Automated Machine Learning Framework for Differential Diagnosis of Alzheimer's Disease and Frontotemporal Dementia using Targeted EEG Biomarkers

Amira Houichette* **Ph.D**
SITI Laboratory, National School of Engineers of Tunis (ENIT), University of Tunis El Manar, Tunis, Tunisia
University of Carthage, Electrical Engineering Department, National School of Engineers of Cartage (ENICarthage), Tunis, Tunisia

Imen Messaoudi
SITI Laboratory, National School of Engineers of Tunis (ENIT), University of Tunis El Manar, Tunis, Tunisia
University of Carthage, Industrial Computing Department, Higher Institute of Information Technologies and Communications (ISTIC), Tunis, Tunisia

Afef Elloumi Oueslati
SITI Laboratory, National School of Engineers of Tunis (ENIT), University of Tunis El Manar, Tunis, Tunisia
University of Carthage, Electrical Engineering Department, National School of Engineers of Cartage (ENICarthage), Tunis, Tunisia

Sabir Jacquir
Paris-Saclay University, CNRS, Paris-Saclay Institute of Neuroscience, Saclay, France

Zied Lachiri
SITI Laboratory, National School of Engineers of Tunis (ENIT), University of Tunis El Manar, Tunis, Tunisia

Abstract:
Differential diagnosis between Alzheimer's Disease (AD) and Frontotemporal Dementia (FTD) is critical for clinical management but remains challenging due to overlapping symptomatic profiles. This study proposes an automated machine learning framework utilizing resting-state EEG biomarkers for the multiclass classification of AD, FTD, and health controls (CN). Using an open-access clinical dataset of 88 participants (36 AD, 23 FTD, 29 CN), we implemented a robust preprocessing pipeline incorporating Artifact Subspace Reconstruction (ASR) and Independent Component Analysis (ICA) for signal denoising. To optimize computational efficiency, nine sensitive electrodes (P3, P4, O1, O2, T4, T6, Cz, Pz, F4) were strategically selected based on their relevance to neurodegenerative alterations.

We extracted a high-dimensional feature set of 126 temporal, spectral, and time-frequency variables, including Shannon, Tsallis, and Spectral entropies, as well as wavelet energy and band powers. To address class imbalance, the SMOTE technique was applied. Six classification models (SVM, KNN, NB, DT, MLP, and RF) were benchmarked. The Random Forest (RF) model demonstrated superior performance, achieving a multiclass accuracy of 86.4% and a precision of 86.5%. Binary classification tasks yielded accuracies of 88.9% for CN/AD and 86.0% for AD/FTD. Notably, occipital sensors (O1, O2) emerged as the most discriminating regions for early AD detection, providing accuracies up to 82%.

These findings highlight the efficacy of optimized EEG biomarkers and ensemble learning as a non-invasive, high-precision tool for the differential diagnosis of dementias.

Keywords:
EEG Signal Processing, Alzheimer's Disease, Frontotemporal Dementia, Machine Learning, Targeted Biomarkers, Random Forest.