QEEG-based discernment of dementia pathologies through machine learning: Lewy body and Alzheimer's disease

P2-140

iMediSync

Taegyun Jeong[1] (MSc), Ukeob Park[1] (MSc), Seung Wan Kang[1,2] (MD, PhD)

(1) iMediSync, Inc., Seoul, South Korea, (2) Data Center for Korean EEG, College of Nursing, Seoul National University, Seoul, South Korea

"Identify dementia pathologies through QEEG"

INTRODUCTION

- **Alzheimer's disease (AD)**, the most common cause of dementia, destroys nerve cells in the brain through accumulation of **beta amyloid plaques**.
- However, various other pathologies of dementia also exist, such as accumulation of **Lewy body (LB) peptides**.
- Different dementia pathologies carry distinguishing symptoms and treatment methods; hence we cannot disregard the importance of correct identification of the pathology.
- Positron emission tomography (PET) is widely used to screen for pathologies. However, it is **expensive** and results in **exposure to harmful ionizing radiation**.
- Therefore, the present study proposes a quantitative electroencephalography (**QEEG**)-based screening method which overcomes the disadvantages of current screening methods.

METHODS

- EEG data employed in the present study were recorded at electrode locations defined by the international 10-20 system, in eyes-closed resting-state condition.
- Figure 1 summarizes the data preprocessing/ denoising procedure.

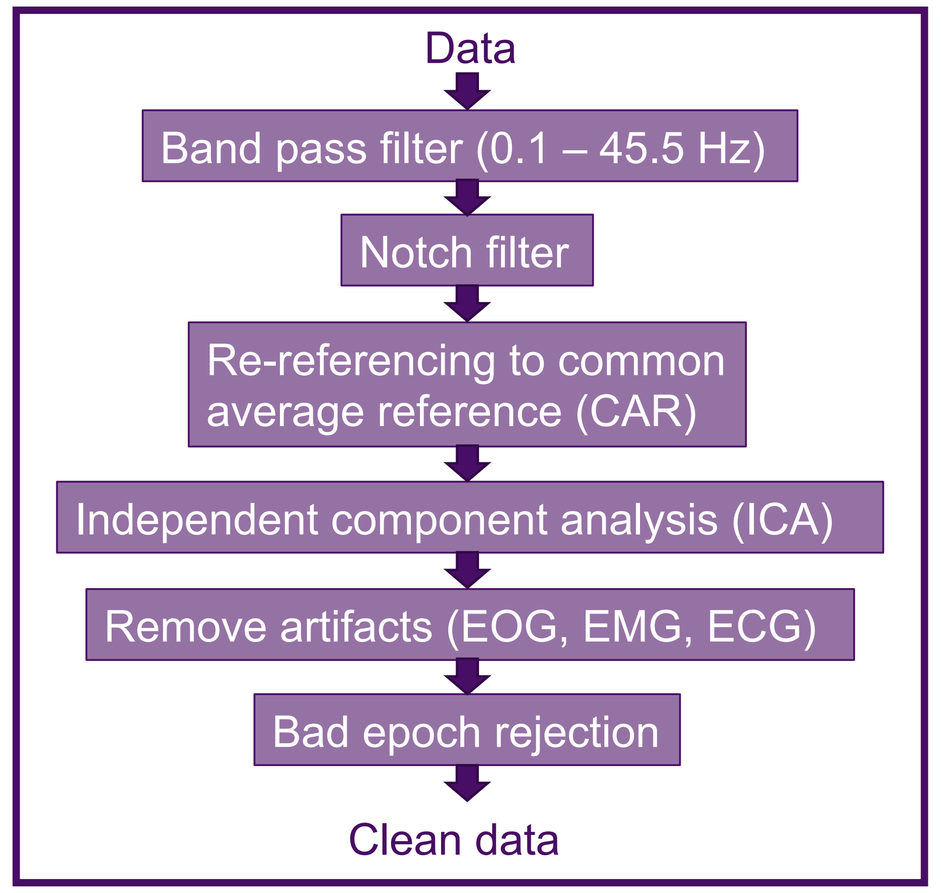

Figure 1. Preprocessing/ denoising procedure

- sLORETA was used to estimate source cortical activity at 68 regions defined by the Desikan-Killiany atlas.
- The final dataset: **N = 104; 30 AD; 74 LB**.
- 20% of the data were randomly selected as test data.
- Tree-based algorithms – Random forest, XGBoost, LightGBM were trained with various sets of key hyperparameters.
- **Feature reduction criteria:**
  - Features with p-value < 0.05.
  - Feature importance determined through Shapley values.
  - Exclusion of gamma band (30-45Hz) features due to its vulnerability to high-frequency noise.

RESULTS

- The best classification performance was achieved by an XGBoost model, with test accuracy of **85.7%, AD dementia (ADD)** sensitivity of **83.3%** and **LB Dementia (LBD)** sensitivity of **86.7%**. 5-fold cross validation accuracy was at **82.1%**.

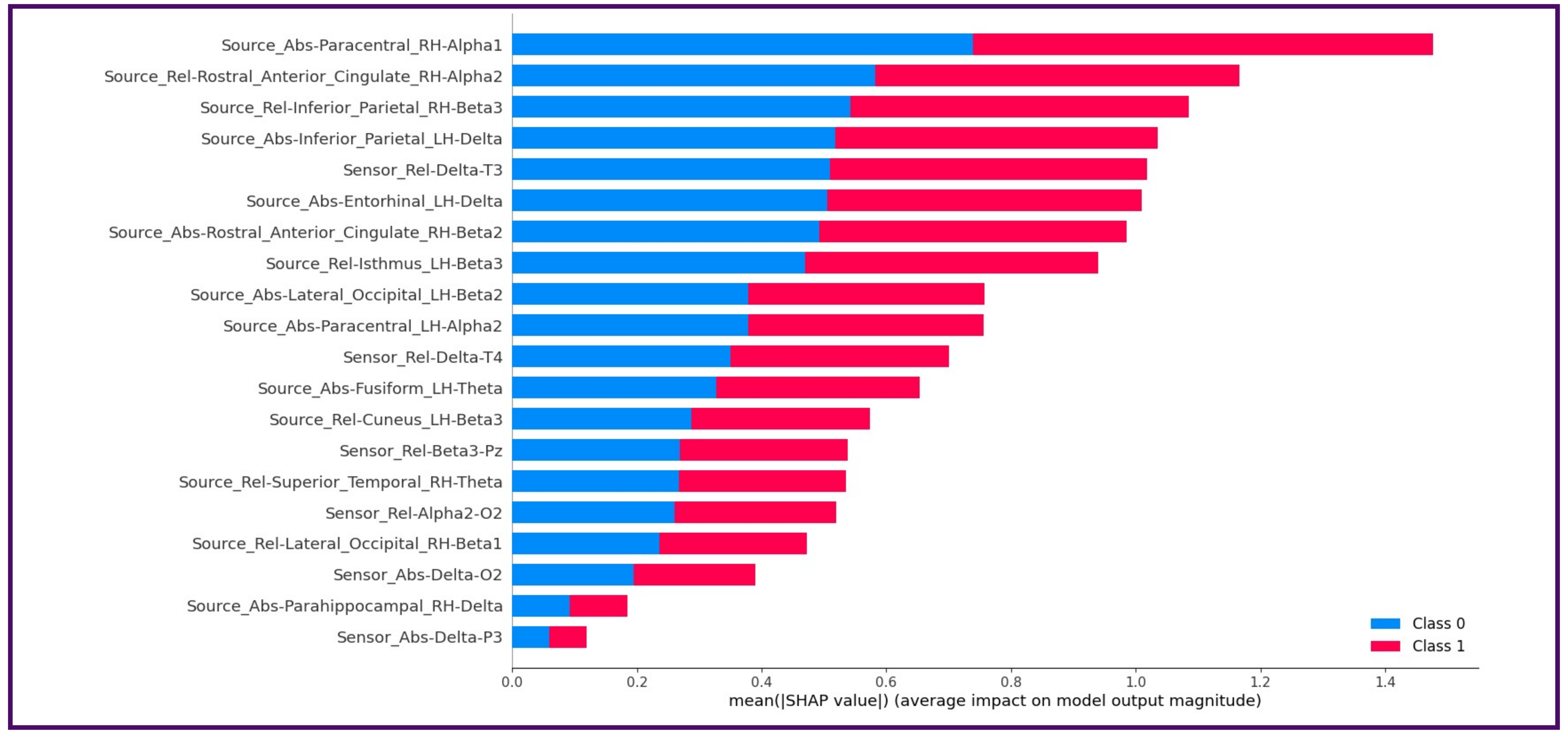

Figure 2. Top 20 features that mainly affected classification results

Sensor & Source level features	True ADD	True LBD
Pred ADD	5	2
Pred LBD	1	13

No. features: 25

Table 1. Confusion matrix

- Majority of the features with high importance values were related to delta (1-4Hz), alpha1 (8-10 Hz), alpha2 (10-12Hz), beta2 (15-20Hz) and beta3 (20-30Hz) frequency bands.
- Through a group comparison, we further verified that LBD **delta and alpha band** (8-12 Hz) powers are **stronger** than that of ADD, and LBD **beta band** (15-30 Hz)power is **weaker** than that of ADD.

CONCLUSIONS

- The classification model developed in the present study showed a promising classification performance, through quantitative EEG data which is **cheap and harmless to record**.
- Such QEEG-based classification models carry a great potential to replace the PET in future, resolving conventional disadvantages.

CONTACT

Presenting author: Taegyun Jeong

Email: jtaegyun@imedisync.com

Second author: Ukeob Park

Email: hoanouo@imedisync.com

Corresponding author: Seung Wan Kang

Email: seungwkang@imedisync.com

iMediSync, Inc.

Website: https://www.imedisync.com/en/

Visit us at booth **# 920** if you wish to explore our products or become our research partner.

ALZHEIMER'S ASSOCIATION

AAIC 22 ALZHEIMER'S ASSOCIATION INTERNATIONAL CONFERENCE®