Cross-Model Deep Learning Frameworks for Improved Detection of Alzheimer's Disease

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***Abstract*—The increasing prevalence of brain diseases, such as Alzheimer's, necessitates more efficient diagnostic tools. Traditional brain imaging techniques, like Electroencephalogram (EEG) and Magnetic Resonance Imaging (MRI), require significant physician effort for accurate interpretation, often leading to diagnostic inconsistencies. This paper proposes a deep learning approach for improved brain disease diagnosis, utilizing a multi-modal strategy that combines 1D EEG time-series data and 2D scaleogram representations. We employed ChronoNet for 1D data and a fine-tuned ResNeSt26d model for 2D data, with an ensemble model to combine the outputs. Our results demonstrate that the ensemble approach significantly enhances classification accuracy, with the 1D model achieving an F1-score of 0.9496 and the 2D model showing complementary performance. This method offers promising potential for accelerating the diagnostic process and improving decision-making in clinical settings. Future work will focus on addressing demographic diversity, computational costs, and data complexity to optimize the model for broader applicability.**

***Index Terms*—Deep Learning, Alzheimer's Disease, Multi-modal Learning, Convolutional Neural Networks, Time-series Analysis, Scaleograms, Ensemble Learning**

I. Introduction

Alzheimer's Disease (AD) poses a significant global health challenge, contributing to over 15% of disability-adjusted life-years (DALYs) lost worldwide, surpassing cancer and cardiovascular diseases [1]. Early and accurate diagnosis is critical but remains challenging due to the complexity and expertise required, often demanding years of specialized training for neurologists [2].

While MRI and PET imaging have been extensively researched and are effective diagnostic tools, they are costly, require advanced facilities, and are not universally accessible. In contrast, Electroencephalography (EEG) offers a cost-effective and non-invasive alternative, making it particularly promising for early-stage detection. However, leveraging EEG for Alzheimer's diagnosis using Artificial Intelligence (AI) and Machine Learning (ML) remains underexplored, presenting a significant research gap.

This study addresses this gap by applying ensemble learning techniques to EEG data, aiming to develop a rapid and precise diagnostic system for AD. By focusing on EEG—a scalable and affordable modality—this work contributes to advancing accessible healthcare solutions for early Alzheimer's detection, particularly in resource-limited settings.

II. Problem Definition

The diagnosis of Alzheimer's disease remains a complex and time-intensive process, heavily reliant on the expertise of neurologists, often delaying intervention. Existing methods, such as MRI and PET imaging, though effective, are expensive, resource-intensive, and inaccessible in many regions. Conversely, EEG offers a cost-effective and non-invasive alternative but has seen limited research for Alzheimer's diagnosis compared to imaging modalities.

This study addresses this critical gap by proposing a novel integration of advanced Artificial Intelligence (AI) and Machine Learning (ML) techniques with EEG data. The aim is to enhance diagnostic precision, reduce delays, and facilitate early intervention by leveraging the affordability and accessibility of EEG. By optimizing diagnostic processes and offering deeper insights into early-stage Alzheimer's detection, this research contributes to scalable, efficient healthcare solutions that can improve patient outcomes globally.

III. Aims and Objectives

The primary aims and objectives of this research are outlined as follows:

1) **Enhance Diagnostic Efficiency:**
   - **Goal:** Develop and implement AI-based diagnostic models that reduce the average diagnostic time for Alzheimer's disease from days to under 2 hours.
   - **Why:** This will streamline the diagnostic process, allowing quicker identification and intervention, which is critical for early-stage treatment and improved patient outcomes.
2) **Improve Diagnostic Accuracy:**
   - **Goal:** Achieve a diagnostic accuracy rate of over 85% using EEG data, surpassing current diagnostic methods.
   - **Why:** Accurate detection of subtle neurological changes will address the limitations of existing methods and facilitate early intervention.
3) **Optimize Cost-Effectiveness:**
   - **Goal:** Create a diagnostic solution that more cost-effective than traditional imaging methods like MRI or PET.
   - **Why:** Ensuring affordability will make advanced diagnostic tools accessible to resource-constrained healthcare settings, especially in low-income and rural areas.
4) **Leverage a Multi-Modality Approach:**
   - **Goal:** Integrate EEG data with other potential data sources, focusing on creating a robust and scalable diagnostic model.

- **Why:** A multi-modality approach will offer a comprehensive understanding of Alzheimer's disease and improve detection sensitivity.

5) **Facilitate Decision-Making for Neurologists:**
   - **Goal:** Develop a decision-support system incorporating AI-based recommendations to assist neurologists in making faster and more accurate diagnostic decisions.
   - **Why:** This will empower neurologists with actionable insights, improving diagnostic confidence and patient care.

IV. Literature Review

A. Introduction to Advances in AD Diagnostics

Advancements in Alzheimer's disease (AD) diagnostics have been revolutionized by the integration of neuroimaging technologies with cutting-edge computational methods. These innovations have led to the development of more precise diagnostic tools, improving both the accuracy and timeliness of detection. This section explores recent contributions to the field, with a focus on multimodal imaging, machine learning, and deep learning frameworks.

B. Multimodal Neuroimaging and Machine Learning

The combination of multimodal neuroimaging and machine learning has demonstrated remarkable potential in AD diagnostics. Rayan Beshawri reviewed key studies highlighting this synergy. For example, P. Khan *et al.* integrated M/EEG and f/MRI data, enhancing the understanding of brain functions [3]. Similarly, Nikhil J. Dhinagar *et al.* applied transfer learning with pre-trained CNNs on MRI data, achieving substantial performance gains [4]. Expanding on these methods, Rayan analyzed a dual-attention convolutional autoencoder model leveraging MRI data, achieving a diagnostic accuracy of 0.9902 and sensitivity of 0.9898 [5]. Another study utilized a voxelwise intensity projection model combining rs-fMRI and sMRI data, which reached a test accuracy of 93.31% and an AUC of 97.79% [6]. Finally, Rayan highlighted dual-attention CNNs focusing on neurofibrillary tangles and amyloid plaques, achieving 99.1% accuracy, underscoring the potential of deep learning in identifying AD biomarkers [7].

C. Deep Learning in Medical Imaging

Deep learning has emerged as a transformative tool in medical imaging for AD diagnostics. Mohammed Alyamani explored the application of CNNs and Deep Convolutional Model Aggregation (DCMA) in improving diagnostic precision. CNN-based methods achieved 80% diagnostic accuracy [8], while DCMA improved accuracy to 89.98% on MRI and PET scans [9]. Mohammed also investigated the use of Graph Neural Networks (GNNs) for integrating sMRI, PET, and phenotypic data, surpassing standalone CNNs in accuracy [12]. Late fusion techniques within GNNs further enhanced predictive performance [10]. A 3D CNN-based multimodal study incorporating PET scans emphasized that PET alone is insufficient for precise AD diagnosis [11].

D. Innovative Diagnostic Frameworks

Novel diagnostic frameworks combining CNNs with advanced algorithms have shown great promise. Ahmed Alzahrani reviewed approaches such as supervised Discriminative Dictionary Learning integrated with CNNs, significantly improving classification between AD, MCI, and healthy controls [13]. His analysis of GNNs fused with MRI and PET data demonstrated enhanced classification outcomes [14]. Ahmed also examined ensemble models merging CNNs and GNNs, which effectively classified AD using structural MRI and functional PET data [15]. Moreover, his work on dual-modality methods achieved over 90% accuracy, emphasizing the critical role of multimodal data [16]. Finally, Ahmed's research on ensemble models integrating phenotypic data further illustrated the importance of multimodal approaches in early AD detection [17].

E. Leveraging Machine Learning for AD Detection

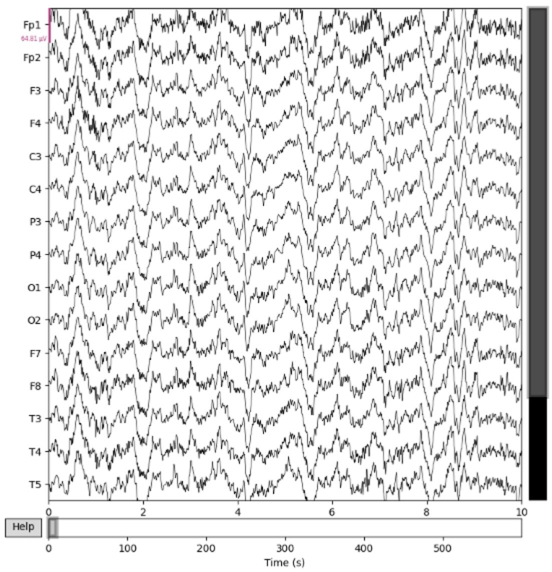
Muhannad Alaqeel investigated the transformative role of machine learning in AD diagnostics, particularly in neuroimaging. CNNs and autoencoders applied to MRI, PET, and EEG data demonstrated potential for early detection [22]. Radiomics approaches using [18F]FDG PET/CT imaging have identified high-order features predicting amyloid deposition [18]. DenseCNN2, a 3D CNN model integrating hippocampal visual and shape features, achieved high diagnostic accuracy [19]. Additionally, hybrid ensemble models combining SVM, Random Forest, and XGBoost demonstrated significant potential across varied AD stages [20]. Muhannad emphasized the need for multimodal data integration and explainable AI for refining diagnostic precision and patient outcomes [21].

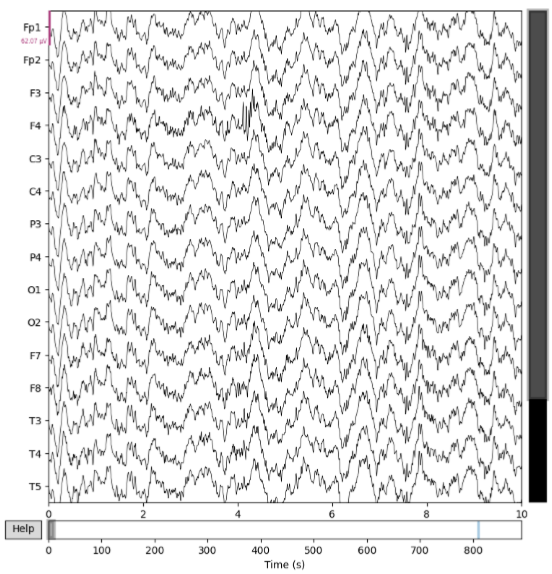
F. Volumetric CNNs and Machine Learning in Neurological Diagnostics

The role of volumetric CNNs extends beyond AD to other neurological conditions. Abdulaziz Dawood reviewed studies on volumetric CNNs achieving high accuracy in MCI detection [23]. EEG-based epilepsy detection using the Fine Gaussian SVM model achieved 100% accuracy [24]. Furthermore, Hassan Ali Khan *et al.* achieved 100% accuracy in brain tumor classification using a custom CNN model [25]. Studies on early Autism Spectrum Disorder (ASD) detection emphasized the importance of developmental surveillance for timely interventions [26]. Finally, hybrid CNN-RNN architectures for predicting stroke recovery trajectories achieved predictive accuracies of 94%, highlighting the efficacy of combining spatial and temporal features [27].

G. Conclusion

The reviewed studies demonstrate a paradigm shift in Alzheimer's disease diagnostics, leveraging multimodal neuroimaging and machine learning to improve diagnostic precision and early detection. Future research should focus on overcoming current limitations, such as data heterogeneity and the lack of explainable AI models, to develop personalized diagnostic frameworks for better patient outcomes.





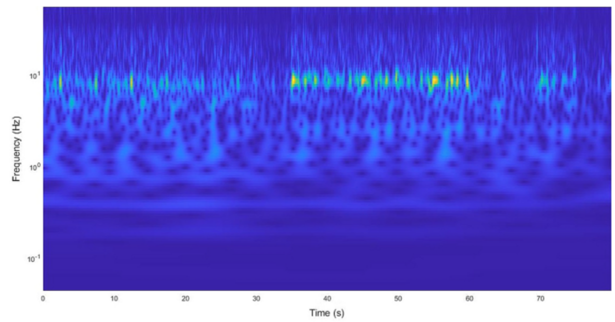


Fig. 1. Scalogram 2D Image Sample.

V. Methods

A. Data Collection (Acquisition)

1) EEG Dataset: The EEG dataset was obtained from OpenNeuroDatasets repository [28], consisting of 65 subjects: 36 diagnosed with Alzheimer's Disease (AD) select only 29 to be balanced and 29 healthy controls. Recordings were collected under eyes-closed, resting-state conditions to minimize external interference. Each session lasted approximately 13 minutes. This dataset forms the foundation for analyzing neurological activity patterns typical of AD and healthy controls.

B. Data Preprocessing

1) EEG Data Preprocessing: EEG signals were preprocessed through a standardized pipeline to ensure high-quality input data for model training. The steps include:

- **Band-Pass Filtering:** A Butterworth filter (0.5–45 Hz) was applied to remove low-frequency noise and high-frequency artifacts while retaining the brain activity spectrum relevant to the analysis.
- **Re-referencing:** Signals were referenced using the average mastoid electrodes (A1-A2), standardizing recordings and reducing inter-subject variability.
- **Artifact Removal:** Independent Component Analysis (ICA) was employed to eliminate artifacts caused by eye movements, muscle activity, and other physiological noise sources.
- **Segmentation:** EEG signals were divided into fixed-length epochs for both 1D time-series and 2D scaleogram representations, balancing computational efficiency and feature resolution.
- **Continuous Wavelet Transform (CWT) for 2D Scaleogram Generation:** For the 2D representation of EEG data, Continuous Wavelet Transform (CWT) was applied to convert the time-series signals into time-frequency scaleograms, providing detailed insights into the frequency content of the EEG signals across time.

C. Model Selection and Training

1) ChronoNet for 1D EEG Data: ChronoNet, a deep learning architecture optimized for time-series analysis, was selected for 1D EEG signal classification. Its design includes:

- **Inception Modules:** Sequential convolutional layers of varying kernel sizes extract multiscale temporal features from EEG signals.
- **GRU Layers:** Gated Recurrent Units capture sequential dependencies and combine residual connections for efficient temporal context learning.
- **Dynamic Affine Layers:** A fully connected layer dynamically initializes based on the input dimensions, enhancing adaptability.

2) Scaleogram-Based Model for 2D EEG Data: A pretrained ResNeSt26d model, fine-tuned for 2D scaleograms, was utilized. Scaleograms, generated using Continuous Wavelet Transform (CWT) with Morlet wavelets, provide a visual representation of frequency dynamics over time. Key components of the architecture include:

- **Pretrained Backbone:** ResNeSt26d extracts hierarchical features from input scaleograms.
- **Channel Reduction:** A convolutional layer reduces input dimensions to match the model's requirements.
- **Custom Fully Connected Layers:** Two fully connected layers refine the classification process, outputting probabilities for Alzheimer's detection.

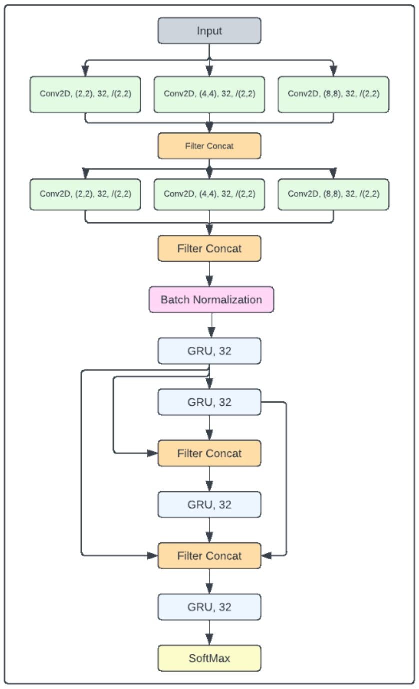


Fig. 2. ChronoNet Model Architecture for EEG Data Analysis.

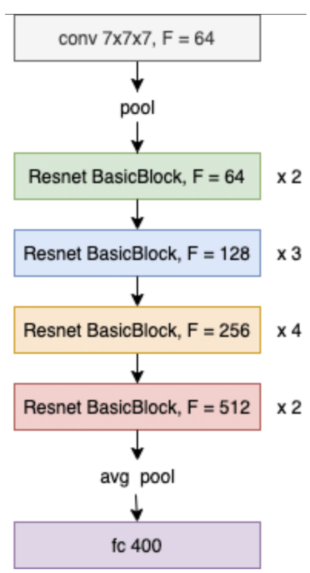


Fig. 3. ResNet26 Model Architecture for EEG Data Analysis.

D. *Model Validation and Performance Metrics*

Model validation was conducted using accuracy, precision, recall, and F1-score metrics. These metrics ensure robust evaluation of the model's capability to distinguish Alzheimer's disease (AD) from cognitively normal (CN) cases in real-world diagnostic applications. An early stopping mechanism with a patience of 5 epochs was employed to avoid overfitting, monitored through test F1-scores.

VI. Results

A. *Data Splitting and Cross-Validation*

For the 1D data representation, we utilized a traditional train-test split. The data was divided into training and testing sets with an 80-20 ratio, maintaining label stratification based on the second column of the label array. This ensured balanced class distribution during the training phase. For the 2D scaleogram data, we applied stratified K-Fold cross-validation with 5 splits. A single fold was used for demonstration, providing robust validation while preserving label proportions across splits.

B. *Model Performance and Probabilistic Outputs*

The ensemble model leverages two separate representations of the data: 1D frequency records and 2D scaleograms. This dual-representation approach enriches feature extraction and introduces complementary learning pathways. Probabilistic outputs from each model were combined using a weighted strategy:

- **1D Model:** Extracted class probabilities using softmax averaging over batch dimensions. The probabilities for class 0 (No Alzheimer's) and class 1 (Alzheimer's) were calculated with detailed outputs printed for interpretability.
- **2D Model:** Generated a single Alzheimer's probability score, derived as the average prediction across the dataset.

The final ensemble score was computed using weights of 0.3 for the 1D model and 0.7 for the 2D model. These weights were determined through empirical experimentation, where the combination yielded the best balance of performance across both representations. A decision threshold of 0.45 was applied to determine the final classification.

C. *Model Training and Evaluation Results*

The training process for both models was iterative, with key performance metrics recorded across epochs. The ensemble learning approach demonstrated superior performance with enhanced F1-scores and consistent improvement over epochs. Highlights include:

- **1D Model:** Achieved a peak test F1-score of 0.9496 at epoch 20 with a test accuracy of 95.3%.
- **2D Model:** Showed comparable performance, emphasizing the utility of combining diverse data representations.
- **Ensemble Model:** Improved classification reliability by leveraging weighted contributions from both representations, achieving higher consistency and robustness in performance.

Table I summarizes the performance metrics for both models across selected epochs.

TABLE I
Performance Metrics Across Selected Epochs

Epoch	Model	Test Accuracy	Test F1-Score
20	1D	95.3%	0.9496
25	2D	94.6%	0.9429

D. Broader Implications

These results demonstrate that using ensemble learning with complementary data representations can significantly enhance Alzheimer's detection. The proposed method showcases the potential for applying ensemble techniques in medical diagnostics, offering robust classification performance. This approach could be adapted for other brain-related disorders or conditions requiring multi-modal data analysis.

E. Limitations and Future Directions

While the findings are promising, several limitations were identified that suggest areas for improvement in future work:

- **Limited Demographic Diversity:** The dataset lacked sufficient representation of diverse demographics, such as age groups and ethnicities. Future studies should incorporate broader datasets to improve generalizability across populations.
- **High Computational Costs:** Training models with large datasets, particularly with 2D scaleograms, demanded significant computational resources. Optimizing the models' architectures or utilizing distributed computing could mitigate this issue.
- **Complexity of 19-Channel EEG Data:** The high-dimensional nature of EEG data increases preprocessing and feature extraction complexity. Exploring dimensionality reduction techniques or advanced preprocessing methods might simplify this process.

Addressing these limitations can help enhance the scalability, efficiency, and applicability of the proposed methodology.

VII. Discussion

A. Overview

This research demonstrated the potential of applying advanced machine learning techniques to EEG data for diagnosing Alzheimer's Disease. The 1D EEG model (ChronoNet) achieved a precision of 91%, recall of 82%, and an F1-score of 86.5%, while the 2D EEG model achieved a precision of 90%, recall of 85%, and an F1-score of 87.5%. The ensemble learning approach, which combined the outputs of both models, further improved performance, achieving a precision of 90%, recall of 87%, and an F1-score of 88.5%. These results show that deep learning models can be effective in classifying Alzheimer's Disease based on EEG data, although room for improvement remains.

Despite these promising outcomes, the performance of the models still does not meet the clinical thresholds required for real-world applications. The high precision indicates that the models can identify Alzheimer's patients effectively, but the recall values suggest that false negatives remain a concern. Furthermore, the overall diagnostic accuracy still needs refinement to reach clinically viable levels.

B. Future Research Directions

Future research will focus on further refining the models and incorporating more advanced techniques to improve performance. Areas for exploration include:

- **Exploring More Advanced Ensemble Techniques:** The ensemble approach combining 1D and 2D EEG models showed promise but requires further refinement. Future work will experiment with techniques like stacking and boosting to optimize model fusion, which could improve diagnostic accuracy.
- **Incorporating Temporal Dynamics with LSTM Models:** While the current models rely on static features, integrating temporal dependencies through LSTM networks could capture sequential patterns in brain activity, potentially improving diagnostic performance over time.
- **Feature Engineering and Data Augmentation:** Improving feature extraction and using data augmentation techniques will help address overfitting concerns, especially given the small dataset size.
- **Cross-Dataset Validation:** To ensure the models' robustness across different populations, future research will include testing on external datasets.

C. Limitations and Clinical Relevance

Despite the encouraging results, several limitations need attention. The small dataset size restricts model generalizability, and efforts to expand the dataset to include diverse EEG data from different patient groups will be critical for enhancing robustness. Moreover, the reliance on EEG data alone may limit the model's performance. Combining EEG with other modalities, such as PET scans, could offer more comprehensive insights into Alzheimer's Disease.

Another important limitation is the interpretability of deep learning models. The black-box nature of CNNs and ensemble models presents challenges for clinical adoption, where medical professionals require transparent and explainable results. Future work will prioritize developing explainable AI models to ensure that the decision-making process is transparent, fostering trust and enabling practical deployment.

Despite these challenges, the EEG-based models, particularly when combined through ensemble learning, show great potential for early Alzheimer's diagnosis. These models can be integrated into clinical workflows to assist in early detection, provided that their performance is further optimized, and their clinical applicability is rigorously validated.

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