# Distinct EEG Spectral Signatures Differentiate Alzheimer's Disease, Frontotemporal Dementia, and Controls

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**Abstract**

Electroencephalography (EEG) provides a non-invasive window into the neural oscillatory patterns associated with neurodegenerative disorders. In this study, we compared EEG power spectral features across Alzheimer's disease (AD), frontotemporal dementia (FTD), and healthy control participants to identify frequency band alterations and assess their utility for automated classification. Power spectral density was computed for five canonical frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz). Group comparisons revealed distinct spectral signatures, including reduced alpha power and elevated theta power in AD, altered gamma power in FTD, and higher alpha power in controls. We further evaluated the discriminative capability of these features using four machine learning algorithms—logistic regression, random forest, multilayer perceptron (MLP), and XGBoost. Classification performance varied across models, with MLP achieving the highest overall accuracy (66.14%), while random forest excelled in distinguishing controls (73.87%) and MLP performed best in classifying FTD (61.70%). These findings highlight characteristic EEG spectral alterations in AD and FTD and demonstrate the feasibility of using band power features for automated differentiation between dementia subtypes and healthy aging. Our results underscore the potential of EEG-based machine learning approaches as accessible, cost-effective tools for early diagnosis and disease monitoring in clinical and research settings.

## Introduction

Alzheimer's disease is a brain disorder that slowly changes how a person thinks, remembers, and manages everyday life[7]. It's the most common cause of dementia, often affecting people in their mid-60s or older, but it can appear even earlier. At the neurobiological level, AD is characterized by the extracellular accumulation of amyloid-$\beta$ peptides into plaques and the intracellular aggregation of hyperphosphorylated tau protein into neurofibrillary tangles. These pathological processes disrupt synaptic communication, impair neuronal metabolism, and trigger widespread neuroinflammation. Over time, neuronal death leads to marked cortical atrophy, particularly in the hippocampus and medial temporal lobes, regions critical for episodic memory. Clinically, patients present with progressive memory impairment, disorientation, difficulty performing routine tasks, and, in advanced stages, profound cognitive and functional decline[6].

Frontotemporal dementia (FTD), in contrast, is a clinically and biologically heterogeneous group of disorders that primarily affect the frontal and temporal lobes [8]. Unlike AD, where memory loss is often the earliest and most salient symptom, FTD is defined by early changes in personality, executive function, behavior, and language [1]. The underlying pathology involves selective neuronal loss and gliosis in the frontal and anterior temporal cortices, accompanied by abnormal accumulations of proteins such as tau, TDP-43, or FUS. These molecular abnormalities disrupt frontotemporal networks governing social behavior, decision-making, and speech production. Patients may show disinhibition, apathy, compulsive behaviors, or progressive language

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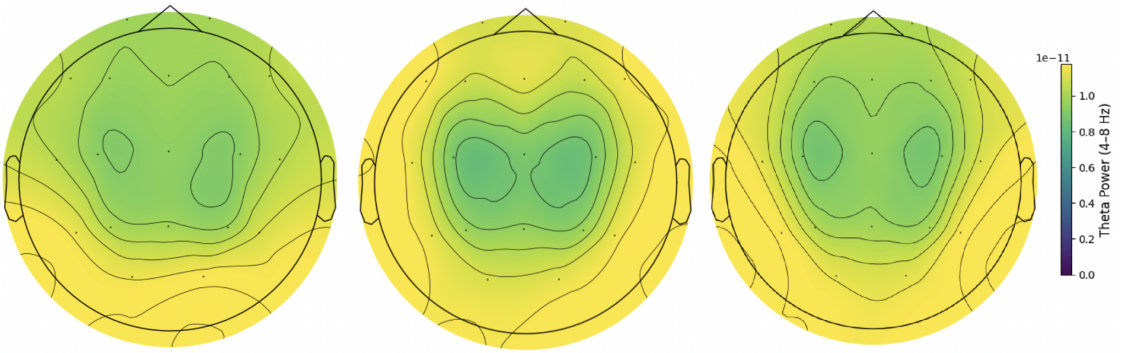


Figure 1: Topographic distribution of theta-band (4–8 Hz) power across scalp electrodes. The left panel shows the control group, the middle panel represents patients with Alzheimer's disease, and the right panel depicts patients with frontotemporal dementia. Warmer colors indicate higher theta power, with notable differences in spatial distribution between groups.

impairments depending on the FTD subtype. Importantly, FTD tends to occur earlier than AD, with symptom onset often in the 40s or 50s, which amplifies its social and economic burden.

By contrast, healthy aging is associated with more gradual and less severe changes in brain structure and function. Although normal aging can involve mild slowing of cognitive processing and subtle memory lapses, it does not produce the extensive protein aggregation or massive neuronal loss characteristic of AD or FTD. Aging brains often show compensatory mechanisms, such as increased recruitment of prefrontal networks during memory tasks, that allow many individuals to maintain functional independence well into later life.

Currently, there are no disease-modifying therapies for either AD or FTD. Available treatments provide only symptomatic relief, and their effectiveness is limited. This reality underscores the urgency of developing reliable biomarkers that can distinguish between neurodegenerative diseases at their earliest stages, when interventions and care planning may have the greatest impact.

In this study, we focus on electroencephalography (EEG)-based biomarkers [5] as a potential diagnostic tool. EEG directly captures neural oscillations and synaptic dynamics, which are altered in both AD and FTD due to disruptions in cortical circuits. For example, AD is often associated with increased slow-wave (theta and delta) activity and reduced alpha and beta rhythms, reflecting impaired long-range connectivity. In FTD, oscillatory disturbances may localize more strongly to frontal and temporal networks, consistent with the selective vulnerability of these regions. By applying advanced machine learning classification techniques, we aim to identify disease-specific electrophysiological signatures that can distinguish early-stage AD, FTD, and healthy controls.

# Methods

EEG recordings were obtained from participants diagnosed with Alzheimer's disease (AD), frontotemporal dementia (FTD), and healthy controls (see Figure 1). Signals were preprocessed to remove artifacts using standard filtering techniques, including notch filtering at 50/60 Hz to eliminate powerline noise and band-pass filtering (0.5–50 Hz) to retain physiologically relevant activity. Segments containing motion or ocular artifacts were excluded from further analysis.

Power spectral density (PSD) was computed using Welch's method, and relative band power was extracted for five canonical frequency ranges: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz). These band power features were averaged across channels and used as input variables for classification.

Four machine learning algorithms[2] were implemented for automated group classification: logistic regression, random forest, multilayer perceptron (MLP), and XGBoost[4]. Models were trained and evaluated using stratified 10-fold cross-validation to ensure balanced representation of

diagnostic groups across folds. Performance metrics included overall accuracy as well as per-class accuracy to assess discriminability between AD, FTD, and control groups.

Statistical analyses were performed to compare spectral power differences between groups, with particular attention to alpha, theta, and gamma alterations that are known to reflect neurodegenerative changes.

# Results

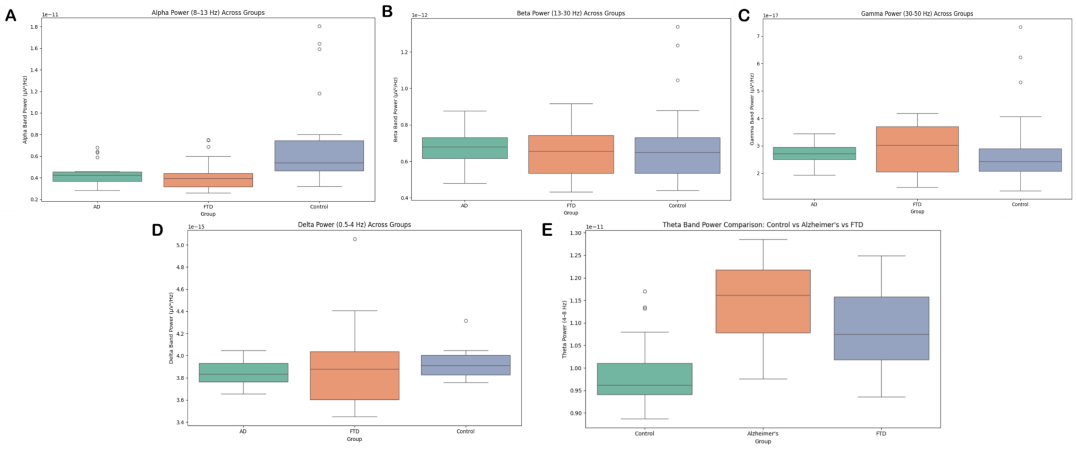


Figure 2: **EEG power spectral differences across Alzheimer's disease (AD), frontotemporal dementia (FTD), and control participants.** (a) Alpha power (8–13 Hz), (b) Beta power (13–30 Hz), (c) Gamma power (30–50 Hz), (d) Delta power (0.5–4 Hz), and (e) Theta power (4–8 Hz) are shown for each group. AD participants exhibited reduced alpha power and elevated theta power compared to controls, while FTD participants displayed altered gamma and theta activity. Controls generally demonstrated higher alpha power. Boxplots display the median, interquartile range, and outliers, highlighting distinct spectral patterns that may serve as biomarkers for differentiating dementia subtypes from healthy aging.

## Analysis Based on Power Wave Plots

The beta power wave, which has a frequency of 13-30 Hz, did not show much difference between the three groups, indicating that it did not show much correlation with that wave. The gamma wave, measured with 30-50 Hz, and the delta wave, which was 0.5 to 4 Hz, did not show much; the only key point was the high variability in patients with frontotemporal dementia. The alpha power wave shows a massive difference in that the control group had a much higher median than the other two groups, which shows a decrease in alertness in a relaxed state and memory for AD and FTD patients. Lastly, in the theta power wave, the median is highest for AD patients, then FTD patients, then lowest for the control population. This indicates abnormal electrical activity in the brain and faster cognitive decline.

| Model | Overall | Control | Alzheimer's | FTD |
|---|---|---|---|---|
| Logistic Regression | 54.95% | 61.01% | 68.74% | 30.79% |
| Random Forest | 64.92% | 73.87% | 66.83% | 51.85% |
| MLP | 66.14% | 67.28% | 68.64% | 61.70% |
| XGBoost | 63.44% | 73.56% | 66.23% | 47.91% |

Figure 3: **Accuracy of classification models for EEG-based differentiation of Alzheimer's disease (AD), frontotemporal dementia (FTD), and control participants.** The table shows the overall classification accuracy as well as class-specific accuracies for each model: Logistic Regression, Random Forest, Multilayer Perceptron (MLP), and XGBoost. MLP achieved the highest overall accuracy (66.14%), Random Forest performed best in identifying control participants (73.87%), and MLP obtained the highest accuracy for FTD classification (61.70%). These results indicate that machine learning models trained on EEG spectral features can distinguish between dementia subtypes and healthy aging with moderate accuracy.

### Analysis on the four classification algorithms

The data used in Figure 2 is the EEG signal for the control, Alzheimer's and Frontotemporal dementia classes. The data was fed into machine learning models to train it to identify classes. After training, a test set was used to measure the accuracy of the algorithms. Based on the results, the MLP algorithm was the most accurate with 66.14%, followed by Random Forest with 64.92%, XGBoost with 63.44%, and lastly Logistic Regression with 54.95%. For this table, 80% of the data was used for the training set and 20% was used for the test set.

## Conclusion

We investigated EEG power spectral features across Alzheimer's disease (AD), frontotemporal dementia (FTD), and healthy control participants to identify disease-specific alterations and evaluate their potential for automated classification. Our analysis revealed distinct oscillatory patterns in the canonical EEG frequency bands, with AD patients exhibiting reduced alpha power and elevated theta activity, FTD patients showing altered gamma and theta power, and controls demonstrating generally higher alpha power. These differences are consistent with previous findings on neural slowing in neurodegenerative disorders and suggest that frequency-specific disruptions may serve as non-invasive biomarkers for differential diagnosis.

To assess the feasibility of automated classification, we implemented and compared four machine learning algorithms: logistic regression, random forest, multilayer perceptron (MLP), and XGBoost. Among these, MLP achieved the highest overall classification accuracy (66.14%), while random forest excelled in identifying control participants (73.87%) and MLP outperformed others in detecting FTD cases (61.70%). Although the accuracies indicate that perfect separation is not yet achievable, the results demonstrate that EEG spectral features contain meaningful discriminative information for distinguishing between dementia subtypes and healthy aging.

The integration of EEG-based spectral analysis with machine learning has several practical advantages. EEG is relatively inexpensive, widely available, and well-tolerated, making it a viable option for routine screening and longitudinal monitoring. Automated classification tools could assist clinicians by providing rapid, objective assessments, potentially improving early diagnosis and facilitating targeted interventions. Furthermore, the identification of frequency band alterations specific to AD and FTD could inform personalized treatment strategies and contribute to the understanding of underlying neuropathophysiological mechanisms.

Future work should focus on expanding datasets to include more diverse populations, integrating additional EEG-derived features such as connectivity measures and entropy, and exploring advanced deep learning architectures capable of capturing spatiotemporal dynamics. Combining EEG with other biomarkers, such as structural MRI or cerebrospinal fluid analyses[3], may further enhance diagnostic accuracy. Overall, our findings underscore the potential of EEG spectral features, coupled with machine learning, as a cost-effective and accessible approach for aiding in the differentiation of neurodegenerative disorders in both clinical and research settings.

### Software and Reproducibility

The software used to code these methods was on google colab and the dataset used for these tests was from openneuro.org. The code for these figures can be shown through reasonable request from the authors.

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