UNIVERSITY OF THE PELOPONNESE – FACULTY OF ENGINEERING
ELECTRICAL & COMPUTER ENGINEERING DEPARTMENT

DIPLOMA THESIS

EEG-based Connectivity Analysis for Differentiating Alzheimer's Disease and Frontotemporal Dementia.

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Introduction

🌍 According to the World Health Organization (WHO), more than 55 million people are currently living with dementia worldwide.

❗ A number projected to rise to 78 million by 2030 and 139 million by 2050.

✓Alzheimer's disease (AD) is the most prevalent, accounting for 60–80% of all cases globally.

✓Frontotemporal dementia (FTD) represents approximately 10% of cases.

⚠️ In response to these challenges, the WHO has recognized dementia as a public health priority, advocating for heightened global awareness, preventive strategies, and improve early diagnosis and care services .

✔ Early and accurate diagnosis is critical for timely intervention and effective care planning.

Theoretical Background

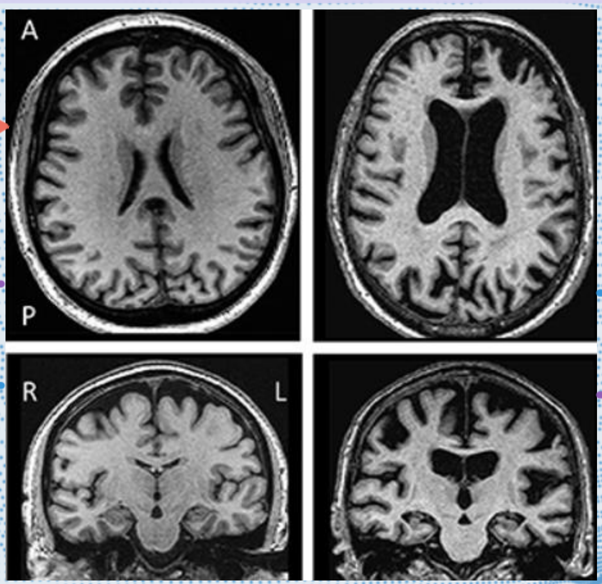
Alzheimer Disease

- AD primarily affects memory and cognitive functions, beginning with memory loss and progressing to severe confusion and disorientation.
- It is marked by the buildup of amyloid plaques and tau tangles in the brain, leading to neuronal death, particularly in the hippocampus.

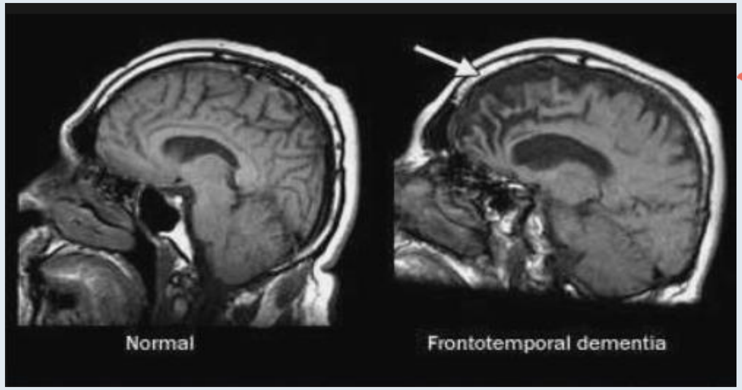
Frontotemporal Dementia

- FTD primarily affects behavior, personality, and language, often appearing earlier in life (before age 65).
- It results from the degeneration of the frontal and temporal lobes due to abnormal proteins like tau, TDP-43, and FUS, causing dramatic personality and emotional changes.

AD Patient



Healthy Patient



Risk Factors

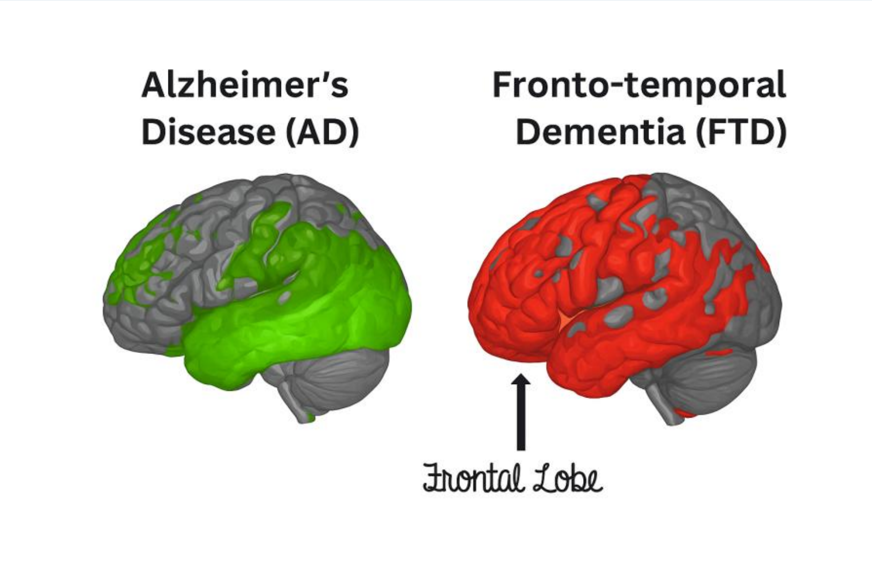
- ✓Age 65+ is the strongest risk factor
- ✓Hypertension, diabetes, obesity
- ✓Smoking, alcohol overuse, inactivity
- ✓Air pollution and poor lifestyle habits
- ✓Social isolation and depression

Early Signs & Symptoms

- ❑Memory loss and confusion in familiar places
- ❑Misplacing items or getting lost easily
- ❑Trouble making decisions or solving problems
- ❑Difficulty communicating or finding words
- ❑Mood and personality changes, social withdrawal

Differences Between AD vs FTD

Alzheimer's disease	Frontotemporal degeneration
Mostly affects adults age 65 and older.	Usually affects adults between ages 40 and 65.
Time between the start of symptoms and a diagnosis is usually less than three years.	Time between the start of symptoms and a diagnosis is often more than is often more than three years.
Most common cause of dementia.	Accounts for 1 in 10 cases of dementia or fewer.
Memory loss is an early symptom.	Memory loss develops later on.
Behavior changes tend to happen later on.	Behavior changes are one of the first noticeable signs.
Getting lost in familiar places is a common symptom.	Getting lost in familiar places is not common.
Seeing or hearing things that aren't real is common as the disease progresses.	Seeing or hearing things that aren't real is not common.



EEG Basics

What is EEG?

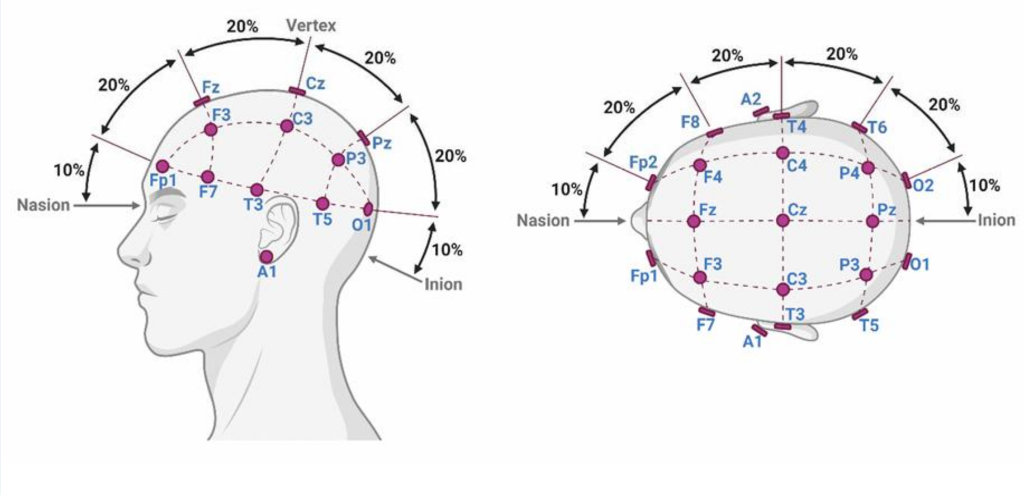
- ➢Electroencephalography (EEG) records brain activity through scalp electrodes.
- ➢It measures electrical signals produced by synchronized neuron firing.
- ➢Non-invasive, portable, inexpensive, and provides *millisecond-level* temporal resolution.

Why EEG for Dementia?

- ✓Detects functional (not structural) brain changes, revealing neural network disruptions.
- ✓Identifies early abnormalities before structural atrophy appears on MRI/CT.
- ✓Useful for tracking disease progression and evaluating treatment response.

EEG Setup

Uses the *10–20 international system* for electrode placement.
Covers frontal **(F)**, central **(C)**, parietal **(P)**, temporal **(T)**, and occipital **(O)** brain regions.
Left hemisphere = **odd** numbers
Right = **even** numbers
Midline = **"z"**

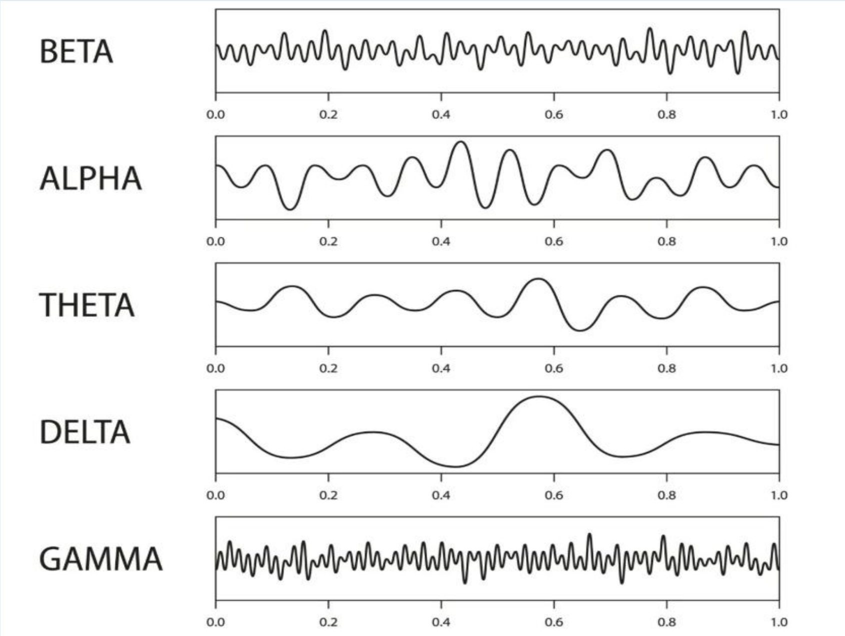


EEG results provide important information about the brain's electrical activity across different frequency bands

Band	Frequency (Hz)	Functional Role
Delta (δ)	0.5 - 4	Deep sleep, brain injury markers
Theta (θ)	4 - 8	Memory, drowsiness, early AD signs
Alpha (α)	8 - 13	Relaxed wakefulness, reduced in AD/FTD
Beta (β)	13 - 25	Active thinking, reduced in dementia
Gamma (γ)	25 - 45	High cognition, disrupted in dementia

✓AD: Reduced alpha/beta power, increased delta/theta slowing — posterior brain disruption.

✓FTD: Frontal alpha reduction and localized delta increases — anterior brain dysfunction.

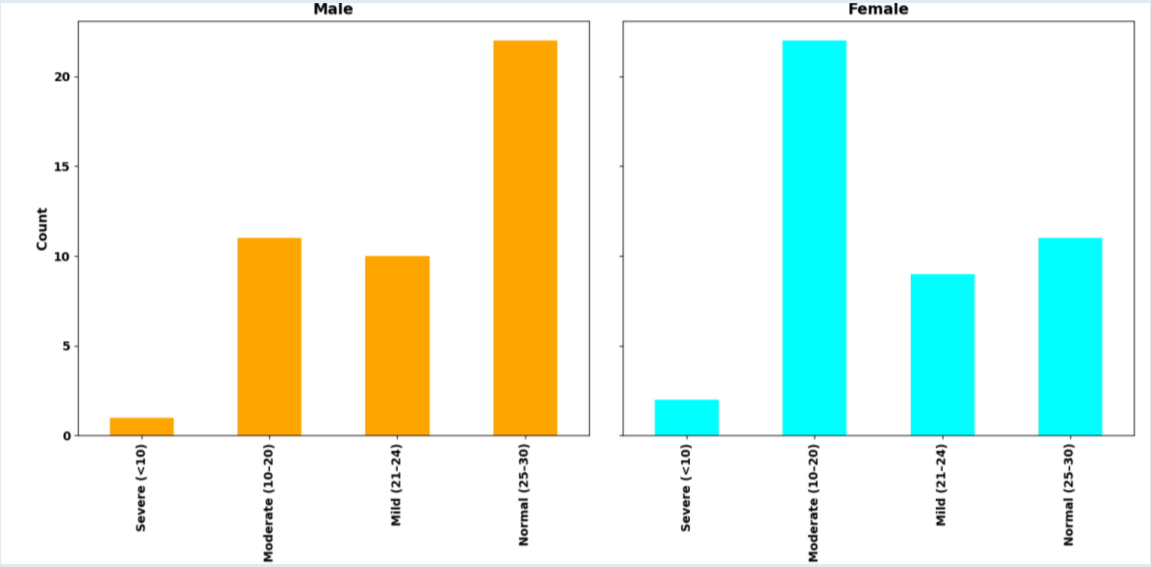


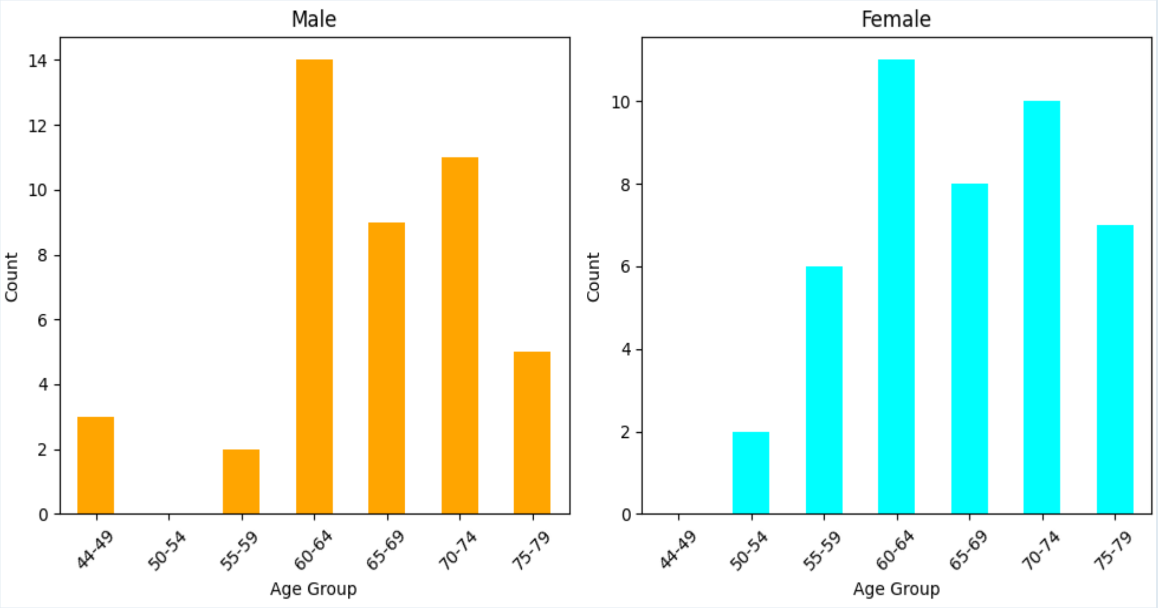
Data

The study uses a publicly available EEG dataset from Greek researchers with **88** participants (OpenEuro):
36 with Alzheimer's disease (AD)
23 with Frontotemporal Dementia (FTD)
29 healthy controls (CN)
EEG recordings were conducted using 19 scalp electrodes adhering to the 10–20 system during eyes-closed resting state sessions

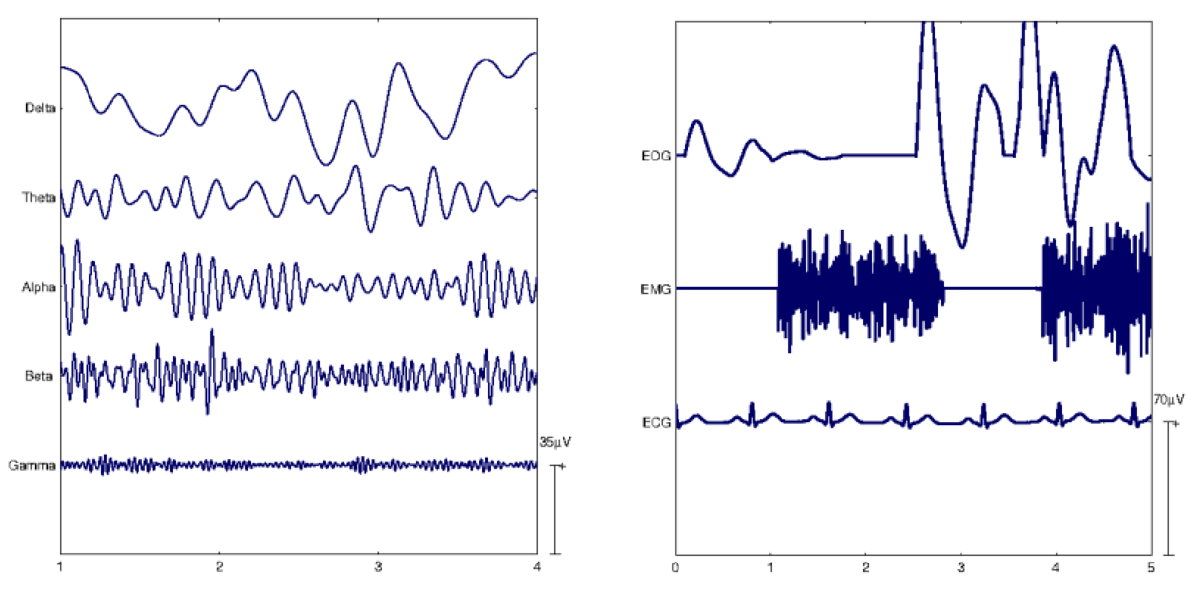
AD group: Mean age 66.4, mostly female
FTD group: Mean age 67.9
Each participant completed the **MMSE** cognitive assessment: **AD mean score ~18 FTD ~21, CN ~29**

Total EEG recording time:
485 min (AD)
276 min (FTD)
402 min (CN)





Preprocessing



(a) Brain Rhythms (b) Artifacts

EOG (eye)
EMG (muscle)
ECG (cardiac)

- ✓ Data sourced from derivatives folder (pre-prepared files)
- ✓ Butterworth band-pass filter (0.5–45 Hz) applied
- ✓ Signals re-referenced to average of A1 & A2 electrodes
- ✓ Artifact reduction via Automatic Subspace Reconstruction (ASR)
- ✓ Window: 0.5 s, SD threshold: 17
- ✓ Independent Component Analysis (ICA) using RunICA algorithm
- ✓ 19 channels → 19 independent components
- ✓ Eye/jaw artifacts auto-rejected via ICLabel (EEGLAB)
- ✓ Even with eyes closed, residual eye movement artifacts were detected

Feature extraction

Spectral Domain

➢Computed using ***Welch's method***

➢**EEG frequency bands:**

δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–25 Hz), γ (25–45 Hz)

➢**Relative Band Power (RBP):**

$RBP = P_{band} / P_{total}$

➢**Key Ratios:**

Alpha/Theta

cognitive performance arousal

Beta/Theta

attention, executive Function

Time Domain

⑩Capture

⑩***signal amplitude, morphology, variability***

⑩**Basic statistics**

⑩*Mean, SD, Variance, Skewness, Kurtosis*

⑩**Additional features:**

- *Zero-Crossing Rate Root Mean Square Peak-to-Peak Amplitude*
- *Mean Absolute* Deviation

Complexity Domain

⑩Capture

- ***irregularity and unpredictability*** *of EEG signals*

⑩**Hjorth Parameters:**

- *Mobility*
- *Complexity*

⑩**Entropy Measures:**

- *Approximate Entropy (ApEn)*
- *Sample Entropy (SampEn)*
-

→ Higher entropy

- *= more complex neural activity*

Functional Connectivity

⑩ Quantifies ***synchronization across EEG channels***

⑩Computed

⑩*via* ***Pearson correlation*** *between channels*

⑩**Connectivity metrics per channel:**

- *Mean, Median, SD, Maximum, 90th Percentile*
- *Strong Connection Ratio (|r| > 0.5)*

⑩Reflects

⑩***network-level coupling*** *and* ***integration***

Final feature set (~266 per channel):

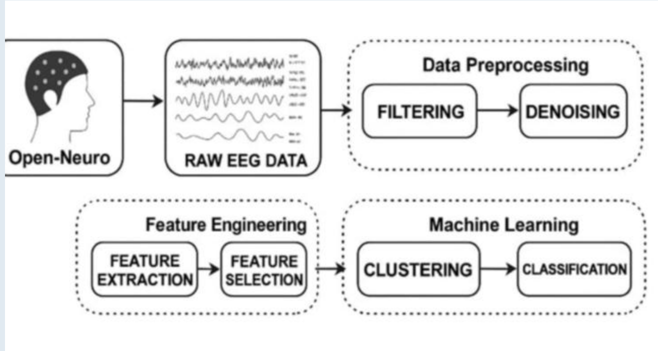
a)49 Spectral

b)63 Time-domain

c)28 Nonlinear

d)6 Connectivity

Machine Learning



Machine Learning Algorithms

1. ***Support Vector Machines (SVMs):***
   Utilized both linear and RBF kernels to capture linear and nonlinear separability in high-dimensional EEG feature space.
2. ***Linear Discriminant Analysis (LDA):***
   Employed for interpretable classification by maximizing class separability through linear discriminant functions with shrinkage regularization.
3. ***Gaussian Naive Bayes (GNB):***
   Probabilistic model assuming feature independence; provides fast, stable classification for high-dimensional EEG data.
4. ***Random Forest (RF):***
   Ensemble of 200 decision trees with class-balanced weighting and depth limitation (max depth = 5) to control overfitting and enhance generalization.

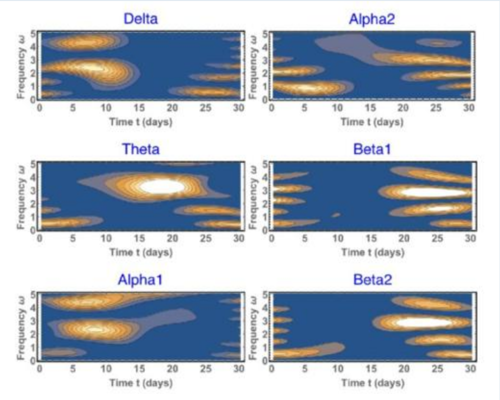
Cross-Validation Strategy
Leave-One-Out Cross-Validation (LOOCV)
→ robust for 88-subject dataset
Oversampling applied only to training folds
→ balance classes without data leakage
Ensures fair, unbiased model evaluation

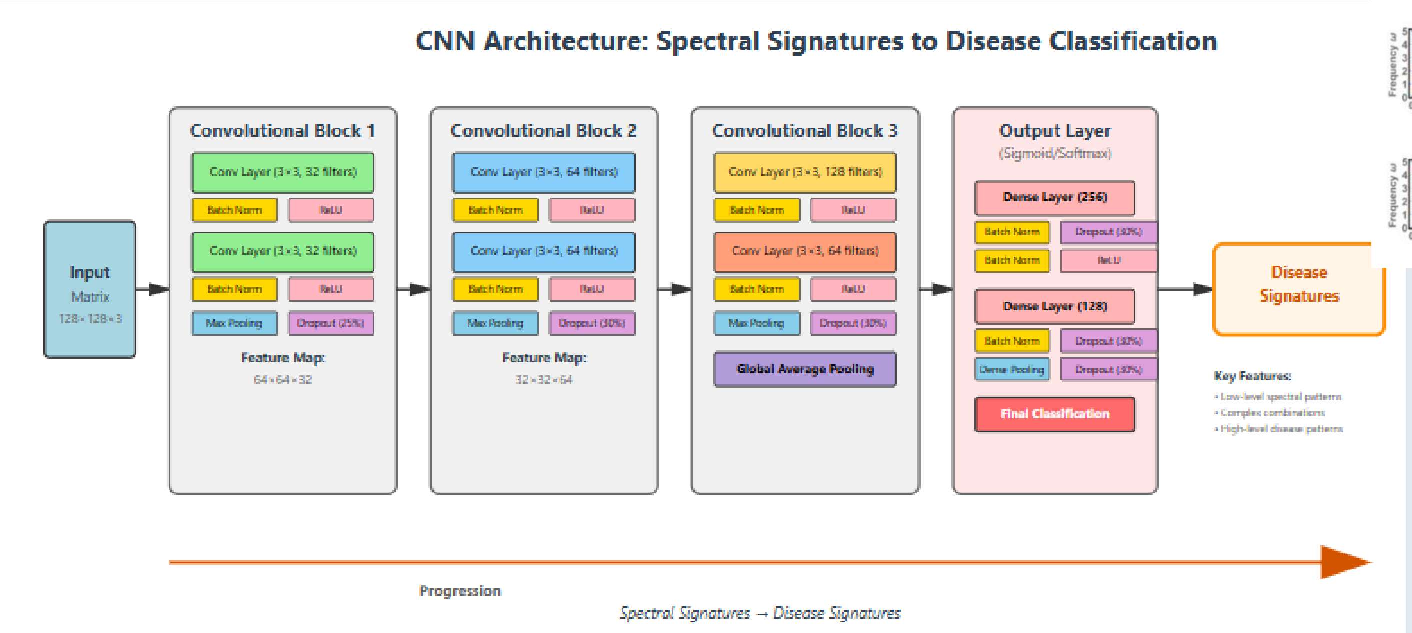
Libraries:
- `scikit-learn` – ML algorithms, feature selection, metrics
- `MNE`, `Pandas`, `NumPy` – EEG processing & data handling
- `Matplotlib`, `Seaborn` – visualization (ROC, confusion matrices)

Performance Evaluation Metrics
- **Accuracy** – overall correct predictions
- **Balanced Accuracy** – adjusts for class imbalance
- **Specificity** – true negative rate
- **F1-Score** – harmonic mean of precision & recall
- **ROC & AUC** – measure separability; higher = better
- **Confusion Matrix** – visualize classification outcomes

For multi-class → *One-vs-Rest AUC averaging*

CNN Basic Architecture





Architecture

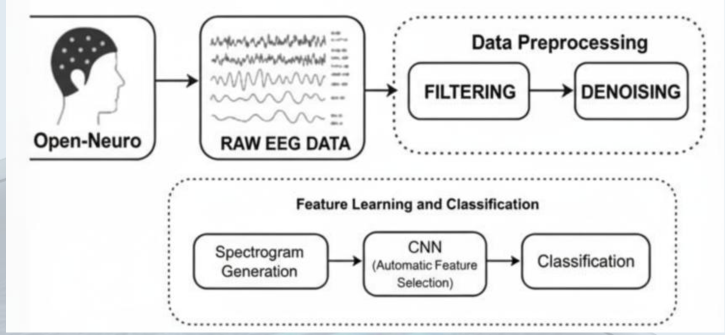
3 Convolutional Blocks (filters = 32 → 64 → 128)
Batch normalization, ReLU, Max Pooling, Dropout (25–30%)
Global average pooling → Dense layers (256, 128 units) → Output (Softmax/Sigmoid)
Purpose: Baseline for performance comparison with advanced model

Data Representation

EEG → 2D **spectrograms** (2 s windows, 50% overlap)
Two spectrogram strategies:

- **Multi-Channel**: Each electrode processed independently (0.5–45 Hz)
- **Spatial Spectrogram**: Electrodes mapped to 5×5 grid (10–20 system, Gaussian interpolation)

CNN Advanced Architecture



a) Enhanced Input Representation
EEG spectrograms: Multi-Channel, Spatial, Frequency-Band, or Hybrid
Window length: 4 s, Overlap: 75%
Expanded 8×5 electrode grid for improved anatomical resolution

b) Hierarchical Convolutional Architecture
3 Convolutional blocks: 32 → 64 → 128 filters
Each block: Convolution → BatchNorm → ReLU → MaxPooling → Dropout

c) Dense Layers & Classification
Dense layers: 256 → 128 units with BatchNorm and Dropout
Output: Sigmoid (binary) / Softmax (multi-class)

d) Regularization & Optimization
Focal loss to address class imbalance
L2 weight regularization, dropout, and batch normalization

Key Advantages
Captures longer temporal dependencies and richer spectral features
Handles multiple EEG input strategies simultaneously
Robust to noise and inter-subject variability

EEG Topographic Maps: Group Differences

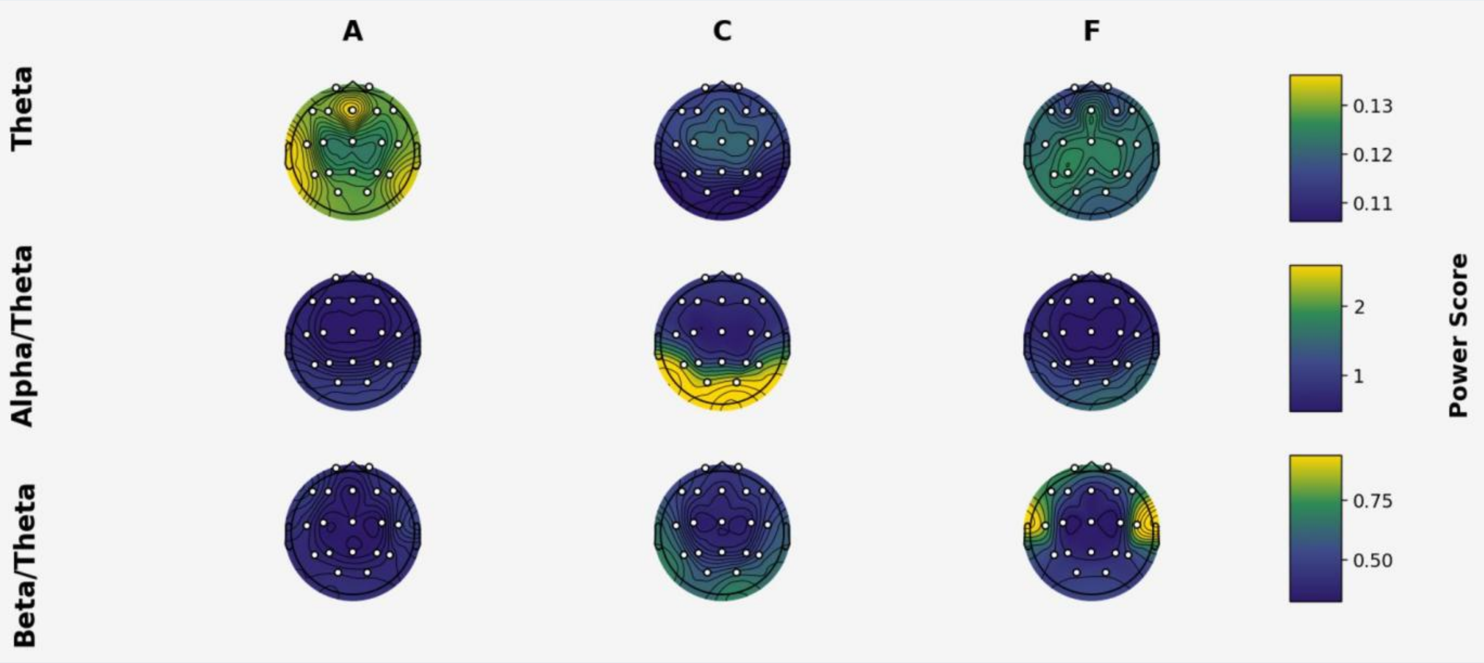
Visual summary: Topographic EEG maps show where brain rhythms differ across groups—Alzheimer's Disease (AD), Controls (CN), and Frontotemporal Dementia (FTD).

Theta Power (4–8 Hz):

AD: Markedly increased frontal-central theta—signals abnormal slow-wave activity.
Controls & FTD: Lower frontal theta—normal.
Takeaway: High frontal theta often signals AD.

Alpha/Theta Ratio:

Controls: High at the back (posterior)—shows normal brain rhythm.
AD & FTD: Reduced, evenly spread ratio—suggests less alpha, more theta.
Takeaway: Low ratio may indicate dementia.
Beta/Theta Ratio:
FTD: High in both temporal lobes—specific to FTD.
AD: Low overall—shows strong theta, weak beta.
Takeaway: High temporal beta/theta helps spot FTD



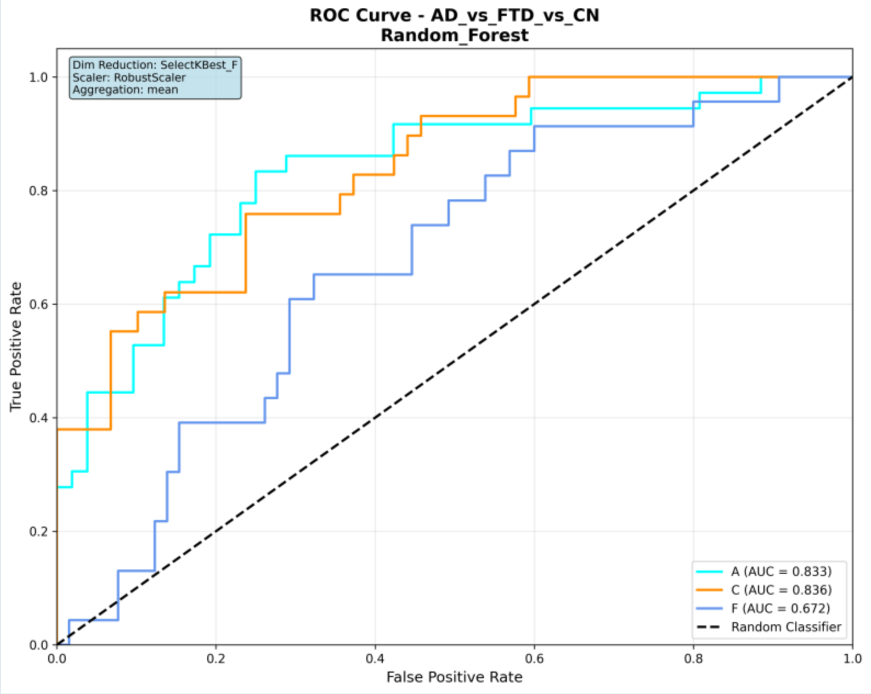
Beta/Theta Ratio:

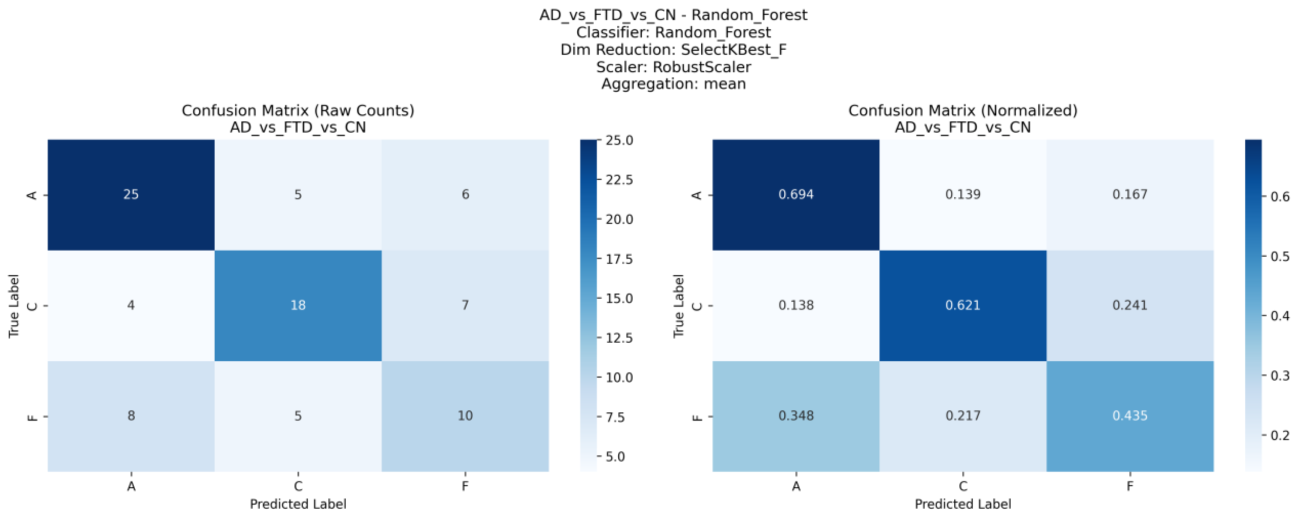
FTD: High in both temporal lobes—specific to FTD.
AD: Low overall—shows strong theta, weak beta.
Takeaway: High temporal beta/theta helps spot FTD.

Why topomaps matter:
They make region-specific changes in brain activity visible, helping identify distinctive EEG biomarkers for clinical diagnosis.

Machine Learning Results

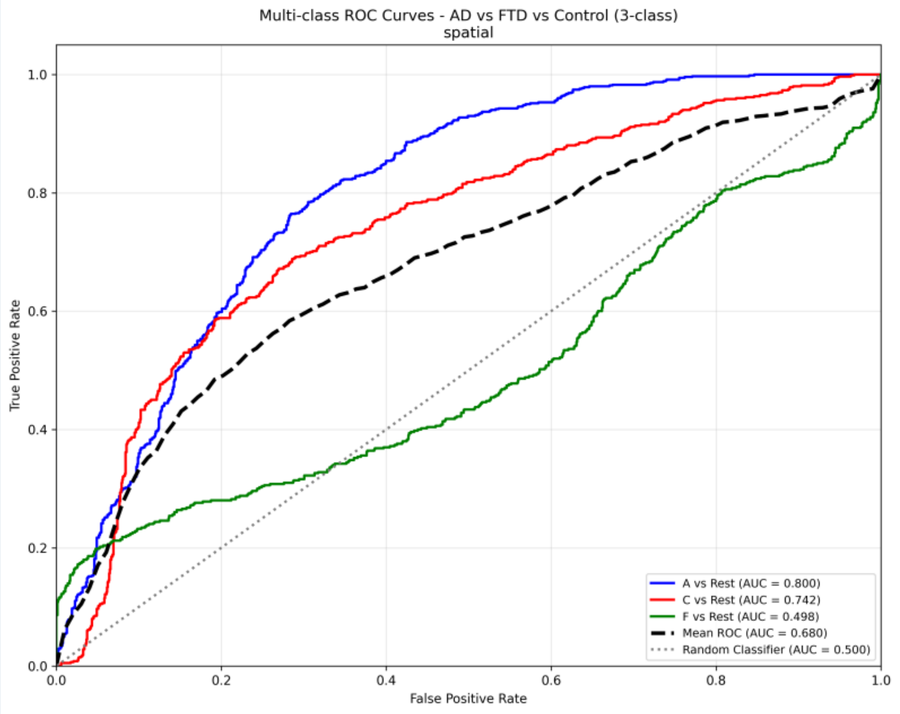
Task	Classifier	Dim_Reduction	Accuracy	Balanced Accuracy	Specificity	F1 Score	AUC	N_Samples
AD vs FTD	SVM_linear	None	0.661	0.636	0.75	0.658	0.638	59
AD vs CN	Random Forest	None	0.815	0.810	0.861	0.815	0.876	65
CN vs FTD	Random Forest	Variance Threshold	0.769	0.766	0.793	0.769	0.772	52
AD vs FTD vs CN	Random Forest	SelectKBest_F	0.614	0.599	0.807	0.616	0.762	88

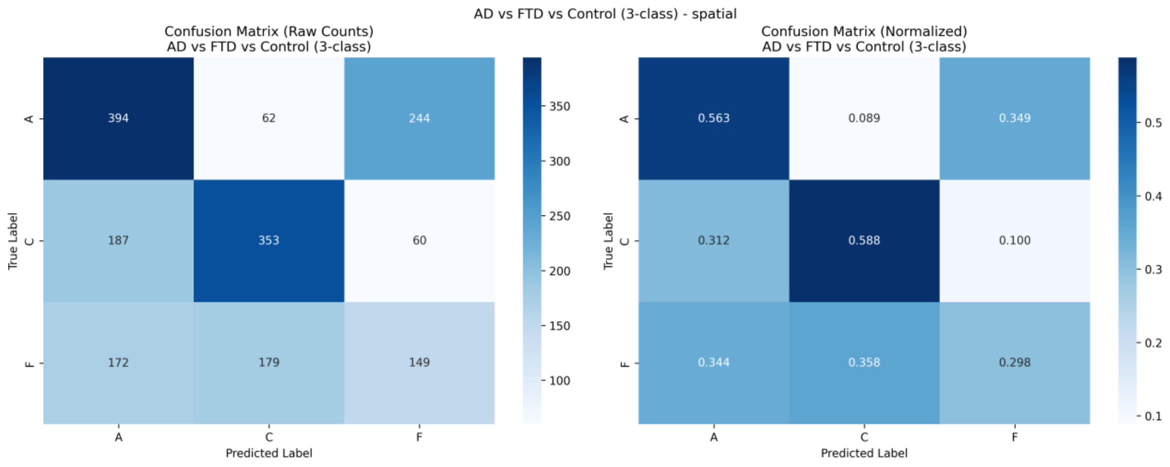




Basic CNN Results

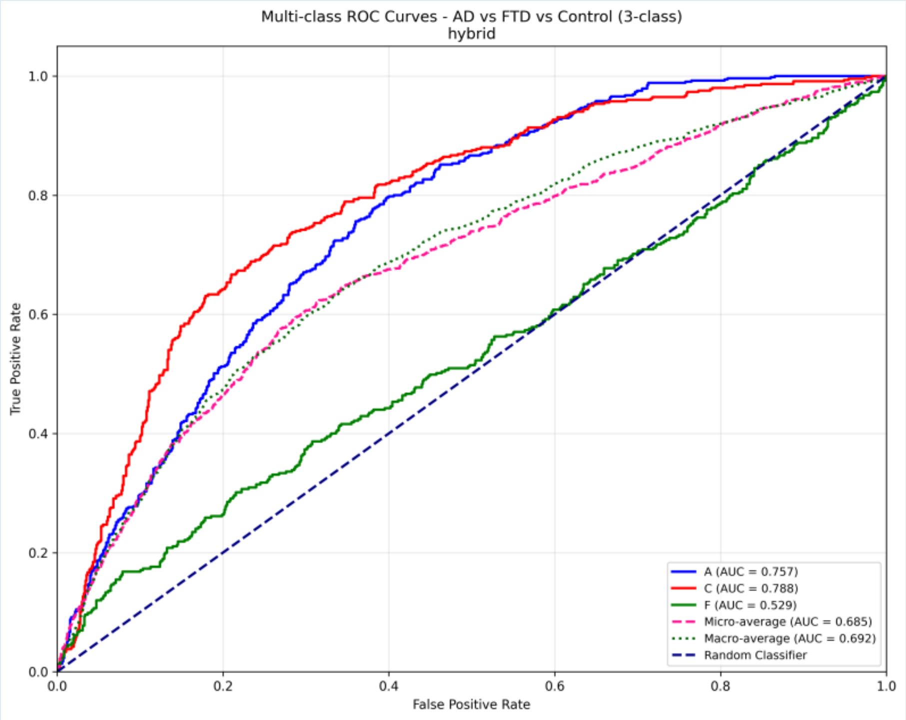
Task	Method	Accuracy	Balanced Accuracy	Specificity	F1 Score	AUC
AD vs_FTD	Multi_Channel	0.601	0.525	0.525	0.433	0.705
AD vs CN	Multi_Channel	0.733	0.728	0.728	0.729	0.769
CN vs FTD	Multi_Channel	0.685	0.684	0.684	0.683	0.703
AD vs FTD vs CN	Spatial	0.498	0.483	0.746	0.482	0.678

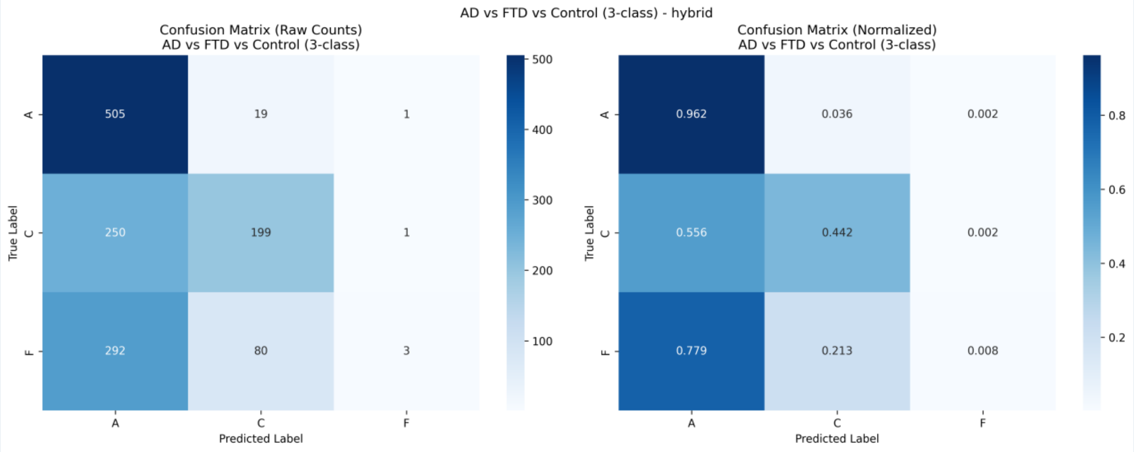




Advanced CNN Results

Task	Method	Accuracy	Balanced Accuracy	Specificity	F1 Score	AUC
AD vs FTD	Hybrid	0.587	0.506	0.992	0.036	0.497
AD vs CN	Hybrid	0.704	0.714	0.577	0.726	0.775
CN vs FTD	Multi_Channel	0.632	0.639	0.556	0.641	0.703
AD vs FTD vs CN	Hybrid	0.524	0.471	0.744	0.397	0.691





Which Model performance wins?

AD vs FTD

Best Method: SVM_linear **(Machine Learning)**

Performance:

Accuracy = 0.661, AUC = 0.638

This outperforms both the basic and advanced CNN approaches for this task.

AD vs CN

Best Method: Random Forest (**Machine Learning**, no dimensionality reduction)

Performance:

Accuracy = 0.815, AUC = 0.876

This is higher than both basic and advanced CNN models.

CN vs FTD

Best Method: Random Forest + Variance Threshold **(Machine Learning)**

Performance:

Accuracy = 0.769, AUC = 0.772

This method produced better results than both CNN approaches for this comparison.

AD vs FTD vs CN (Multi-class)

Best Method: Random Forest + SelectKBest_F (**Machine Learning**)

Performance:

Accuracy = 0.614, AUC = 0.762

Again, this outperforms the CNN-based approaches.

🤔 Why Traditional ML **outperformed**

Reasons:

- **Limited dataset size** → CNNs need more data to generalize effectively.
- **EEG variability & noise** → end-to-end learning is challenging; handcrafted features help.
- **ML advantages:** Random Forests, SVMs efficiently use physiologically meaningful features; more stable and interpretable.
- **Ensemble & kernel methods** → better handle small, imbalanced, or noisy datasets.

Conclusion:

- **Classical ML** is better suited for current EEG-based dementia classification.
- **CNNs** may perform better with larger datasets, advanced architectures, and data augmentation.

“Our memories are what make us who we are; without them, we are like a book with its pages torn out.”

Dr. Kay Redfield Jamison


THANK YOU