

A Data-Driven Eeg Framework For Multiclass Dementia Classification Via Spectral, Microstate, And Connectivity Features

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Abstract—Accurate differential screening of Alzheimer’s disease (AD) and frontotemporal dementia (FTD) remains difficult, motivating scalable EEG-based decision support; however, prior work often benchmarks spectral, microstate, and connectivity features separately and uses heuristic dimensionality reduction. Using a public OpenNeuro eyes-closed resting-state EEG dataset (N=88; 10–20 montage; 500 Hz), we built a standardized pipeline including EEGLAB preprocessing (filtering, ICA artifact removal), temporal standardization (60–360 s), multi-domain feature extraction (spectral band power, theta-alpha ratio, aperiodic 1/f exponent, alpha peak frequency; wPLI-based connectivity with graph metrics; four-class microstate parameters), and leakage-controlled dimensionality reduction via PCA with parallel analysis to automatically determine retained components within each training fold. We compared Elastic Net, RBF-SVM, and Random Forest (500 trees) using repeated 5-fold cross-validation over 100 cycles, evaluating classwise precision/recall/F1 and an integrated radar-area index capturing balanced multi-class performance across AD/FTD/controls. Across models, FTD was frequently misclassified as AD, indicating limited intrinsic separability from resting EEG alone. Feature representation was the dominant determinant of performance: microstate features yielded the largest and most balanced radar areas, spectral features were intermediate, and connectivity features were weakest. The proposed workflow provides a reproducible benchmarking template and practical guidance for EEG/BCI-oriented dementia screening systems.

Keywords— Alzheimer’s Disease, Electroencephalography (EEG), Machine Learning, Dementia Classification, Resting State.

I. INTRODUCTION

Alzheimer’s disease (AD) and frontotemporal dementia (FTD) represent major neurodegenerative disorders with significant societal and economic impact worldwide [1]. Early and differential identification of these conditions remains challenging in clinical practice, particularly in resource-limited settings. Electroencephalography (EEG), as a non-invasive, low-cost, and portable neurophysiological recording modality, has attracted increasing attention for computer-aided diagnosis and brain-computer-interface-based screening applications [2, 3]. Resting-state EEG is particularly suitable for clinical translation due to its minimal task demands and standardized acquisition protocols [4, 5].

A growing body of research has reported that resting-state EEG contains discriminative information for dementia classification [6, 7]. Three major feature families are commonly investigated: spectral features, e.g., power spectral density, theta-alpha ratio [8], aperiodic 1/f slope [9, 10], alpha peak frequency [11], microstate features derived from canonical four-class segmentation [12, 13], and functional connectivity metrics such as the weighted phase lag index (wPLI) [14]. Each feature family captures distinct aspects of large-scale brain dynamics and has been independently used in machine learning models for AD detection [6, 15]. However, most existing studies evaluate these feature domains separately, making it difficult to determine their relative discriminative utility under a unified computational framework. Furthermore, cross-model comparisons (e.g., linear vs. non-linear classifiers) are often limited, and performance metrics are inconsistently reported, reducing reproducibility and comparability.

From an engineering perspective, two methodological limitations remain prominent. First, feature selection is frequently theory-driven and manually constrained to a small subset of predefined metrics, which may introduce bias and limit scalability when extending to higher-dimensional EEG descriptors [6, 16]. Second, dimensionality reduction strategies are often arbitrarily defined (e.g., retaining a fixed number of principal components), rather than statistically determined [17, 18]. To address these issues, we implemented a fully data-driven feature reduction strategy based on principal component analysis (PCA) combined with parallel analysis (PA) to automatically determine the optimal number of retained components. This approach enables adaptive dimensionality control without relying on prior assumptions about feature importance, improving generalizability and deployment feasibility in real-world BCI pipelines.

Using eyes-closed resting-state EEG from AD, FTD, and healthy control groups, we constructed a standardized computational pipeline integrating preprocessing, multi-domain feature extraction (spectral, microstate, and connectivity), PCA with parallel analysis-based dimensionality reduction, and supervised classification. Three machine-learning models with distinct inductive biases were evaluated, including Elastic Net as a regularized linear baseline, Random Forest as an ensemble-based non-linear model, and Support Vector Machine as a margin-optimization classifier. To ensure statistical robustness and mitigate variance induced by data partitioning, repeated five-fold cross-validation was conducted over 100 cycles. Model performance was assessed using precision, recall, and F1 score, and further aggregated across diagnostic groups to provide a balanced evaluation of multi-class discrimination.

The primary contribution of this study lies in the establishment of a reproducible, data-driven EEG classification framework in which feature dimensionality is automatically determined via PCA combined with parallel analysis rather than predefined heuristics. This design enables adaptive control of model complexity while preserving the latent structure of high-dimensional EEG descriptors. In addition, by evaluating spectral, microstate, and connectivity features under identical preprocessing, reduction, and validation conditions, the present work provides a systematic horizontal benchmarking of feature families that are typically investigated in isolation. Finally, through direct comparison of linear and non-linear classifiers within the same experimental setup, this study offers practical guidance for model selection in EEG-based dementia screening systems. Collectively, the proposed workflow emphasizes algorithmic robustness, scalability, and deployment feasibility, contributing to the development of engineering-oriented BCI solutions for automated neurodegenerative disease identification.

II. METHODS

A. Participants and EEG data

We used a publicly available EEG dataset from OpenNeuro [19], comprising 88 participants assigned to three diagnostic groups: Alzheimer's disease (A), frontotemporal dementia (F), and healthy controls (C) based on the Mini-Mental State Examination (MMSE). Diagnostic labels provided by the dataset were used as ground-truth classes for all machine learning analyses. All EEG recordings were obtained from the same OpenNeuro dataset [19]. Recordings were collected in an eyes-closed resting-state condition for about 15 min. EEG was recorded following the 10–20 international system, with a sampling rate of 500 Hz.

B. EEG Preprocessing

EEG preprocessing was performed using standard pipelines implemented in EEGLAB [20]. The workflow consisted of band-pass filtering, independent component analysis (ICA),

and artifact rejection. Artifactual components were identified and removed prior to signal reconstruction. All subsequent analyses were conducted on the cleaned EEG signals. To ensure comparability across participants, resting-state recordings were temporally standardized. Continuous EEG data were cropped to a fixed interval between 60 and 360 seconds whenever available, and this standardized segment served as the basis for all feature extraction procedures described below.

C. Participants Resting-State EEG Feature Extraction and EEG data

Spectral Analysis: Spectral features were extracted from the standardized resting-state segment for each channel. Power spectral density (PSD) was estimated using Welch's method across the 0.5–45 Hz frequency range with 10-second windows and 90% overlap between adjacent segments. Band-specific power was calculated through numerical integration within canonical frequency bands spanning delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz).

In addition to band power, complementary spectral descriptors were derived. The theta-alpha ratio (TAR) was calculated as the ratio of theta power to alpha power with numerical stabilization applied when necessary. The aperiodic 1/f exponent was estimated by regressing log-transformed PSD values against log-transformed frequency across 0.5–45 Hz while excluding the alpha band to reduce oscillatory peak contamination. Alpha peak frequency was defined as the frequency within the 8–13 Hz range showing the maximum residual after subtraction of the fitted 1/f trend in log-log space. All spectral measures were concatenated into a unified feature matrix for subsequent modeling.

Functional Connectivity Analysis: Functional connectivity was quantified using the weighted Phase Lag Index (wPLI) within each canonical frequency band [21]. Signals were band-pass filtered and transformed into their analytic representations prior to connectivity estimation. Pairwise wPLI values were computed for all channel combinations to quantify consistent phase-lag relationships while minimizing volume conduction effects. To characterize network organization, connectivity matrices were summarized using graph-theoretical metrics. Weighted clustering coefficient was averaged across nodes to index local segregation, whereas characteristic path length and global efficiency were derived from weighted shortest paths after transforming connectivity strengths into connection lengths via reciprocal mapping. Appropriate numerical safeguards were applied to handle zero or infinite values before computing shortest paths. Connectivity-derived features, including global network metrics and vectorized connectivity matrices, were concatenated into a subject-level feature matrix for machine learning analyses.

Microstate Analysis: Microstate analysis was conducted on ICA-cleaned resting-state EEG. Signals were band-pass filtered to 5–20 Hz, cropped to the standardized interval, and re-referenced to the average reference prior to template estimation [22]. Microstate maps were derived using a clustering procedure, i.e., k-means, allowing four classes [23]. Global field power peak selection was employed to enhance signal-to-noise ratio during template extraction, and polarity invariance was enforced to ensure physiologically meaningful clustering. Multiple random initializations were used to enhance solution stability. Microstate-derived parameters were prepared as an additional feature family when required for modeling.

D. Dimensionality Reduction: PCA with Parallel Analysis

Dimensionality reduction was performed using principal component analysis (PCA), with the number of retained components determined through Parallel Analysis (PA). To prevent data leakage, all dimensionality reduction procedures were conducted exclusively on training data within each cross-validation fold. Features were standardized

using statistics derived from the training set, and variance stabilization procedures were applied when necessary. PA involved generating random reference datasets with identical dimensionality to the empirical training data. Eigenvalues obtained from PCA on the real data were compared to the 95th percentile of eigenvalues derived from random data. Components exceeding this threshold were retained, with at least one component enforced. The trained PCA transformation was subsequently applied to both training and test data to obtain low-dimensional feature representations.

E. Machine Learning Models and Repeated Cross-Validation

Model performance was evaluated using repeated 5-fold cross-validation over 100 independent cycles to obtain stable and generalizable performance estimates. For each cycle, data were randomly partitioned into five folds. Within each fold, dimensionality reduction was fitted exclusively on the training subset and then applied to the held-out test subset.

Three supervised classification algorithms were trained using the PCA-reduced features. Elastic Net multinomial logistic regression was implemented with mixed L1/L2 regularization to balance sparsity and stability. A Support Vector Machine (SVM) with a radial basis function kernel was employed to capture potential nonlinear decision boundaries. A Random Forest classifier consisting of 500 decision trees was used to model complex interactions through ensemble learning. Predictions were generated for the held-out test data within each fold and aggregated across folds and cycles for final evaluation.

F. Performance Metrics and Visualization

For each cross-validation cycle, predicted labels were compared with true labels to construct confusion matrices. Precision, recall, and F1-score were computed in a one-vs-rest framework for each diagnostic class. Macro-averaged, weighted-by-support, and micro-averaged summary metrics were calculated per cycle, and overall performance was reported as mean $\pm$ standard deviation across the 100 cycles. To facilitate visual comparison of classification performance across diagnostic classes, radar plots were generated based on classwise metrics. Radar plot area was calculated using an equiangular polygon formulation and normalized relative to the theoretical maximum area obtained when all classwise metrics equal one.

G. Statistical Analysis

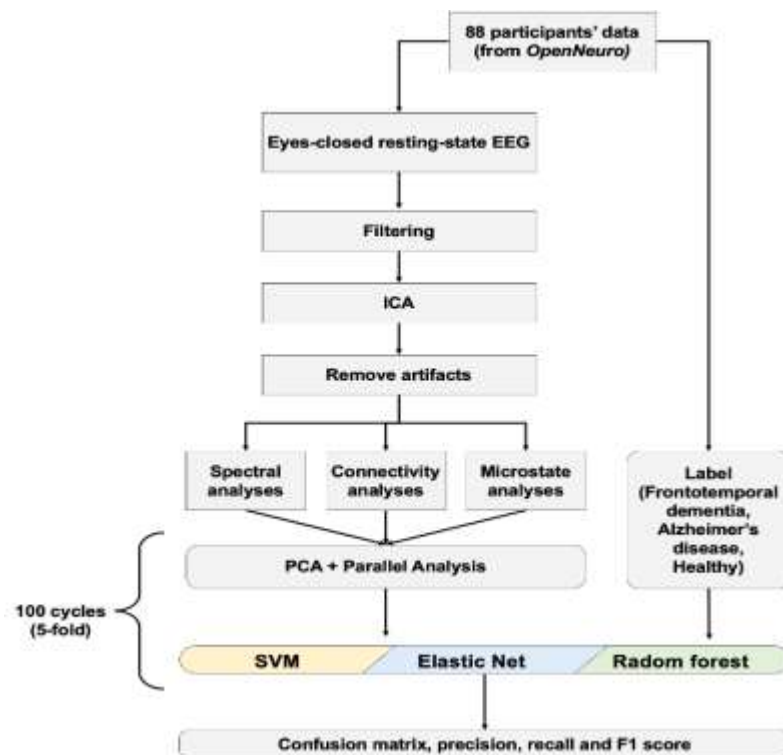
Statistical analyses were conducted using GraphPad Prism (v9). When radar plot area was used as the dependent variable for comparing models or feature configurations, effects were assessed using two-way analysis of variance (ANOVA). Statistical significance was determined according to conventional criteria.

III. RESULTS

We first established a multimodal classification framework using eyes-closed resting-state EEG data from 88 participants obtained from OpenNeuro (Figure 1). After standard preprocessing, including band-pass filtering, ICA, and artifact removal, three categories of EEG features were extracted: spectral measures, functional connectivity indices, and microstate parameters. To reduce dimensionality while preserving major variance components, PCA combined with parallel analysis was applied. The resulting components were then entered into three classifiers, i.e., SVM, Elastic Net, and Random Forest, across 100 repeated cycles. Classification performance was evaluated using confusion matrices and standard metrics including precision, recall, and F1 score.

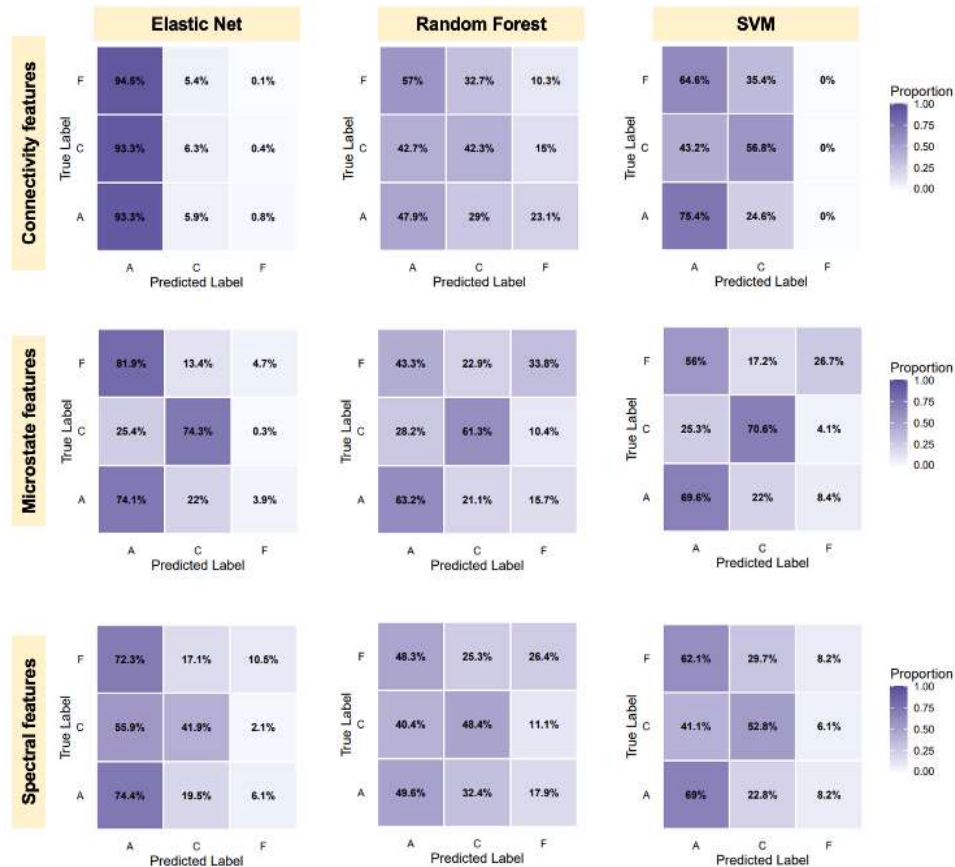
Clear differences in classification performance were observed across feature families and model types (Figure 2). Connectivity features demonstrated moderate discriminatory capacity among Alzheimer's disease (A), frontotemporal dementia (F), and healthy controls (C). As shown in Figure 2 (top row), the Elastic Net model exhibited a strong classification bias toward the Alzheimer's disease group, assigning the majority of participants to this category. The SVM model showed some ability to distinguish healthy controls; however, its overall accuracy remained limited and it failed to reliably identify frontotemporal dementia cases.

Fig. 1 Workflow of the EEG processing and machine learning pipeline.



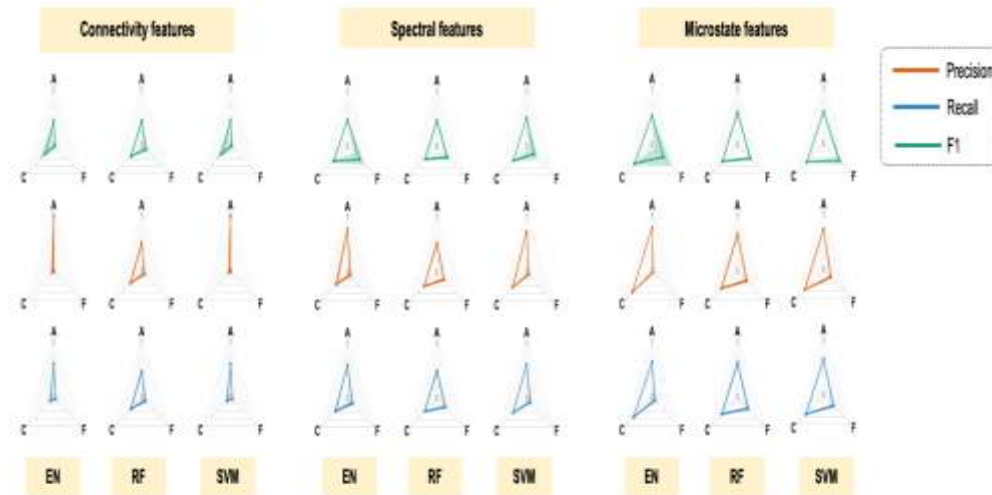
Although the Random Forest model was capable of assigning samples to all three groups, its class-wise accuracies were uniformly modest, indicating limited separability based on connectivity features alone. Microstate features yielded relatively improved classification performance compared to connectivity features (Figure 2, middle row). Under the Elastic Net model, frontotemporal dementia cases were poorly identified, with most F participants misclassified as Alzheimer's disease. In contrast, both Random Forest and SVM models demonstrated better group discrimination, although residual misclassification persisted, particularly with a subset of F cases incorrectly assigned to A. Spectral features showed intermediate discriminatory power (Figure 2, bottom row). Both Elastic Net and SVM models failed to reliably classify frontotemporal dementia, again exhibiting misclassification bias toward the Alzheimer's disease group. While the Random Forest model demonstrated some capacity to identify F, overall classification accuracy across all three groups remained suboptimal. Collectively, classification performance varied by feature family and model, with microstate features yielding the strongest (though still imperfect) discrimination among A/F/C, whereas connectivity and spectral features showed weaker separability and Elastic Net displayed a marked bias toward predicting Alzheimer's disease with persistent misclassification of F.

Fig. 2 Confusion matrices are shown for Connectivity, Spectral, and Microstate (MS) feature sets using Elastic Net (EN), Random Forest (RF), and Support Vector Machine (SVM) classifiers. Each matrix represents the mean performance across 100 cross-validation cycles. Rows correspond to true labels and columns to predicted labels (A = Alzheimer's disease, C = Healthy control, F = Frontotemporal dementia).



To provide a unified performance index integrating precision, recall, and F1 score, we quantified the geometric area of the radar plots defined by these three metrics for each model-feature combination (Figure 3). In each radar plot, the three vertices correspond to the diagnostic groups (A, C, and F), such that each axis represents the class-specific value of the given metric (i.e., the radius along the A, C, or F axis reflects performance for that group). For each metric (precision, recall, and F1), a triangular polygon was formed by connecting the class-specific values across the three axes, and its area was used as a composite measure capturing the overall balance between class-wise predictive value, sensitivity, and harmonic-mean performance. Larger radar areas therefore indicate more balanced and globally stronger classification performance across diagnostic groups and evaluation metrics. Visually, microstate-based features show the largest and most symmetric radar areas overall, particularly under the SVM and Random Forest models, which indicated comparatively more balanced performance across classes, whereas connectivity and spectral features frequently produce shrunken and skewed triangles, reflecting uneven class performance and weaker discrimination.

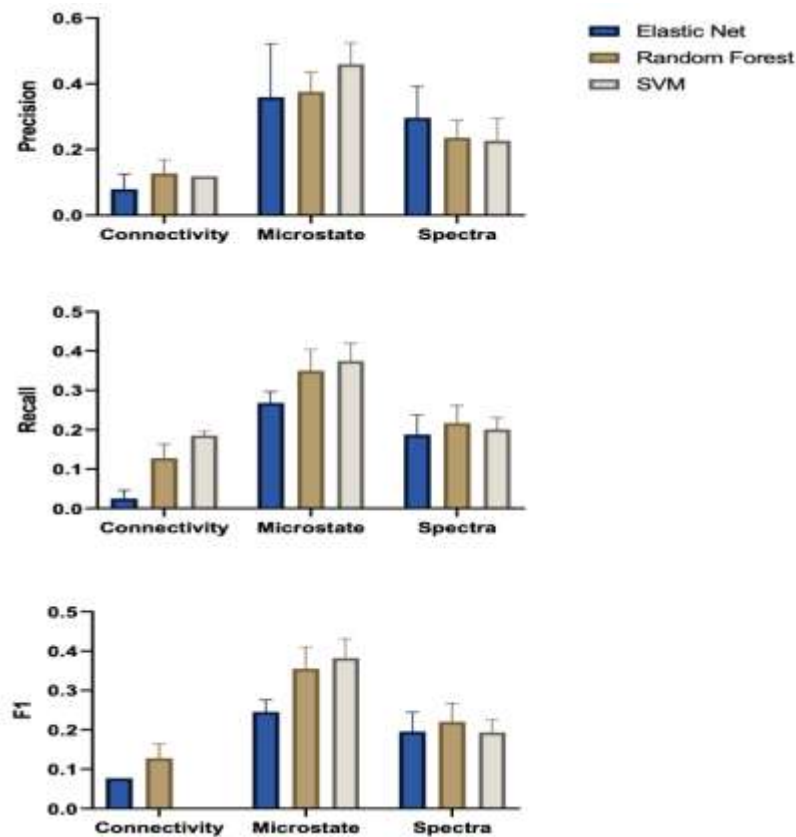
Fig. 3 Confusion Radar plots of class-wise precision, recall, and F1-score for individual feature domains. Solid lines of radar represent mean class-specific precision, recall, and F1-scores across 100 cross-validation cycles for Connectivity, Spectral, and MS features using EN, RF, and SVM classifiers. Shaded areas represent standard deviation. Axes correspond to diagnostic classes (A, C, F). Radar area reflects balanced multi-class performance, integrating per-class behavior into a single geometric measure.



To quantify the radar plots, the two-way ANOVA performed on the radar-derived area. Precision values revealed a significant interaction between feature family and algorithm for precision-derived areas (Table I, $F(4,707) = 28.09$, $p < 0.0001$), as well as a robust main effect of feature type ($F(2,707) = 248.3$, $p < 0.0001$). In contrast, the main effect of algorithm was not significant ($F(2,707) = 0.3196$, $p = 0.7265$), indicating that overall performance, as quantified by the integrated metric area, was primarily driven by the intrinsic discriminative properties of the EEG feature family rather than by classifier choice alone. For recall-based areas, both feature family (Table II, $F(2,891) = 2525$, $p < 0.0001$) and algorithm ($F(2,891) = 499.6$, $p < 0.0001$) showed highly significant main effects, accompanied by a strong interaction ($F(4,891) = 97.04$, $p < 0.0001$). This suggests that sensitivity-driven performance differed not only between feature representations but also depended on classifier architecture. Similarly, F1-derived area values demonstrated significant main effects of feature family (Table III, $F(2,642) = 583.2$, $p < 0.0001$) and algorithm ($F(2,642) = 11.82$, $p < 0.0001$), together with a significant interaction effect ($F(4,642) = 56.06$, $p < 0.0001$). Across all composite metrics, microstate features consistently exhibited the largest radar areas, followed by spectral features, whereas connectivity features yielded smaller integrated areas when averaged across algorithms.

Taken together, these findings indicate that when classification performance is evaluated as a balanced integration of precision, recall, and F1, the dominant determinant is feature representation rather than classifier type. Although certain algorithm–feature pairings (e.g., connectivity features under Elastic Net) showed strong class-specific separability in confusion matrices, aggregated geometric performance metrics highlight microstate features as providing the most stable and globally balanced discrimination across diagnostic categories.

Fig. 4 Quantitative comparison of radar area for precision, recall, and F1-score across individual feature domains. Bar charts represent the mean radar area ($\pm$ SD) computed from 100 cross-validation cycles for Connectivity, Microstate (MS), and Spectral feature sets. Radar area quantifies the geometric area of class-wise precision, recall, and F1 plots, providing a global measure of balanced multi-class performance. Statistical comparisons were performed using repeated-measures 2-way ANOVA.



IV. DISCUSSION

In the present study, we established an engineering-oriented, reproducible pipeline for three-class classification of AD, FTD, and healthy controls using eyes-closed resting-state EEG. A central methodological contribution is the unified horizontal benchmarking of three commonly used EEG feature families, i.e., spectral, microstate, and functional connectivity, under identical preprocessing, dimensionality reduction, validation, and reporting conditions. Critically, instead of manually selecting a small, theory-driven subset of features (a common source of bias and limited scalability), we adopted a fully data-driven dimensionality control strategy based on PCA combined with PA, which is widely recognized as a robust empirical method for determining the number of components to retain [24, 25]. This design helps decouple “feature representation” effects from “classifier” effects and provides an experimentally grounded methodological template for EEG-based dementia screening and BCI-style deployment workflows.

Across models, FTD samples were consistently prone to being classified as AD, suggesting that separability between these two dementia syndromes remains intrinsically difficult when relying on resting-state EEG alone. Clinically, FTD is well known to be frequently misdiagnosed as AD (and vice versa) [26, 27], reflecting

overlapping symptom profiles, heterogeneous phenotypes, and imperfect ground-truth labeling in real-world diagnostic pathways—factors that can compress inter-class differences and inflate within-class variance in supervised learning [28]. From a neurophysiological perspective, AD is strongly associated with resting-state spectral slowing (e.g., increased theta power and elevated theta/alpha-related indices, alongside reduced posterior alpha), and such global slowing signatures can partially overlap with other neurodegenerative conditions or emerge in mixed/atypical presentations [29–31], making AD-like patterns an “attractor” for classifiers trained on limited samples. In addition, FTD is a pathologically and clinically heterogeneous umbrella, which can further weaken a single [32], stable EEG fingerprint and increase the likelihood that discriminative boundaries are dominated by the more stereotyped AD-related slowing profile.

When comparing feature representations under the same pipeline, microstate features yielded the strongest overall and most balanced discrimination, spectral features showed intermediate performance, and connectivity features exhibited the weakest separability. This pattern is consistent with the idea that microstates capture sub-second, whole-brain spatiotemporal organization that may better reflect large-scale network dynamics relevant to dementia syndromes [33, 34]. Supporting this interpretation, prior work has suggested that EEG microstate measures can be sensitive to early-onset dementia phenotypes and may aid differentiation between AD and FTD beyond conventional EEG impressions [35, 36]. In contrast, connectivity metrics, even those designed to reduce volume conduction such as phase-lag-based indices, can remain vulnerable to confounds from limited montage density, reference choice, signal-to-noise variability, and the difficulty of summarizing high-dimensional networks into stable subject-level descriptors [37, 38], which may help explain their comparatively weaker performance in this dataset. At the classifier level, SVM showed a slight advantage over Elastic Net and Random Forest in achieving more balanced classwise performance, consistent with SVM’s tendency to generalize well in small-to-moderate samples when decision boundaries are non-linear but the effective dimensionality has been controlled via PCA/PA.

A. Limitations

Several limitations should be noted. First, results were derived from a single public dataset with modest sample size and potentially imbalanced/heterogeneous class structure, so external validity across sites, acquisition systems, and diagnostic standards remains to be established. Second, we used the dataset-provided clinical diagnoses as ground-truth labels for supervised learning; however, clinical differentiation between AD and FTD can be challenging in practice, and overlap in symptom profiles and underlying pathology may reduce separability in resting-state EEG. Thus, some misclassifications may reflect inherent diagnostic and biological overlap rather than model failure alone. Third, our feature sets were computed in sensor space; future work could test whether source-level representations, individualized alpha-theta parametrization (including aperiodic components), or multimodal fusion (e.g., EEG + clinical measures) improves AD-FTD separability. Finally, to move toward real-world BCI-style screening, the next step is rigorous cross-dataset validation with domain-shift handling, complemented by calibrated uncertainty estimates (e.g., abstention on ambiguous AD/FTD cases) so that the system can support clinical triage rather than force overconfident categorical decisions.

V. CONCLUSION

Our study establishes a reproducible, data-driven resting-state EEG classification pipeline for differentiating Alzheimer’s disease, frontotemporal dementia, and healthy controls. By

benchmarking spectral, microstate, and connectivity features under identical preprocessing and validation, and by using PCA with parallel analysis for automatic dimensionality control, we reduce manual feature-selection bias and improve methodological comparability. Overall, the proposed framework provides practical guidance for building scalable EEG/BCI-oriented dementia screening systems and highlights key challenges for future improvements in AD–FTD separation.

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TABLES

TABLE I TWO-WAY ANOVA FOR PRECISION

	SS (Type III)	DF	MS	F (DFn, DFd)	P
Interaction	0.7968	4	0.1992	F (4, 707) = 28.09	<0.0001
Feature Factor	3.522	2	1.761	F (2, 707) = 248.3	<0.0001
Algorithm Factor	0.004534	2	0.002267	F (2, 707) = 0.3196	0.7265
Residual	5.015	707	0.007093		

TABLE II TWO-WAY ANOVA FOR RECALL

	SS (Type III)	DF	MS	F (DFn, DFd)	P
Interaction	0.5549	4	0.1387	F (4, 891) = 97.04	<0.0001
Feature Factor	7.220	2	3.610	F (2, 891) = 2525	<0.0001
Algorithm Factor	1.428	2	0.7141	F (2, 891) = 499.6	<0.0001
Residual	1.274	891	0.001429		

TABLE III TWO-WAY ANOVA FOR F1 SCORE

	SS (Type III)	DF	MS	F (DFn, DFd)	P
Interaction	0.4416	4	0.1104	F (4, 642) = 56.06	<0.0001
Feature Factor	2.297	2	1.149	F (2, 642) = 583.2	<0.0001
Algorithm Factor	0.04655	2	0.02327	F (2, 642) = 11.82	<0.0001
Residual	1.264	642	0.001969		

REFERENCES

1. J. Bang, S. Spina, and B. L. Miller, "Frontotemporal dementia," *The Lancet*, vol. 386, no. 10004, pp. 1672-1682, 2015, doi: 10.1016/S0140-6736(15)00461-4.
2. R. Cassani, M. Estarellas, R. San-Martin, F. J. Fraga, and T. H. Falk, "Systematic Review on Resting-State EEG for Alzheimer's Disease Diagnosis and Progression Assessment," *Disease Markers*, vol. 2018, no. 1, p. 5174815, 2018, doi: <https://doi.org/10.1155/2018/5174815>.
3. D. Pirrone, E. Weitschek, P. Di Paolo, S. De Salvo, and M. C. De Cola, "EEG Signal Processing and Supervised Machine Learning to Early Diagnose Alzheimer's

- Disease," *Applied Sciences*, vol. 12, no. 11, p. 5413, 2022. [Online]. Available: <https://www.mdpi.com/2076-3417/12/11/5413>.
4. C. Babiloni et al., "Measures of resting state EEG rhythms for clinical trials in Alzheimer's disease: Recommendations of an expert panel," (in eng), *Alzheimers Dement*, vol. 17, no. 9, pp. 1528-1553, Sep 2021, doi: 10.1002/alz.12311.
5. N. Huidobro, R. Meza-Andrade, I. Méndez-Balbuena, C. Trenado, M. Tello Bello, and E. Tepichin Rodríguez, "Electroencephalographic Biomarkers for Neuropsychiatric Diseases: The State of the Art," *Bioengineering*, vol. 12, no. 3, p. 295, 2025. [Online].
6. M. Naderi and A. Jahanian-Najafabadi, "A systematic review of EEG-based machine learning classifications for obsessive-compulsive disorder: current status and future directions," (in eng), *BMC Psychiatry*, vol. 25, no. 1, p. 854, Sep 9 2025, doi: 10.1186/s12888-025-07296-z.
7. Vallesi et al., "Resting-state EEG spectral and fractal features in dementia with Lewy bodies with and without visual hallucinations," *Clinical Neurophysiology*, vol. 168, pp. 43-51, 2024/12/01/ 2024, doi: <https://doi.org/10.1016/j.clinph.2024.10.004>.
8. K.-I. Jang, Y. I. Kim, H. J. Ju, S. J. An, and P. W. Park, "Dementia classification using two-channel electroencephalography features," *Sci Rep-Uk*, vol. 15, no. 1, p. 11513, 2025/04/03 2025, doi: 10.1038/s41598-025-93513-4.
9. T. S. Warren, S. A. Shende, J. Ashrafi, G. M. Clements, and R. A. Mudar, "Resting-State EEG Power and Aperiodic Activity in Individuals with Mild Cognitive Impairment and Cognitively Healthy Controls," (in eng), *Brain Sci*, vol. 15, no. 12, Dec 3 2025, doi: 10.3390/brainsci15121305.
10. P. Martínez-Cañada, E. Perez-Valero, J. Minguillon, F. Pelayo, M. A. López-Gordo, and C. Morillas, "Combining aperiodic 1/f slopes and brain simulation: An EEG/MEG proxy marker of excitation/inhibition imbalance in Alzheimer's disease," (in eng), *Alzheimers Dement (Amst)*, vol. 15, no. 3, p. e12477, Jul-Sep 2023, doi: 10.1002/dad2.12477.
11. S. Schopp et al., "EEG alpha peak frequency: cognitive impairment severity marker in isolated REM sleep behavior disorder," *npj Parkinson's Disease*, vol. 11, no. 1, p. 185, 2025/07/01 2025, doi: 10.1038/s41531-025-01059-z.
12. M. Lassi et al., "Degradation of EEG microstates patterns in subjective cognitive decline and mild cognitive impairment: Early biomarkers along the Alzheimer's Disease continuum?," *NeuroImage: Clinical*, vol. 38, p. 103407, 2023/01/01/ 2023, doi: <https://doi.org/10.1016/j.nicl.2023.103407>.
13. H. Hou, J. Yu, S. Hao, X. Zhang, and D. Zang, "Electroencephalography microstates as biomarkers for screening Alzheimer's disease: Feasibility analysis and a machine learning classification scheme," *Journal of Alzheimer's Disease*, vol. 108, no. 2, pp. 693-702, 2025, doi: 10.1177/13872877251379072.
14. Y. Yan et al., "Functional Connectivity Alterations Based on the Weighted Phase Lag Index: An Exploratory Electroencephalography Study on Alzheimer's Disease," (in eng), *Curr Alzheimer Res*, vol. 18, no. 6, pp. 513-522, 2021, doi: 10.2174/1567205018666211001110824.
15. Z. Deng et al., "Diagnosis of Alzheimer's Disease Via Machine Learning Approaches with Integrated Resting-State EEG and ERP Characteristics," *Cognitive Computation*, vol. 17, no. 6, p. 166, 2025/11/17 2025, doi: 10.1007/s12559-025-10528-9.
16. N. Pudjihartono, T. Fadason, A. W. Kempa-Liehr, and J. M. O'Sullivan, "A Review of Feature Selection Methods for Machine Learning-Based Disease Risk Prediction," (in eng), *Front Bioinform*, vol. 2, p. 927312, 2022, doi: 10.3389/fbinf.2022.927312.
17. D. Iacobucci, A. Ruvio, S. Román, S. Moon, and P. M. Herr, "How many factors in factor analysis? New insights about parallel analysis with confidence intervals," *Journal of*

- Business Research, vol. 139, pp. 1026-1043, 2022/02/01/ 2022, doi: <https://doi.org/10.1016/j.jbusres.2021.09.015>.
18. G. A. Buzzell, Y. Niu, S. Aviyente, and E. Bernat, "A practical introduction to EEG Time-Frequency Principal Components Analysis (TF-PCA)," *Developmental Cognitive Neuroscience*, vol. 55, p. 101114, 2022/06/01/ 2022, doi: <https://doi.org/10.1016/j.dcn.2022.101114>.
 19. A. Miltiadous et al. A dataset of EEG recordings from: Alzheimer's disease, Frontotemporal dementia and Healthy subjects, doi: 10.18112/openneuro.ds004504.v1.0.8.
 20. A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods*, vol. 134, no. 1, pp. 9-21, Mar 15 2004, doi: 10.1016/j.jneumeth.2003.10.009.
 21. F. Zhang, F. Wang, L. Yue, H. Zhang, W. Peng, and L. Hu, "Cross-Species Investigation on Resting State Electroencephalogram," *Brain Topography*, vol. 32, no. 5, pp. 808-824, 2019/09/01 2019, doi: 10.1007/s10548-019-00723-x.
 22. Z. Chen, Y. Xie, and C. Li, "Longitudinal Analysis of EEG Microstate Alterations Induced by Cumulative Fatigue from Consecutive Day-Long Tasks," presented at the Proceedings of the 9th International Conference on Electronic Information Technology and Computer Engineering, 2025. [Online]. Available: <https://doi.org/10.1145/3766671.3766720>.
 23. L. Tait et al., "EEG microstate complexity for aiding early diagnosis of Alzheimer's disease," *Sci Rep-Uk*, vol. 10, no. 1, p. 17627, 2020/10/19 2020, doi: 10.1038/s41598-020-74790-7.
 24. J. L. Horn, "A rationale and test for the number of factors in factor analysis," *Psychometrika*, vol. 30, no. 2, pp. 179-185, 1965/06/01 1965, doi: 10.1007/BF02289447.
 25. H. Lee and H. Cham, "Comparing Accuracy of Parallel Analysis and Fit Statistics for Estimating the Number of Factors With Ordered Categorical Data in Exploratory Factor Analysis," *Educational and Psychological Measurement*, vol. 84, no. 6, pp. 1173-1202, 2024, doi: 10.1177/00131644241240435.
 26. I. O. Woollacott and J. D. Rohrer, "The clinical spectrum of sporadic and familial forms of frontotemporal dementia," (in eng), *J Neurochem*, vol. 138 Suppl 1, pp. 6-31, Aug 2016, doi: 10.1111/jnc.13654.
 27. D. C. Perry et al., "Clinicopathological correlations in behavioural variant frontotemporal dementia," (in eng), *Brain*, vol. 140, no. 12, pp. 3329-3345, Dec 1 2017, doi: 10.1093/brain/awx254.
 28. R. Ossenkoppele et al., "Prevalence of amyloid PET positivity in dementia syndromes: a meta-analysis," (in eng), *Jama*, vol. 313, no. 19, pp. 1939-49, May 19 2015, doi: 10.1001/jama.2015.4669.
 29. Y. Özbek, E. Fide, and G. G. Yener, "Resting-state EEG alpha/theta power ratio discriminates early-onset Alzheimer's disease from healthy controls," (in eng), *Clin Neurophysiol*, vol. 132, no. 9, pp. 2019-2031, Sep 2021, doi: 10.1016/j.clinph.2021.05.012.
 30. Y. Pan, L. Zhu, and Z. L. Wang, "EEG spectral power differences in Alzheimer's disease and frontotemporal dementia," (in eng), *Int J Neurosci*, pp. 1-9, Nov 21 2025, doi: 10.1080/00207454.2025.2591129.
 31. R. Nardone et al., "Usefulness of EEG Techniques in Distinguishing Frontotemporal Dementia from Alzheimer's Disease and Other Dementias," (in eng), *Dis Markers*, vol. 2018, p. 6581490, 2018, doi: 10.1155/2018/6581490.

32. K. Rascovsky et al., "Sensitivity of revised diagnostic criteria for the behavioural variant of frontotemporal dementia," (in eng), *Brain*, vol. 134, no. Pt 9, pp. 2456-77, Sep 2011, doi: 10.1093/brain/awr179.
33. C. M. Michel and T. Koenig, "EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review," (in eng), *Neuroimage*, vol. 180, no. Pt B, pp. 577-593, Oct 15 2018, doi: 10.1016/j.neuroimage.2017.11.062.
34. A. Khanna, A. Pascual-Leone, C. M. Michel, and F. Farzan, "Microstates in resting-state EEG: current status and future directions," (in eng), *Neurosci Biobehav Rev*, vol. 49, pp. 105-13, Feb 2015, doi: 10.1016/j.neubiorev.2014.12.010.
35. K. Nishida et al., "EEG microstates associated with salience and frontoparietal networks in frontotemporal dementia, schizophrenia and Alzheimer's disease," (in eng), *Clin Neurophysiol*, vol. 124, no. 6, pp. 1106-14, Jun 2013, doi: 10.1016/j.clinph.2013.01.005.
36. L. Tait et al., "EEG microstate complexity for aiding early diagnosis of Alzheimer's disease," (in eng), *Sci Rep*, vol. 10, no. 1, p. 17627, Oct 19 2020, doi: 10.1038/s41598-020-74790-7.
37. M. Vinck, R. Oostenveld, M. van Wingerden, F. Battaglia, and C. M. Pennartz, "An improved index of phase-synchronization for electrophysiological data in the presence of volume-conduction, noise and sample-size bias," (in eng), *Neuroimage*, vol. 55, no. 4, pp. 1548-65, Apr 15 2011, doi: 10.1016/j.neuroimage.2011.01.055.
38. A. M. Bastos and J. M. Schoffelen, "A Tutorial Review of Functional Connectivity Analysis Methods and Their Interpretational Pitfalls," (in eng), *Front Syst Neurosci*, vol. 9, p. 175, 2015, doi: 10.3389/fnsys.2015.00175.