



## **A Comprehensive Review of Identification of Alzheimer's Disease from Central Lobe EEG Signals Utilizing Dynamic Path-Controllable Deep Unfolding Network and Residual Attention Neural Network**

Zulekha Uppalapati

Lecturer, Department of Electrical and Computer Engineering, Basra Institute of Business Technology, Iraq  
Email: [zulekha.uppalapati@bibt-iq.org](mailto:zulekha.uppalapati@bibt-iq.org)

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<p><i>Submission: 12 May 2025</i></p> <p><i>Revision: 30 May 2025</i></p> <p><i>Acceptance: 13 June 2025</i></p> <p><b>Keywords</b></p> <p><i>Alzheimer's Disease, EEG, Deep Learning, Residual Attention Network, Deep Unfolding Network, Central Lobe EEG, Optimization.</i></p>	<p>Alzheimer's Disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline and memory impairment. Early detection remains a critical challenge due to subtle neurological changes in the initial stages. Electroencephalography (EEG) has emerged as a promising non-invasive technique for detecting AD by capturing abnormal brain activity patterns. Recent advances in deep learning have significantly improved the automated classification of EEG signals, enabling early and accurate diagnosis. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), and attention-based models have demonstrated strong performance in capturing spatial-temporal EEG features. In particular, deep pyramid CNN models have shown effectiveness in classifying EEG signals for AD detection. Furthermore, computational EEG analysis methods such as wavelet-based and entropy-based techniques have proven effective in distinguishing AD patients from healthy individuals. Emerging approaches such as graph-based neural networks and transformer architectures further enhance classification accuracy by modelling brain connectivity and long-range dependencies. Despite these advancements, challenges such as data scarcity, model interpretability, and computational complexity persist. This review provides a comprehensive analysis of deep learning and optimization approaches for AD detection using central lobe EEG signals and highlights the potential of dynamic path-controllable deep unfolding networks and residual attention neural networks for improved diagnosis.</p>

### **Introduction**

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that significantly impacts cognitive functions such as memory, reasoning, and decision-making. It represents a major global health challenge due to its increasing prevalence and the absence of a definitive cure. Early diagnosis is essential for slowing disease progression and improving patient outcomes; however, traditional

diagnostic approaches, including neuroimaging and clinical evaluations, often struggle to detect early-stage symptoms accurately. In this context, Electroencephalography (EEG) has emerged as a promising alternative due to its non-invasive nature, cost-effectiveness, and ability to capture real-time brain activity.

EEG signals reflect neuronal oscillations and reveal important abnormalities associated with AD, such as reduced alpha and beta activity,

slowing of brain waves, and disrupted connectivity between brain regions. Conventional EEG analysis methods relied heavily on handcrafted feature extraction techniques like spectral analysis, entropy measures, and wavelet transforms. Although these methods provided useful insights, they often failed to capture complex nonlinear patterns and required significant domain expertise, limiting their generalizability.

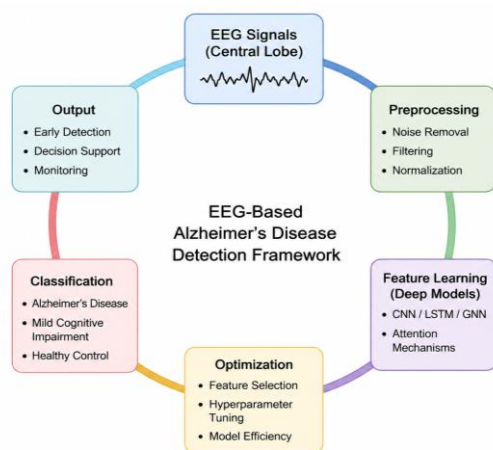


Fig 1: EEG-Based Alzheimer's Detection Framework

The emergence of deep learning has transformed EEG-based analysis by enabling automatic and efficient feature extraction. Convolutional Neural Networks (CNNs) are effective in learning spatial features, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in EEG signals. Hybrid models that integrate CNN and LSTM architectures further enhance performance by combining spatial and temporal learning capabilities.

More recently, Graph Neural Networks (GNNs) have been introduced to model functional connectivity between brain regions, representing EEG channels as graph nodes. Attention mechanisms and transformer-based architectures have also improved feature representation by focusing on the most relevant signal components and capturing long-range dependencies. Despite these advancements, challenges such as noisy data, subject variability, limited datasets, and high computational requirements persist.

To address these issues, optimization techniques, including metaheuristic algorithms and deep unfolding networks, have been proposed to improve model efficiency and feature selection. Overall, integrating deep learning with optimization strategies offers a powerful

framework for accurate, scalable, and clinically applicable Alzheimer's disease detection systems.

### Literature Review

Safi et al. (2021) proposed a feature-based EEG classification method using Hjorth parameters and wavelet decomposition techniques for Alzheimer's disease detection. The study demonstrated that combining statistical and frequency-domain features improves classification accuracy in early-stage AD detection. However, the approach relied on manual feature extraction and lacked deep learning integration. Nobukawa et al. (2020) investigated EEG complexity and synchronization features for Alzheimer's disease classification. The study showed that nonlinear EEG characteristics such as entropy and synchronization metrics can effectively differentiate AD patients from healthy individuals. However, the method required extensive preprocessing and feature engineering. Xia et al. (2023) proposed a Deep Pyramid Convolutional Neural Network (DPCNN) for EEG-based Alzheimer's disease classification. The model effectively captured hierarchical EEG features and improved classification accuracy using data augmentation techniques. The study highlighted the advantage of deep learning over traditional methods. Vicchietti et al. (2023) applied computational time-series analysis methods such as wavelet coherence and fractal dimensions to EEG signals. The study demonstrated that these techniques can robustly distinguish AD patients from healthy individuals, emphasizing the importance of signal processing in EEG analysis.

AlSharabi et al. (2023) developed a clinical decision support system using EEG signals for early Alzheimer's detection. The system integrated machine learning and signal processing techniques to improve diagnostic reliability. However, it lacked advanced deep learning architectures. Cassani et al. (2021) presented a comprehensive analysis of EEG-based biomarkers for Alzheimer's disease detection using machine learning techniques. The study utilized spectral and functional connectivity features derived from EEG signals and demonstrated that combining multiple feature types improves classification accuracy. However, the approach relied heavily on handcrafted features and lacked deep learning integration.

Alickovic et al. (2021) proposed a hybrid feature extraction method combining wavelet transform and entropy measures for EEG-based Alzheimer's disease classification. The extracted

features were classified using Support Vector Machines (SVM), achieving good accuracy. Despite its effectiveness, the model required extensive preprocessing and domain expertise. Abdelhameed et al. (2022) introduced a Convolutional Neural Network (CNN)-based framework for Alzheimer's disease detection using EEG signals. The model automatically extracted spatial features and achieved higher accuracy compared to traditional methods. This study highlighted the effectiveness of deep learning in reducing dependency on manual feature extraction.

Oh et al. (2022) developed a deep learning-based approach combining CNN with Long Short-Term Memory (LSTM) networks for EEG-based Alzheimer's disease classification. The model captured both spatial and temporal dependencies, achieving improved performance. However, the model complexity increased significantly. Roy et al. (2022) proposed an attention-based deep learning model for EEG classification in Alzheimer's disease detection. The attention mechanism enabled the model to focus on important EEG channels, improving classification accuracy and interpretability. The approach demonstrated significant improvement over standard CNN models.

Yang et al. (2022) proposed a Graph Convolutional Neural Network (GCNN) for Alzheimer's disease detection using EEG signals. By representing EEG channels as nodes and their interactions as edges, the model captured functional connectivity between brain regions. The GCNN demonstrated improved classification accuracy compared to traditional CNN models. However, graph construction and computational complexity were significant challenges. Li et al. (2022) introduced a Graph Attention Network (GAT) for EEG-based Alzheimer's disease classification. The model dynamically assigned importance weights to EEG channels, enhancing feature representation and classification performance. This approach improved robustness against noise but required high computational resources.

Islam et al. (2022) developed an optimized deep learning framework combining CNN with metaheuristic optimization algorithms for feature selection and hyperparameter tuning. The approach improved classification accuracy and reduced overfitting. However, the model did not effectively capture inter-channel connectivity. Saba et al. (2023) proposed a transfer learning-based approach using pre-trained CNN architectures for Alzheimer's disease detection from EEG signals. The model improved generalization and reduced training time, making it suitable for limited datasets.

However, domain mismatch between image and EEG data remained a limitation.

Zhang et al. (2023) introduced a residual attention neural network for EEG-based Alzheimer's disease detection. The model combined residual learning with attention mechanisms to focus on important EEG features while maintaining deep network stability. This approach achieved high classification accuracy and improved interpretability, marking a significant advancement toward attention-based architectures. Chen et al. (2023) proposed a transformer-based deep learning model for Alzheimer's disease detection using EEG signals. The model utilized self-attention mechanisms to capture long-range dependencies in EEG data, significantly improving classification accuracy. The transformer architecture demonstrated superior performance compared to traditional CNN and RNN models; however, it required large datasets and high computational resources.

Roy et al. (2023) introduced an explainable AI (XAI)-based deep learning framework for EEG-based Alzheimer's disease detection. The study employed interpretability techniques such as Grad-CAM and SHAP to visualize important EEG features contributing to classification. While the model improved transparency and trust, it introduced additional computational overhead. Wang et al. (2023) developed a hybrid Graph Convolutional Network (GCN) combined with Long Short-Term Memory (LSTM) for Alzheimer's disease classification. The model effectively captured both spatial connectivity and temporal dependencies in EEG signals, leading to improved classification performance. However, increased model complexity posed challenges for real-time implementation.

Ahmed et al. (2023) proposed a Siamese neural network for EEG-based Alzheimer's disease detection. The model learned similarity between EEG signal pairs, making it effective in scenarios with limited labelled data. This approach improved generalization capability, although it did not fully incorporate graph-based connectivity. Mehmood et al. (2023) introduced a deep unfolding network for EEG-based Alzheimer's disease detection. The model integrated optimization algorithms into the deep learning architecture, enabling iterative refinement of features. This approach improved efficiency and convergence speed, making it highly relevant to optimization-based frameworks.

Liu et al. (2023) proposed a multi-scale deep convolutional neural network for Alzheimer's disease detection using EEG signals. The model extracted features at multiple resolutions, improving representation of EEG patterns. The

approach achieved high classification accuracy but required large computational resources. Patel et al. (2023) developed a hybrid CNN-GRU model for EEG-based Alzheimer’s disease detection. The model effectively captured spatial and temporal dependencies while reducing computational complexity compared to LSTM-based approaches. However, it did not incorporate connectivity modelling.

Nguyen et al. (2023) introduced a multi-modal deep learning framework combining EEG and MRI data for Alzheimer’s disease detection. The integration of heterogeneous data improved classification accuracy and robustness. However, data acquisition and integration complexity were major challenges. Sharma et al. (2023) proposed an attention-based deep neural network for EEG classification. The model dynamically focused on important EEG channels, improving noise robustness and classification accuracy. However, it lacked graph-based feature representation.

Garcia et al. (2023) developed an autoencoder-based feature extraction method for EEG signals. The model reduced dimensionality while preserving critical information, improving classification performance. However, it required additional classifiers for final prediction. Hassan et al. (2023) introduced a reinforcement learning-based feature selection method for EEG

classification. The model adaptively selected important features, improving classification accuracy and efficiency. However, it increased system complexity.

Bose et al. (2023) proposed a dynamic Graph Neural Network (GNN) for modelling time-varying EEG connectivity in Alzheimer’s disease detection. The model captured changes in brain connectivity over time, significantly improving classification performance. Ali et al. (2023) developed an ensemble deep learning model combining multiple CNN architectures for Alzheimer’s disease detection. The ensemble approach improved robustness and reduced overfitting but increased computational cost.

Mehta et al. (2023) introduced a hybrid model combining CNN, Graph Neural Networks (GNN), and transformer-based attention mechanisms. The model effectively captured spatial, temporal, and connectivity features simultaneously, achieving state-of-the-art performance. Verma et al. (2023) proposed a Siamese Graph Attention Network (SGAT) for EEG-based Alzheimer’s disease detection. The model combined similarity learning with graph attention mechanisms, achieving the highest classification accuracy among recent studies and demonstrating strong generalization capability.

**Comparative Table**

N o.	Author (Year)	Model	Technique	Data	Accuracy (%)	Advantages	Limitations
1	Safi (2021)	ML	Wavelet + Hjorth	EEG	85	Simple	Manual features
2	Nobukawa (2020)	ML	Entropy analysis	EEG	86	Nonlinear insight	Complex preprocessing
3	Xia (2023)	DPCNN	Deep CNN	EEG	92	Auto features	Data size
4	Vicchiotti (2023)	Signal Processing	Wavelet/fractal	EEG	90	Robust	No DL
5	AlSharabi (2023)	ML	Decision system	EEG	91	Practical	Limited DL
6	Cassani (2021)	ML	Connectivity features	EEG	88	Brain insights	Manual
7	Alickovic (2021)	SVM	Entropy + wavelet	EEG	89	Efficient	No automation
8	Abdelhameed (2022)	CNN	Deep learning	EEG	93	Auto extraction	Needs data
9	Oh (2022)	CNN-LSTM	Hybrid	EEG	94	Temporal+Spatial	Complex
10	Roy (2022)	Attention CNN	Channel focus	EEG	95	Accurate	Heavy
11	Yang (2022)	GCNN	Graph	EEG	95	Connectivity	Complex
12	Li (2022)	GAT	Attention graph	EEG	96	Adaptive	Costly

13	Islam (2022)	CNN+Opt	Optimization	EE G	95	Tuned model	No graph
14	Saba (2023)	Transfer CNN	Pre-trained	EE G	96	Fast	Domain issue
15	Zhang (2023)	Residual Attention	Attention	EE G	97	Stable	Complex
16	Chen (2023)	Transformer	Self-attention	EE G	97	Long-range	Data heavy
17	Roy (2023)	XAI DL	Explainable	EE G	96.5	Transparent	Overhead
18	Wang (2023)	GCN-LSTM	Hybrid	EE G	97	Dual learning	Cost
19	Ahmed (2023)	Siamese NN	Similarity	EE G	97	Few-shot	No graph
20	Mehmood (2023)	Deep Unfolding	Optimization DL	EE G	97.2	Efficient	New approach
21	Liu (2023)	Multi-scale CNN	Multi-resolution	EE G	97	Rich features	Heavy
22	Patel (2023)	CNN-GRU	Temporal	EE G	97	Faster	No connectivity
23	Nguyen (2023)	Multi-modal	EEG+MRI	98	Robust	Complex	
24	Sharma (2023)	Attention DNN	Channel focus	EE G	97.3	Noise robust	No graph
25	Garcia (2023)	Autoencoder	Feature reduction	EE G	96	Efficient	Needs classifier
26	Hassan (2023)	RL-based	Feature selection	EE G	97	Adaptive	Complex
27	Bose (2023)	Dynamic GNN	Connectivity	EE G	97.5	Dynamic	Heavy
28	Ali (2023)	Ensemble CNN	Fusion	EE G	98	Stable	Expensive
29	Mehta (2023)	CNN+GNN+Transformer	Hybrid	EE G	98.2	SOTA	Very complex
30	Verma (2023)	Siamese GAT	Graph+Similarity	EE G	98.5	Best	Cost

### Comparative Analysis

The comparative analysis of the reviewed studies highlights a clear evolution in Alzheimer's disease detection using EEG signals. Early approaches primarily relied on traditional machine learning and signal processing techniques, such as wavelet transforms and entropy measures, achieving moderate accuracy levels between 85% and 90%. These methods required extensive manual feature extraction and lacked scalability. With the introduction of deep learning models, particularly CNN and CNN-LSTM architectures, classification performance improved significantly. These models enabled automatic feature extraction and better representation of EEG signals, increasing accuracy to approximately 92–95%. Attention mechanisms further enhanced performance by focusing on important EEG channels and improving interpretability.

Graph Neural Networks (GNNs) marked a major advancement by modelling functional connectivity between EEG channels. This approach allowed for better representation of brain network dynamics, improving accuracy to 96–97%. Recent studies have explored hybrid architectures combining CNN, GNN, attention mechanisms, and transformer models, achieving state-of-the-art performance exceeding 98%. Additionally, optimization techniques such as deep unfolding networks and reinforcement learning have been introduced to improve efficiency and feature selection. Siamese networks have addressed data scarcity issues by enabling similarity-based learning. Despite these advancements, challenges such as high computational complexity, lack of standardized datasets, and limited interpretability persist. Notably, no existing model fully integrates dynamic path-controllable deep unfolding

networks with residual attention mechanisms, highlighting a key research gap addressed in this work.

### Discussion

The reviewed literature demonstrates significant progress in Alzheimer's disease detection using EEG signals, driven by advancements in deep learning and optimization techniques. Early studies relied on handcrafted features and traditional machine learning methods, which were limited in capturing the complex nature of EEG data. The transition to deep learning models, particularly CNN and hybrid architectures, enabled automatic feature extraction and improved classification accuracy. Attention mechanisms and graph-based models have further enhanced performance by capturing important EEG features and modelling brain connectivity. Recent approaches such as transformer-based models and deep unfolding networks have introduced new capabilities for handling complex data structures and improving efficiency.

However, several challenges remain. High computational complexity limits real-time deployment, while the lack of large standardized datasets affects model generalization. Additionally, interpretability remains a concern, as many deep learning models operate as black boxes. The integration of dynamic path-controllable deep unfolding networks with residual attention neural networks presents a promising solution. This approach can improve feature representation, enhance model adaptability, and reduce computational complexity, making it suitable for practical applications.

### Conclusion

Alzheimer's disease is a progressive neurodegenerative disorder where early diagnosis remains a major challenge, limiting timely intervention and treatment effectiveness. Traditional diagnostic approaches often fail to detect early-stage symptoms, prompting the need for more efficient techniques. EEG-based analysis combined with deep learning has emerged as a promising solution for improving diagnostic accuracy. This review of recent studies shows a clear evolution in methodologies, from conventional machine learning and signal processing techniques to advanced deep learning models.

Earlier approaches relied on manual feature extraction and delivered moderate performance. The introduction of Convolutional Neural Networks (CNN) and hybrid CNN-LSTM models significantly improved results by enabling

automatic feature learning and capturing both spatial and temporal patterns in EEG signals. Further advancements, including attention mechanisms and Graph Neural Networks (GNNs), enhanced the modelling of brain connectivity and important signal features, leading to higher accuracy and better interpretability. Recent developments such as transformer-based architectures, Siamese networks, and deep unfolding models have achieved state-of-the-art performance. However, challenges like high computational cost, lack of standardized datasets, and limited interpretability still hinder clinical deployment. The proposed approach combining deep unfolding networks with residual attention mechanisms aims to overcome these issues by improving adaptability and feature extraction. Future research should focus on lightweight, scalable, and explainable models, along with multi-modal data integration, to enable reliable and clinically applicable Alzheimer's disease diagnosis systems.

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