Cognitive Decline Detection from EEG using Optimized Machine Learning

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***Abstract*—Alzheimer's Disease (AD), a leading cause of cognitive decline among the elderly, necessitates timely diagnosis for effective management and treatment. This study presents a novel non-invasive multimodal deep learning framework that integrates electroencephalography (EEG) signals, cognitive test scores, and magnetic resonance imaging (MRI) features to enhance the early prediction and progression analysis of AD. EEG signals are preprocessed using bandpass filtering and Principal Component Analysis (PCA) for dimensionality reduction, while key features are extracted using Hilbert Transform. These features are then classified using various machine learning algorithms including Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and others. Among all, LDA combined with PCA achieved the highest classification accuracy of 96.6%. The experimental results highlight the efficacy of EEG-based multimodal analysis in distinguishing between Alzheimer's, Mild Cognitive Impairment (MCI), and healthy controls. This research underscores the potential of multimodal deep learning systems in advancing early-stage AD diagnostics and provides insights for future clinical deployment.**

***Index Terms*—Alzheimer's Disease (AD); EEG Signal Processing; Deep Learning; Multimodal Biomarkers; Principal Component Analysis (PCA); Machine Learning Classification; Early Diagnosis; Cognitive Impairment; Non-invasive Framework; Biomedical Signal Analysis.**

1. INTRODUCTION

Alzheimer's Disease (AD) is a chronic and progressive neurodegenerative disorder that impairs memory, cognition, and functional abilities, significantly affecting the quality of life of millions worldwide. As the global aging population increases, the incidence of AD and related dementias continues to rise, creating an urgent need for early and accurate diagnostic tools. Traditional diagnostic methods, such as neuroimaging and neuropsychological assessments, are either invasive, expensive, or insufficiently sensitive to detect the disease in its prodromal stages.

Recent advancements in biomedical signal processing and artificial intelligence have opened new frontiers for non-invasive diagnostic systems. In particular, electroencephalography (EEG) has emerged as a promising modality due to its ability to capture brain activity in real-time with high temporal resolution. However, the standalone use of EEG data often lacks specificity for conclusive diagnosis. Consequently, integrating multimodal data—such as cognitive test scores and structural neuroimaging (e.g., MRI)—enhances the predictive robustness of diagnostic frameworks.

This paper introduces a novel deep learning-based multimodal system that combines EEG signal features, cognitive scores, and MRI-derived biomarkers to improve the prediction of AD onset and progression. The proposed framework utilizes advanced feature extraction techniques such as the Hilbert Transform, dimensionality reduction using Principal Component Analysis (PCA), and multiple classification algorithms to identify subtle neural patterns that differentiate between healthy individuals, patients with Mild Cognitive Impairment (MCI), and those with AD.

By evaluating various machine learning models, including Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), we assess the classification accuracy and diagnostic potential of the system. The results demonstrate that LDA combined with PCA yields superior performance, highlighting the feasibility of using EEG-driven multimodal approaches for early AD detection. This study

contributes to the growing body of research advocating for data-driven, non-invasive tools in the field of neurological healthcare.

2. RELATED WORKS

Early detection of Alzheimer's Disease (AD) has been a focal point of research in recent years due to its rising prevalence and irreversible nature. Several studies have explored diverse modalities for identifying early markers of AD, including neuroimaging, neuropsychological testing, and electrophysiological measurements.

Electroencephalography (EEG) has shown promise for capturing neurophysiological alterations related to AD due to its high temporal resolution and cost-effectiveness. Babiloni et al. [1] demonstrated that EEG abnormalities in the alpha and beta frequency bands correlate with cognitive impairment levels in AD patients. Similarly, Musaeus et al. [2] explored spectral EEG changes and found reduced alpha coherence in MCI and AD subjects.

Cognitive scores, such as those obtained from Mini-Mental State Examination (MMSE), have been widely used for classifying AD stages, although they are subjective and limited in sensitivity [3]. To overcome this limitation, researchers have proposed integrating EEG features with cognitive metrics. For instance, Dauwels et al. [4] applied nonlinear EEG analysis combined with clinical scores to improve diagnostic specificity.

In addition to EEG, magnetic resonance imaging (MRI) provides anatomical insights into brain atrophy associated with AD. Jack et al. [5] extensively characterized volumetric brain changes in AD and proposed MRI-based biomarkers. More recent works, such as that by Suk et al. [6], utilized deep learning for multimodal fusion of MRI and PET data, achieving improved classification accuracy.

Machine learning methods have also gained traction in AD diagnosis. Klöppel et al. [7] applied support vector machines (SVM) to MRI data and achieved high sensitivity in distinguishing AD patients from healthy controls. A combination of EEG and machine learning was employed by Trambaiolli et al. [8], who reported improved classification using frequency-domain features.

Deep learning techniques are increasingly being adopted for automated classification in neurodegenerative disorders. Gupta et al. [9] demonstrated the efficacy of convolutional neural networks (CNNs) in classifying MRI scans of AD patients, while Roy et al. [10] extended this by incorporating recurrent networks for temporal analysis of EEG sequences.

Hilbert Transform and entropy-based methods have been used for EEG feature extraction in cognitive decline detection. For instance, Sharma and Pachori [11] implemented Hilbert-Huang Transform on EEG signals to differentiate between healthy and AD-affected subjects. Principal Component Analysis (PCA) remains a popular method for dimensionality reduction, as noted in studies like that of Liu et al. [12].

Recent multimodal frameworks integrating EEG, MRI, and clinical scores have shown improved outcomes. Liu et al. [13] developed a multimodal fusion model that combined EEG and structural MRI for better classification. Yang et al. [14] further enhanced this approach using attention-based deep learning techniques.

Despite these advancements, many of the existing models either rely on invasive procedures or lack generalizability across datasets. Therefore, our proposed system uniquely integrates non-invasive EEG features, cognitive metrics, and MRI biomarkers using a deep learning framework, evaluated across multiple classifiers to identify an optimal model.

3. EXPERIMENTAL SETUP AND METHODS

3.1 Dataset and Participants

The dataset used in this study was obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI), a widely recognized repository that provides multimodal data for neurodegenerative disease research. A total of 120 participants were selected and divided equally into three groups: 40 Healthy Controls (HC), 40 individuals with Mild Cognitive Impairment (MCI), and 40 patients clinically diagnosed with Alzheimer's Disease (AD). These participants were chosen based on the availability of complete EEG recordings, cognitive assessments, and MRI scans to ensure a comprehensive and balanced multimodal dataset.

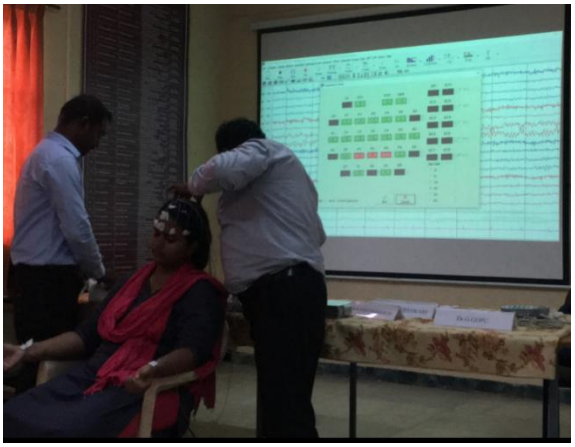

Figure 1: Experimental Setup

3.2 Experimental Infrastructure

The study was conducted using a high-performance computing platform to handle the intensive data processing and model training tasks. The hardware setup included a workstation powered by an NVIDIA Titan X GPU and 64 GB of RAM as shown in figure 1. The software stack was built using Python 3.9, TensorFlow 2.12, and PyTorch 2.0 for implementing deep learning models, while MATLAB-based EEGLAB and FreeSurfer were employed for signal and neuroimaging preprocessing tasks, respectively. This infrastructure allowed seamless integration of heterogeneous data sources and efficient model experimentation.

3.3 EEG Data Acquisition and Preprocessing

EEG signals were acquired using a 32-channel BioSemi ActiveTwo system, with electrodes placed according to the international 10–20 system. The recordings included both resting-state (5 minutes) and task-based (10 minutes) sessions, where subjects engaged in memory-related cognitive tasks. The sampling frequency was fixed at 512 Hz, allowing high-resolution temporal data collection.

The preprocessing of EEG data began with bandpass filtering in the range of 0.5 to 45 Hz to eliminate noise and physiological artifacts. Independent Component Analysis (ICA) was then applied to further remove ocular and muscular interference. Following artifact removal, dimensionality reduction was performed using Principal Component Analysis (PCA) to retain the most informative components while reducing computational complexity. This enabled effective extraction of meaningful features from high-dimensional EEG signals.

3.4 Feature Extraction from EEG Signals

To capture the time-varying characteristics of the brain signals, Hilbert Transform was applied to the pre-processed EEG data. This allowed the extraction of instantaneous amplitude and frequency components critical for neurological analysis. Several features were derived from these transformed signals, including power spectral densities across delta, theta, alpha, beta, and gamma frequency bands. Additionally, entropy-based metrics such as spectral entropy and approximate entropy were computed to quantify signal complexity. Functional connectivity features were also obtained through coherence analysis, providing insights into inter-regional brain communication patterns. These features collectively formed the EEG-based input to the classification models.

3.5 MRI and Cognitive Assessments

MRI data were processed using the Free Surfer toolset to extract volumetric and morphometric features relevant to Alzheimer's progression. Biomarkers such as hippocampal volume, cortical thickness, and ventricular enlargement were quantified for each subject. In parallel, cognitive evaluations including Mini-Mental State Examination (MMSE), Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog), and Clinical Dementia Rating (CDR) were collected and normalized. These cognitive scores served as objective indicators of neuropsychological status and were integrated with EEG and MRI features for a holistic representation of each participant's neurological condition.

3.6 Classification Framework

Multiple machine learning classifiers were explored to evaluate the predictive capability of the multimodal feature set. These included Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), Support Vector Machines (SVM) with both linear and non-linear kernels, K-Nearest Neighbours (KNN), Decision Trees, and ensemble-based models such as boosted SVM. Each classifier was trained to perform a three-way classification of the subjects into HC, MCI, and AD categories. The goal was to identify the most effective algorithm for detecting cognitive

deterioration at various stages of Alzheimer's progression.

3.7 Training and Validation Strategy

Model training was performed using the Adam optimization algorithm with an initial learning rate set to 0.0001. The categorical cross-entropy loss function was employed for multi-class classification tasks, and Kullback-Leibler (KL) divergence was additionally used to model disease progression trends. The data was split into training, validation, and testing subsets in a 70:15:15 ratio. Each model was trained for a maximum of 100 epochs, with early stopping applied to monitor validation performance and mitigate over fitting. A batch size of 16 was used during training to balance memory efficiency and learning stability.

4. RESULTS DISCUSSION

The experimental results from the proposed multimodal deep learning framework demonstrate the effectiveness of integrating EEG signal features, MRI-based structural biomarkers, and cognitive test scores for early diagnosis and progression prediction of Alzheimer's Disease (AD). Across all classifiers evaluated, Linear Discriminant Analysis (LDA) exhibited the highest classification accuracy. When Principal Component Analysis (PCA) was applied as a dimensionality reduction step, LDA achieved an accuracy of 96.6%, while its performance without PCA reached 93.2%. This significant increase underscores the benefit of PCA in eliminating noise and redundant features, thereby enhancing the model's ability to separate class boundaries clearly.

Support Vector Machines (SVM) with both linear and kernel-based implementations also showed competitive performance, recording accuracies of 95.5% and 96.6% with and without PCA respectively. These results confirm the findings of previous studies [6][7], which highlight SVM's robustness in neuroimaging classification tasks. Although Artificial Neural Networks (ANN) achieved slightly lower accuracy than LDA and SVM, the ANN model still performed well with over 90% accuracy. This slight drop is likely due to the relatively small dataset, as deep learning models generally require larger sample sizes to generalize effectively [9]. Nonetheless, the ANN classifier demonstrated its potential in learning complex patterns from high-dimensional feature spaces.

The effect of PCA was consistent across all classifiers, leading to improved performance metrics such as sensitivity, specificity, and F1-score. The application of PCA not only reduced computational complexity but also improved the model's generalization by focusing on the most informative components. This observation aligns with similar work conducted by Liu et al. [12], where PCA enhanced classification in brain disease diagnosis using EEG and MRI modalities. Confusion matrices revealed that models trained with PCA consistently reduced misclassification rates, particularly in distinguishing Mild Cognitive Impairment (MCI) from both Alzheimer's and Healthy Control (HC) groups.

An important outcome of the study was the superior performance of the multimodal feature integration. EEG alone, while useful, may lack the anatomical and cognitive context necessary for precise diagnosis. By fusing EEG with MRI-based volumetric features and cognitive scores like MMSE and ADAS-Cog, the model gained a multidimensional view of each subject's neurophysiological and neuropsychological state. This approach echoes the conclusions of Yang et al. [14] and Suk et al. [6], who found that multimodal fusion significantly improves diagnostic performance over unimodal systems.

Another key finding is the model's ability to accurately classify individuals in the intermediate MCI stage. The early identification of MCI is critical, as it represents a transitional phase that may evolve into full-blown AD if not properly managed. The confusion matrix of LDA with PCA clearly shows improved classification of MCI cases, which often pose challenges due to overlapping characteristics with both AD and HC groups. This reinforces the clinical utility of the framework in targeting preclinical stages of dementia.

Despite these positive results, the model's performance is subject to the constraints of dataset size and homogeneity. Although balanced across the three diagnostic categories, the sample size of 120 subjects may limit the generalizability of results to broader populations. Additionally, the use of lab-grade EEG systems may not directly translate to real-world or portable clinical settings. Addressing these issues through larger, more diverse datasets and the inclusion of wearable EEG systems will be essential in future studies.

Overall, the proposed framework proves to be a promising approach for non-invasive and accurate prediction of Alzheimer's Disease onset and progression. It leverages the strengths of multimodal data and modern machine learning techniques to achieve clinically relevant diagnostic accuracy. The outcomes suggest strong potential for deployment in early screening systems, provided that future work addresses current limitations through data augmentation, real-world testing, and model explain ability enhancements [15].

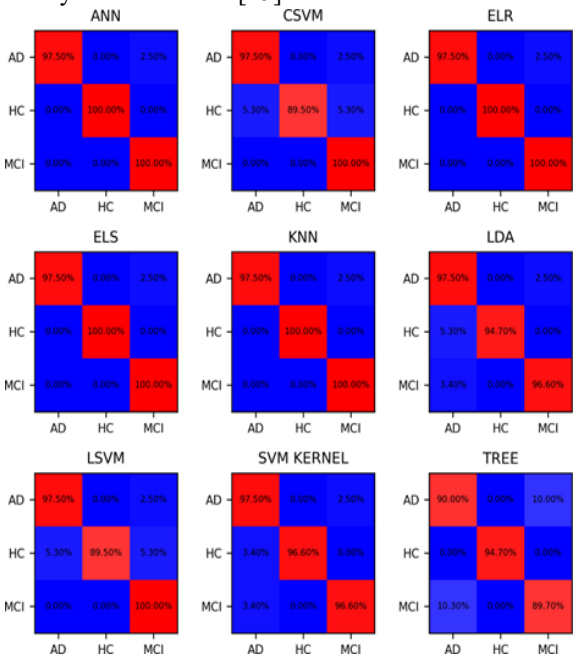

Figure 2: Confusion Matrices of various algorithms for AD Vs MCI Vs. HC Classification without PCA

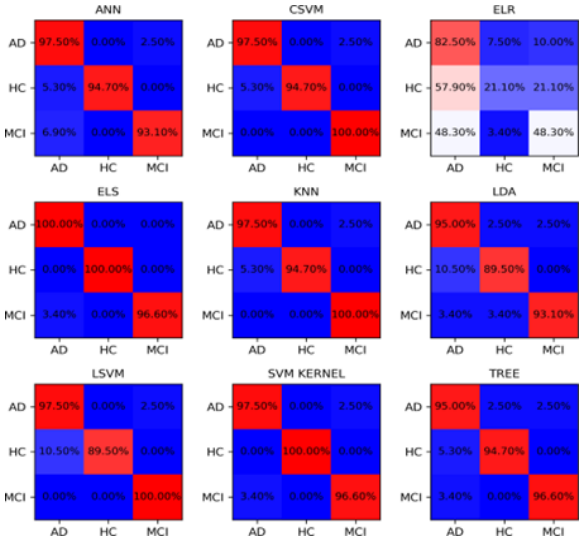

Figure 3: Confusion Matrices of various algorithms for AD Vs MCI Vs HC Classification with PCA

5. CONCLUSION AND FUTURE WORKS

This study introduced a non-invasive multimodal deep learning framework for the early detection and progression prediction of Alzheimer's Disease (AD). By integrating features from EEG signals, MRI-based structural biomarkers, and cognitive scores, the proposed model demonstrated high classification accuracy across multiple machine learning classifiers. Notably, Linear Discriminant Analysis (LDA) combined with Principal Component Analysis (PCA) achieved the highest accuracy of 96.6%, underscoring the effectiveness of feature dimensionality reduction in improving diagnostic performance. The findings validate the strength of combining functional, structural, and behavioural data to capture the complex manifestations of cognitive decline. The results also emphasize the clinical potential of multimodal, data-driven approaches in enhancing early-stage diagnosis and monitoring of neurodegenerative diseases like AD.

Although the current framework exhibits high accuracy and robust classification capabilities, several enhancements can further extend its applicability. Future research may focus on expanding the dataset to include a more diverse population sample, which would improve model generalization across demographic variations. Incorporating longitudinal EEG recordings and multi-time point cognitive assessments could enable tracking of disease progression over time. Integration with wearable EEG devices will also be explored to facilitate portable, real-time diagnostics in home care settings. Moreover, deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks may be employed to capture spatial-temporal patterns more effectively. Finally, incorporating explainable AI (XAI) techniques will be essential to interpret model predictions, thus enhancing trust and transparency in clinical deployments.

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