Clinical Study of PET-validated EEG-machine learning algorithm predicting brain amyloid pathology in pre-dementia Alzheimer's disease

Predicting Aβ Pathology in pre-dementia people using QEEG-based machine learning model

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INTRODUCTION

- Positron Emission Tomography (PET) is the primary biomarker for β-amyloid (Aβ) brain pathology, an indicator of Alzheimer's Disease (AD).
- However, PET scans are costly, often inaccessible, and not always tolerable for patients. Previous research indicates that machine learning (ML)-based EEG biomarkers might be an alternative.
- This study develops a quantitative EEG (QEEG) and ML algorithm to predict Aβ brain pathology in subjective cognitive decline (SCD) and mild cognitive impairment (MCI) patients, validating it against Aβ PET.

METHODS

- EEG (19-channel, eye-closed, resting-state) and Aβ PET data were collected from 160 MCI patients (77 Aβ+, 83 Aβ-). 45 datasets (23 Aβ+, 22 Aβ-) were excluded for test verification.
- QEEG parameters like absolute power, relative power, power ratio, and inter-channel coherence (iCoherence) formed the input features.
- The most relevant predictive features were identified using Random Forest Importance (GBM, XGB), ElasticNet, and Whitney-Mann methods.
- Six ML algorithms (SVM, Logistic, KNN, Naive Bayes, Random Forest(GBM/XGB)) were trained using each relevant feature set, resulting in 24 models (4 sets * 6 algorithms).
- Performance of models was tested on the 45 excluded datasets, then the best model was selected.
- A third validation was performed on 111 MCI (56 Aβ+, 55 Aβ-) and 165 SCD (31 Aβ+, 134 Aβ-) data.

			MCI(+)	MCI(-)	total
Train Data			54	61	115
Test Data			23	22	45
Age(mean±sd)			74.7±6.3	72.5±6.8	73.6±6.7
Gender(M/F)			36/41	37/46	73/87
	SCD(+)	SCD(-)	MCI(+)	MCI(-)	total
3rd Validation	31	134	56	55	276
Age(mean±sd)	72.0±5.9	71.6±6.9	75.8±6.7	76.4±7.2	74.8±7.0
Gender(M/F)	16/18	46/88	24/30	26/29	112/165
Total	31	134	133	138	436

Table 1. Number of subjects by steps, diagnosis, age and gender

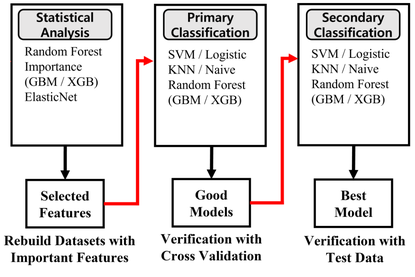

Figure 1. Schematic flowchart of feature selection and modeling

RESULTS

- The best-performing model in test validation showed 77.8% accuracy, 81.8% sensitivity, 73.9% specificity in distinguishing Aβ+ from Aβ-.
- In the 3rd data validation, the model exhibited 72.1% accuracy, 71.4% sensitivity, 72.7% specificity in MCI patients, and 69.1% accuracy, 64.5% sensitivity, 70.2% specificity in SCD patients.

	True Positive	True Negative
Predicted Positive	40	15
Predicted Negative	16	40

Table 2. Confusion matrix of 3rd data validation

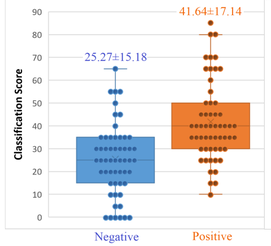

Figure 2.(a)

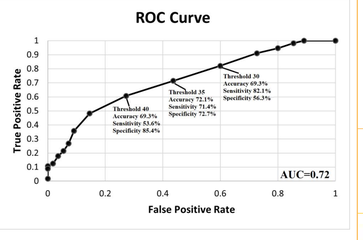

Figure 2.(b)

Figure 2. (a) Box plot and swarm plot representing classification scores of each data for 3rd data validation.(b) ROC curve for 3rd data validation.

CONCLUSIONS

- The ML-based QEEG biomarker succeeded in predicting Aβ brain plaque presence.
- The biomarker offers advantages like reduced cost, widespread availability, and high-throughput screening.
- Future research will explore its utility as primary AD screens, its combined use with PET, and its role in clinical decision-making for Aβ PET and AD treatment.

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