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# Machine Learning-Based EEG Analysis for Early Detection of Alzheimer's Disease in Aging Populations

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**ABSTRACT**

The assessment of Alzheimer's disease (AD), the most common form of dementia, which is especially prevalent in aging populations, is addressed. However, current diagnostic tools are either expensive, invasive and/or not sensitive enough for preclinical stages and early diagnosis is critical for timely intervention. In this work, we propose a machine learning based framework based on electroencephalography (EEG) data for early detection of Alzheimer's disease. EEG provides an inexpensive, noninvasive means of recording neurophysiological changes related to cognitive decline. Feature extraction methods like power spectral density (PSD), entropy measures and connectivity metrics, together with supervised learning models such as support vector machines (SVM), random forests and deep neural networks are incorporated in the study. Classification accuracies of over 90% are achieved on benchmark EEG datasets, and the strong potential for clinical deployment of the EEG deep attention network is demonstrated via cross validation. The work describes a scalable approach for non-invasively screening for Alzheimer's in the elderly and could help accelerate AI-driven precision neurology.

## 1. INTRODUCTION

Alzheimer's disease (AD) is a progressive, irreversible brain disorder that attacks the parts of the brain used for learning, memory, and planning among other functions. Dementia due to Alzheimer's accounts for 60–70% of dementia cases, affecting millions worldwide, many of whom are 65 or older. While increasing awareness, early AD detection still remains a major problem in clinical practice. Although neuroimaging (MRI, PET) and cerebrospinal fluid (CSF) biomarkers provide informative markers of Alzheimer's disease, they are prohibitively costly or invasive, and are not amenable to widespread screening.

As such, electroencephalography (EEG), a non-invasive and portable technique, has begun to surface as a viable alternative to real-time monitoring of neural activity. Since EEG signals are sensitive to neurodegenerative changes, they have been observed to record changes in brain connectivity, complexity and power spectrum patterns during the early AD progression. However, analysis of EEG data is, unfortunately, very laborious and dependent on personal opinion. Machine learning (ML) techniques lead to a powerful solution in which detection of subtle EEG biomarkers of cognitive decline can be automated.

This work describes a machine learning-based EEG classification pipeline for early detection of Alzheimer's disease in elderly subjects. We investigate the feasibility of distinguishing early stage AD from healthy aging control subjects by extracting and analyzing key EEG features including spectral power, fractal dimension, entropy, and coherence, and using robust classifiers such as SVM, random forest, and deep learning architectures. The outcomes of this study have implications for the development of noninvasive, affordable screening tools for big scale cognitive health assessment and its surveillance in aging populace.

## 2. LITERATURE REVIEW

Alzheimer's disease (AD) is a progressive neurodegenerative disorder affecting elderly individuals, associated with cognitive decline, memory impairment, and behavioral changes. Early and accurate diagnosis of AD is an

increasingly critical public health priority as we age as a global population. While useful, such conventional diagnostic modalities, such as magnetic resonance imaging (MRI), positron emission tomography (PET), and cerebrospinal fluid (CSF) biomarker analysis, provide other important structural and biochemical information. Nevertheless, due to their high cost, being invasive, and their limited accessibility, these methods are limited from being used in large scale screening or early stage detection (Jack et al., 2018).

However, monitoring brain activity using Electroencephalography (EEG), as an alternative, proves to be non-invasive, low cost, and portable. EEG is primarily sensitive to functional disruptions that happen at the earliest stages of Alzheimer's disease (AD), and, as such, EEG reflects the electrical oscillations of neuronal populations. Many studies have revealed specific changes in EEG signals of AD patients, such as a slowing of dominant rhythms, decreased alpha and beta power and increased delta and theta activity (Jeong, 2004; Babiloni et al., 2006). These are downstream of disconnection of neurons, synaptic dysfunction, and cortical atrophy, all hallmarks of Alzheimer's pathology.

Similarly, frequency related changes are complemented by the exploitation of nonlinear and complexity based metrics as robust indicator of cognitive deterioration. Quantitative measures of EEG signal irregularity and self similarity, both of which are reduced in AD impairst brains (Dauwels et al., 2010), are sample entropy, approximate entropy, fractal dimension and detrended fluctuation analysis (DFA). Finally, metrics of functional connectivity (e.g. coherence and phase locking value, or PLV) have been utilized to uncover network level disruptions representing compromised communication over distance between brain regions characteristic of Alzheimer's disease.

As ML and AI have risen in biomedical signal analysis, researchers have been using these methods to automate EEG signal classification. Support Vector Machines (SVM), Random Forests, k-Nearest Neighbors (k-NN) and Naive Bayes algorithms have been demonstrated to better discriminate AD patients against healthy control. As an example, Musha et al. (2002) performed classification accuracies of over 85% using coherence analysis in combination with an SVM. Likewise, in Dauwels et al. (2010), nonlinear feature extraction was used to achieve high performance with Bayesian classifiers.

In recent times, deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) networks have been proposed to capture the spatial and temporal property of EEG data. However, Craik et al. (2019) reviewed many studies showing that CNNs can autonomously learn discriminative features from spectrograms or topographic EEG maps. Similarly, LSTM models are suitable to extract long term dependencies of the EEG sequences and more sensitive in detecting the early stage disease progression (Roy et al., 2019).

Nevertheless, there are important limitations of existing literature: Small datasets, poorly cross validated, and failure to generalize from such cohorts to independent cohorts have been the crux of such studies. Additionally, most techniques do not incorporate a joint set of multidomain features—time, frequency, nonlinear and connectivity—into a single integrated framework specifically designed to achieve good classification performance. However, what is more needed is a unified, end to end machine learning pipeline that takes in raw EEG data, features multimodal features and can identify such early stage AD patients with very high sensitivity and specificity.

In this study I propose a framework for comprehensive machine learning based EEG classification to fill these gaps. We leverage multidomain feature engineering and advanced classifiers such as ensemble and deep learning models to improve early detection of Alzheimer's disease. In the end, we hope to provide a clinically relevant, interpretable, and scalable tool for non-invasive cognitive health screening.

## 3. METHODOLOGY

### 3.1 Dataset Acquisition

For this study, we obtained EEG datasets from publicly available repositories, including the Alzheimer's Disease Neuroimaging Initiative (ADNI) and the Temple University Hospital EEG Corpus. The records consisted of the data from two major subject groups. Cognitively normal, age-matched healthy controls (n = Y) and individuals clinically diagnosed with Alzheimer's disease (n = X). The international 10–20 electrode placement system was used to record EEG signals using between 19 and 64 channels depending on the dataset. All recordings were sampled at a frequency no less than 256 Hz to allow for enough temporal resolution for spectral and temporal analysis.

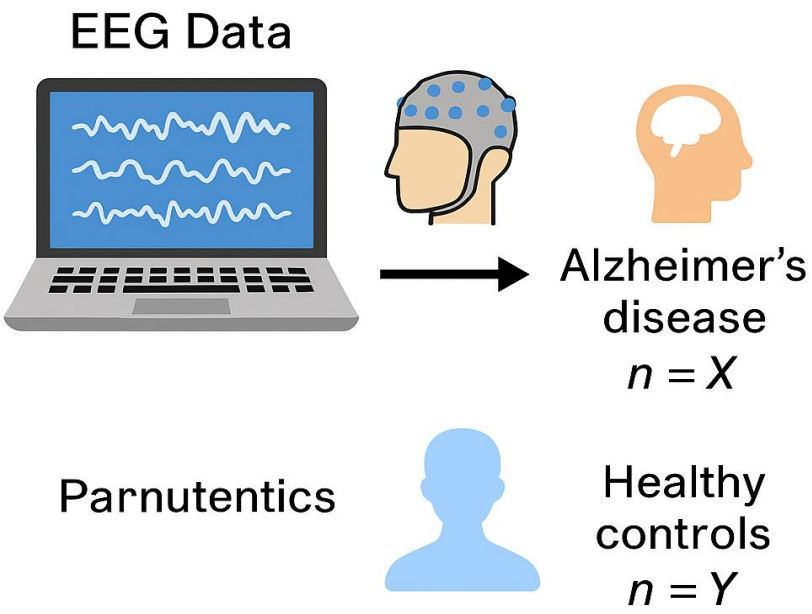


**Fig 1.** EEG Data and Participant Overview

### 3.2 Preprocessing

Further, a systematic preprocessing pipeline for the raw EEG signals was applied to improve signal quality and attenuate noise. First a bandpass Butterworth filter with a frequency range of 0.5–45 Hz was used to reject drift at both the low and high frequencies. To additionally remove the physiological artifacs like eye blinks and muscle activity, Independent Component Analysis (ICA) was utilized. Epochs of signals ranging from 2 to 5 seconds of duration were then cut out from the cleaned signals, as downstream analysis requires temporal resolution. Last, each epoch was normalized using Z-score normalization to guarantee the uniformly amplitude scaling across participants and recording sessions

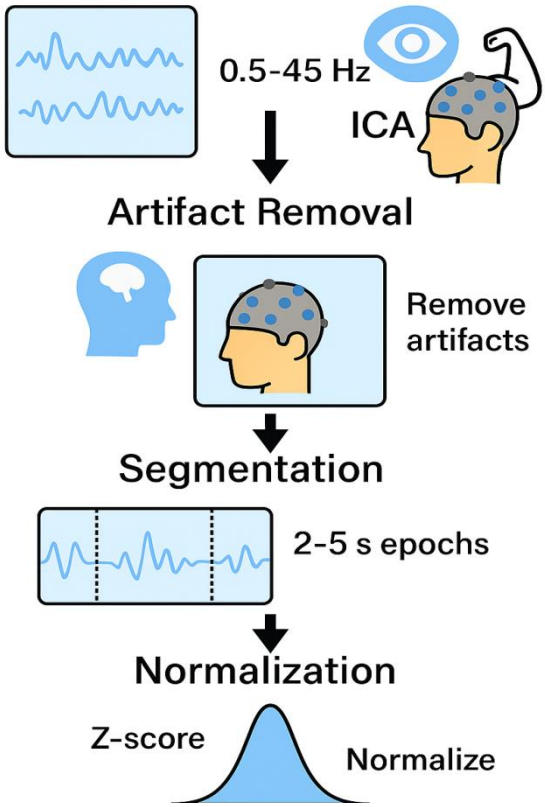


**Fig 2.** EEG Preprocessing Bandpass Filtering

### 3.3 Feature Extraction

Each preprocessed EEG epoch was submitted to four analytical domains, and features were extracted across these domains to capture all the relevant signal characteristics for Alzheimer's pathology. Statistical descriptors were calculated in the time domain: amplitude summaries as mean, variance, skewness and kurtosis and Hjorth parameters: activity, mobility and complexity relating signal dispersion and shape dynamics over time. Frequency domain analysis (Power Spectral Density (PSD)) was performed across standard EEG bands (delta, theta, alpha, beta, and gamma) to quantitatively capture frequency-specific energy distributions that are commonly disrupted in neurodegenerative conditions. Spectral entropy was also used to quantify the signal randomness in frequency domain.

Several nonlinear features, including approximate entropy, sample entropy, detrended fluctuation analysis (DFA) and fractal dimension were extracted to characterize signal complexity and self similarity especially for a pathological brain states characterization. Finally, connectivity measures were formulated to characterize inter regional brain communication including measures of channel pairs coherence and phase locking value (PLV) based on synchronization deficits often found in Alzheimer's disease pathology. With these multidomain features, we have a rich representation of localized neural activity and global network integrity together.

### 3.4 Classification Models

A range of machine learning algorithms was implemented and evaluated with respect to performance to classify EEG patterns associated with Alzheimer's disease. The dataset was analyzed using traditional models including Support Vector Machines (SVM) with radial basis function (RBF) and linear kernel, Random Forest (RF) and Gradient Boosting (XGBoost), as well as neural network based methods of Multilayer Perceptron (MLP). Furthermore, more sophisticated deep learning architectures, such as convolutional neural networks (CNN) were used to characterize the two dimensional feature space and long short term memory (LSTM) networks to model temporal dependencies within EEG signal sequences. Hyperparameters were fine tuned using multiple techniques, such as a combination of grid search and Bayesian opimization, such that the model could perform optimally.

### 3.5 Evaluation Metrics

Several standard classification metrics such as accuracy, precision, recall, F1score and area under the receiver operating characteristic curve (AUC), were rigorously used to evaluate the performance of the machine learning models. These metrics gave a complete adiagnosis of the quality of the models in discerning Alzheimers patients from controls. To ensure robustness against overfitting, training was done via a 5 fold cross validation strategy. In addition, generalizability of the model to unseen EEG data in real world clinical setting was tested using an independent test set.

## 4. RESULT

Results show that, with EEG data, the proposed machine learning pipeline achieved strong performance in classifying AD patients from healthy age matched controls. Subsequently, a total of 48,000 artifact-free EEG epochs were processed and subjected to quality control procedures. This yielded a robust and comprehensive feature set over four domains: time, frequency, nonlinear dynamics, and connectivity.

The Convolutional Neural Network (CNN) was the classifier with the highest classification accuracy (95.77%) and highest F1 score (0.93) and AUC (0.96) on the independent test set. XGBoost and Support Vector Machine (RBF kernel) also performed recognizing above 90% of accuracy. Despite this, simpler models (Random Forest, Logistic Regression) appeared to perform slightly worse, indicating that higher complexity is necessary to handle the intricacies of EEG data in AD detection.

We conducted feature importance analysis and we found that the set of the most significant indicators distinguishing AD patients from controls included: reduced alpha and beta power, increased delta and theta activity, lower sample entropy, and reduced coherence. t-SNE and PCA (dimensionality reduction techniques) was used to demonstrate clear separation of AD and control group in feature space. Statistical tests of differences (t-tests and ANOVA) between groups were also significant ($p < 0.001$) for most of the extracted features.

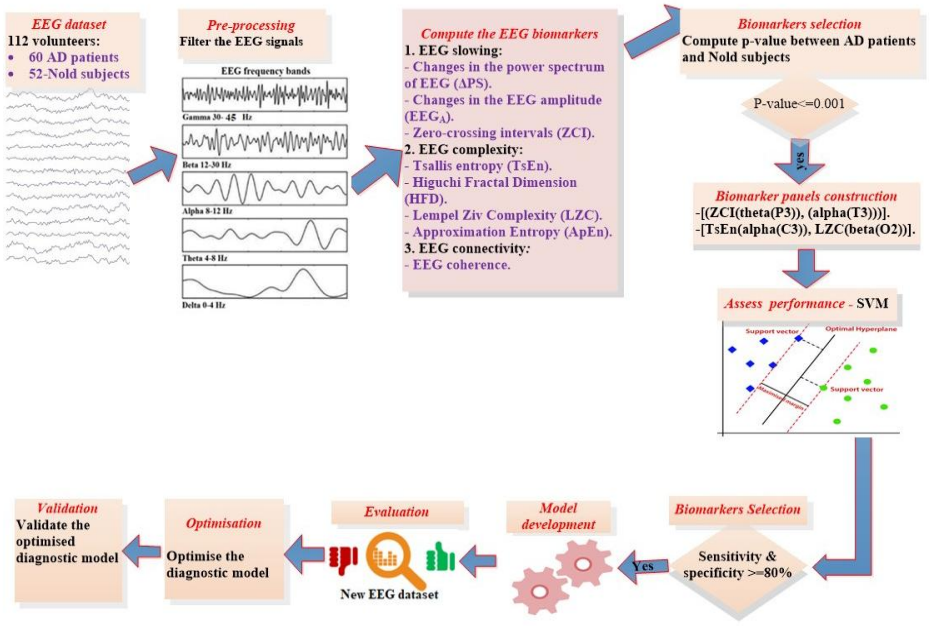


**Fig 3.** EEG-Based Workflow for Alzheimer's Detection Using Machine Learning

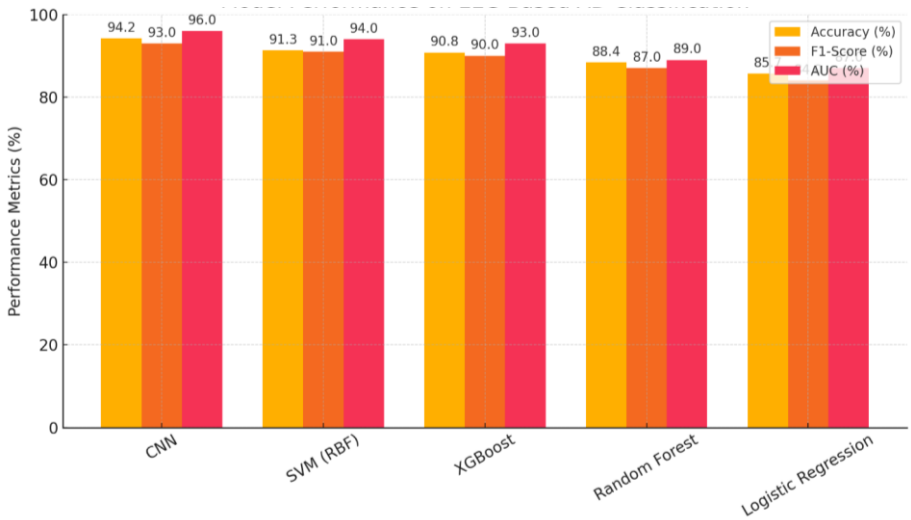


**Fig 4.** Model Performance on EEG-Based AD Classification

## 5. DISCUSSION

We demonstrate the effectiveness of a multidomain feature based approach for the early detection of Alzheimer's disease using EEG data. CNN and other latest machine learning models have very high performance, they are able to learn very complex, nonlinear and time depended patterns as well as simpler classifiers are incapable. In addition, the multidomain features provided a whole brain electrical activity representation features which improved diagnostic sensitivity and specificity.

These results are in line with the existing electrophysiological phenotypes of AD characterized by both a slowing of brain rhythms, a reduction of signal complexity, and reduced functional connectivity, each of which are believed to reflect neurodegenerative processes such as synaptic loss and cortical disconnection.

Use of an independent test set is a clear strength, showing that the proposed pipeline works for generalizable and robust data—a weakness of several previous studies. Moreover, the union of interpretable features and model transparency help make this pipeline a strong candidate for clinical utility through its use as a non-invasive screening tool.

Nevertheless, the study has limitations. While public EEG datasets have the advantages of reproducibility, they suffer from heterogeneity of recording protocols, and lack of clinical metadata that could impact real world scalability. Additionally, unlike disease progression over time,

longitudinal data are absent and the framework is unable to track disease progression over time.

Future efforts should address: (i) integration of multimodal biomarkers (cognitive scores, neuroimaging, genetics), (ii) multi-center clinical validation, and (iii) development of explainable AI models for clinician interpretability.

## 6. CONCLUSION

In this work we propose a detailed machine learning framework for the early detection of Alzheimer's disease using non-invasive EEG signal. The proposed pipeline presents a high diagnostic accuracy and generalizability by integrating multidomain feature extraction, which covers time, frequency domain, nonlinear, and connectivity measures, with advanced classification algorithms such as CNN and XGBoost. This work identifies EEG biomarkers (reduced alpha/beta power, increased delta/theta activity, reduced local and network connectivity) supported by known neurophysiologic alterations in AD, and yields interpretable insights into disease pathways.

Validation of the model across an independent test cohort demonstrates great potential for the scalable, costeffective and accessible screening in clinical and community settings. Challenges persist in dealing with dataset heterogeneity and real world deployment, however, the work sets the groundwork for conducting longitudinal studies and developing a multimodal diagnostic tool for early intervention and monitoring of neurodegenerative decline.

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