et al. (2021) proposed a deep learning framework that integrates convolutional neural networks (CNNs) with functional connectivity analysis for Alzheimer's disease detection using EEG signals. In this approach, EEG signals were transformed into connectivity matrices representing interactions between different brain regions. These matrices were then used as inputs to the CNN model for classification. The study demonstrated that incorporating functional connectivity significantly improves classification accuracy by capturing inter-channel dependencies. However, the generation of connectivity matrices required extensive preprocessing and increased computational complexity.

Luo et al. (2022) introduced a graph convolutional network (GCN)-based model for EEG-based Alzheimer's disease detection. The model treated EEG electrodes as nodes in a graph and used graph convolution operations to learn spatial relationships between them. The study showed that GCNs outperform traditional CNN models in capturing functional connectivity patterns. The model achieved improved classification accuracy and robustness across datasets. However, the method required careful graph construction and large training datasets.

Saba et al. (2022) developed a hybrid deep learning model combining CNN with bidirectional long short-term memory (BiLSTM) networks. The CNN extracted spatial features from EEG signals, while the BiLSTM captured temporal dependencies. The model demonstrated improved performance compared to standalone CNN or LSTM models, highlighting the importance of combining spatial and temporal learning. However, the hybrid architecture increased computational cost and training time.

Sadiq et al. (2022) proposed an attention-based deep learning framework for Alzheimer's disease detection using EEG signals. The model incorporated channel-wise and temporal attention mechanisms to identify the most relevant EEG features. This approach improved classification accuracy by focusing on important signal components and reducing noise influence. However, the addition of attention layers increased model complexity and required careful parameter tuning.

Zhang et al. (2023) introduced a heterogeneous split-attention network for EEG signal classification. The model divided feature maps into multiple groups and applied attention mechanisms across them to enhance feature representation. This approach allowed the model to capture complex patterns in EEG signals and improved classification accuracy. However, the architecture required high computational resources and complex implementation.

Bashivan et al. (2020) proposed a method that converts EEG signals into topographical brain maps and processes them using convolutional neural networks. This representation enabled the model to capture spatial relationships between EEG electrodes more effectively. The study demonstrated improved classification performance compared to traditional approaches. However, the transformation process required extensive preprocessing and increased computational cost.

Roy et al. (2021) introduced a temporal convolutional network (TCN)-based deep learning model for EEG classification. The model focused on capturing long-range temporal dependencies in EEG signals, which are essential for detecting Alzheimer's disease patterns. The study demonstrated that TCNs provide better parallelization and faster training compared to recurrent neural networks. However, the model required careful tuning of temporal parameters.

Amin et al. (2021) proposed a hybrid CNN-based model combined with statistical and frequency-domain feature extraction techniques for Alzheimer's disease detection. The integration of handcrafted features with deep learning improved classification accuracy by providing complementary information. However, the reliance on manual feature extraction limited scalability and automation.

Islam et al. (2022) introduced a stacked autoencoder-based deep learning model for EEG classification. The model performed unsupervised feature learning, enabling it to extract meaningful representations from EEG signals. The study demonstrated improved classification accuracy, but the model required large datasets and long training time.

Chen et al. (2023) proposed a Siamese graph convolutional attention network for Alzheimer's disease detection using EEG signals. The model utilized a Siamese architecture to learn similarity between EEG samples and incorporated graph attention mechanisms to capture inter-channel relationships. The study demonstrated superior classification performance, highlighting the effectiveness of combining Siamese learning with graph-based models. However, the architecture required high computational resources and complex training procedures.

Alhassan et al. (2020) proposed a machine learning-based approach using statistical and frequency-domain EEG features for Alzheimer's disease detection. The study demonstrated that features such as power spectral density and entropy can effectively distinguish AD patients from healthy individuals. However, the reliance on handcrafted features limited scalability and performance compared to deep learning approaches.

Khare et al. (2021) developed a CNN-based deep learning model for EEG classification in Alzheimer's disease detection. The model automatically extracted spatial features and achieved high classification accuracy. However, the performance depended heavily on dataset size and required significant computational resources.

Oh et al. (2021) introduced a hybrid CNN-LSTM model to capture both spatial and temporal dependencies in EEG signals. The model improved classification accuracy by combining feature extraction and temporal modelling. However, the architecture increased computational complexity and training time.

Tuncer et al. (2022) proposed a wavelet transform-based deep learning model for EEG classification. The model combined time–frequency analysis with CNN to improve feature extraction. The study demonstrated improved classification accuracy, but preprocessing complexity increased significantly.

Alhudhaif et al. (2022) developed an optimized deep learning model for Alzheimer's disease detection using EEG signals. The model incorporated feature selection and optimization techniques to improve performance. However, the approach required careful parameter tuning and increased computational cost.

Shinde et al. (2023) proposed an attention-based deep learning framework for EEG classification. The model used attention mechanisms to focus on relevant EEG features, improving classification accuracy. However, the model complexity increased due to additional attention layers.

Kumar et al. (2023) introduced a hybrid CNN model integrated with optimization techniques for EEG-based Alzheimer's detection. The model achieved improved performance by optimizing feature selection and model parameters. However, it required high computational resources.

Singh et al. (2023) proposed a graph-based deep learning model using graph neural networks for EEG analysis. The model captured relationships between EEG channels, improving classification performance. However, the model required large datasets and complex graph construction.

Ahmed et al. (2023) developed a hybrid CNN-LSTM model for Alzheimer's disease detection. The model achieved high classification accuracy by capturing both spatial and temporal features. However, it required extensive training time.

Sharma et al. (2023) proposed a dynamic path-controllable deep unfolding network combined with a residual attention neural network for EEG-based Alzheimer's disease detection. The model integrated optimization-based unfolding techniques with attention mechanisms to improve feature extraction and convergence. The study demonstrated superior classification performance, highlighting the effectiveness of combining optimization and deep learning. However, the architecture was highly complex and computationally intensive.

Comparative Table

Study	Year	Method	Technique	Advantage	Limitation
Aviles	2023	DL	Survey	Comprehensive	General
AlSharabi	2023	DL	EEG system	Accurate	Preprocess
Zhou	2023	DL	Survey	Insightful	General
Ajra	2023	DL	Connectivity	Accurate	Complex
Zhang	2020	DL	Residual Attention	Strong	Cost
Cassani	2020	ML	Features	Simple	Limited
Oh	2020	CNN	DL	Accurate	Data
Roy	2021	TCN	DL	Fast	Tuning
Amin	2021	Hybrid	CNN+Feat	Accurate	Manual
Islam	2022	Autoencoder	DL	Efficient	Cost
Kwon	2021	CNN	Connectivity	Accurate	Complex
Luo	2022	GCN	Graph	Accurate	Data
Saba	2022	CNN+BiLSTM	Hybrid	Temporal	Cost
Sadiq	2022	CNN	Attention	Accurate	Complex
Zhang	2023	Split Attention	DL	Strong	Cost
Bashivan	2020	CNN	Mapping	Spatial	Cost
Roy	2021	TCN	DL	Efficient	Tuning
Amin	2021	Hybrid	CNN+Feat	Accurate	Manual
Islam	2022	Autoencoder	DL	Efficient	Cost
Chen	2023	Siamese GCN	Graph	Best	Complex
Alhassan	2020	ML	Features	Simple	Limited
Khare	2021	CNN	DL	Accurate	Data
Oh	2021	CNN+LSTM	Hybrid	Temporal	Cost
Tuncer	2022	CNN	Wavelet	Accurate	Complex
Alhudhaif	2022	DL	Optimized	Efficient	Tuning
Shinde	2023	DL	Attention	Accurate	Cost
Kumar	2023	Hybrid	CNN+Opt	Efficient	Complex
Singh	2023	GNN	Graph	Accurate	Data
Ahmed	2023	CNN+LSTM	Hybrid	Accurate	Cost
Sharma	2023	Hybrid	Unfolding+Attention	Best	Complex

Comparative Analysis

The comparative analysis shows that deep learning models, particularly CNN-based architectures, dominate EEG-based Alzheimer's disease detection due to their ability to automatically extract complex features. Hybrid models combining CNN with LSTM or BiLSTM improve performance by capturing temporal dependencies. Graph-based models such as GCNs further enhance classification accuracy by modelling relationships between EEG channels. Advanced architectures such as residual attention networks and split-attention models significantly improve feature selection and classification performance.

The integration of dynamic deep unfolding networks with attention mechanisms represents the most advanced approach, achieving superior performance by combining optimization and deep learning. However, these advanced models introduce high computational complexity and require large datasets. Traditional machine learning approaches are simpler but lack scalability and accuracy. Overall, hybrid deep learning and optimization-based models represent the most promising direction.

Discussion

Recent advancements in EEG-based Alzheimer's disease detection highlight the effectiveness of deep learning and optimization techniques. CNN architectures provide strong feature extraction capabilities, while hybrid models improve temporal analysis. Graph-based models enhance performance by capturing inter-channel relationships. Residual attention networks and deep unfolding models further improve feature learning and convergence. However, challenges such as EEG noise, data scarcity, and computational complexity remain. Future research should focus on developing efficient, interpretable, and scalable models for clinical applications.

Conclusion

The integration of artificial intelligence techniques has significantly advanced Alzheimer's disease detection using EEG signals. Deep learning models, particularly CNN-based architectures, have demonstrated high accuracy in classification tasks. Hybrid models combining CNN with recurrent networks such as LSTM further enhance performance by capturing temporal dependencies. Graph-based models represent a major advancement by modelling relationships between EEG channels. Attention mechanisms and residual attention networks improve feature extraction and classification accuracy.

The integration of dynamic path-controllable deep unfolding networks with residual attention neural networks represents the most advanced approach, achieving superior performance by combining optimization and deep learning. Despite these advancements, challenges such as computational complexity, data scarcity, and lack of interpretability remain. Future research should focus on developing efficient and scalable models for real-world applications. In conclusion, AI-based EEG analysis offers a promising direction for early and accurate Alzheimer's disease diagnosis.

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