QEEG-based TabNet classifier for dementia pathologies: Alzheimer's disease and Lewy body disease

Hyerin Jeong¹, Ukeob Park¹, Byong Seok Ye, PhD, MD², Seung Wan Kang, PhD, MD^{1,3}

(1) iMediSync, Inc., Seoul, South Korea

- (2) Yonsei University College of Medicine, Seoul, South Korea
- (3) Data Center for Korean EEG, College of Nursing, Seoul National University, Seoul, South Korea

TabNet classifier of Alzheimer's Disease and Lewy Body Disease using QEEG

INTRODUCTION

- We used a QEEG-based algorithm to differentiate Alzheimer's disease(AD) and Lewybody dementia(LBD).
- Despite current diagnostic measures, a significant number of LBD cases are undetected or misdiagnosed as AD [2].
- [1] attempted a study on the classification of AD and LBD using RandomForest. Further, the objective of [3] was to contrast the EEG characteristics among LBD/AD+, 'pure'LBD(LBD/AD-) and AD.
- We aimed to address the diagnostic bias in which approximately 70% of dementia diagnoses are attributed to AD, potentially overlooking the presence of LBD.
- The model's efficacy is further evaluated on mixed dementia cases presenting both Alzheimer's and Lewy body symptoms.

METHODS

- 19 channel EEG data, recorded according to the 10-20 system in a resting state, were processed through iSyncBrain®, and automated QEEG platform, to extract sensor-level features for TabNet structure training.
- To address data imbalance, time window-based augmentation applied to EEG sensor level features, creating a final dataset of 7292 samples (AD = 3376, LBD = 3916).
- The dataset was the divided in an 8:2 ratio for model training and testing,
- Mixed type dementia cases were also used to further validate the model's performance.



 $\begin{bmatrix} x_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

Fig 2. The process feature selection is performed at each step using DNN and the

Mask M: [0, 1]

 $\int [x_1]$

Step 1

optimal hyperparameters

Mask M: [1, 0]



Fig 3. Top10 Global feature importance barplot



Fig 4. Masked Feature subset ; red circle represents the features in fig 3.

RESULTS

 γ : 1.3

Mask type: sparsemax

Input dim : 342

Output_dim : 2

pure LBD sensitivity 80%.

	Pred pureAD	Pred pureLBD
True pureAD	8	2
True pureLBD	4	16

Table 2. Confusion matrix for the testset of the QEEG TabNet classifier



iMediSync

	Global Feature Importance Rank
Sensor_Abs-Alpha2- O1	1
Sensor_Abs-Beta2- T6	2
Sensor_Abs-Beta2- Fp2	3
Sensor_TAR-T6	4
Sensor_Abs-Delta- C4	7
Sensor_Rel-Beta2- C3	9

This classifier yielded test accuracy of 80% with pure AD sensitivity at 80% and

CONCLUSIONS

- Moreover, the predicted probability for mixed dementia data were prominently concentrated around 0.5.
- This model successfully identifies distinctive markers and differentiates between AD and LBD.

REFERENCES

- Dauwan, M., van der Zande, J. J., van Dellen, E., Sommer, I. E., Scheltens, P., Lemstra, A. W., & Stam, C. J. (2016). Random forest to differentiate dementia with Lewy bodies from Alzheimer's disease. Alzheimer's & Dementia: Diagnosis Assessment & Disease Monitoring, 4, 99-106.
- McKeith, I. G., Boeve, B. F., Dickson, D. W., Halliday, G., Taylor, J. P., Weintraub, D., ... & Kosaka, K. (2017). Diagnosis and management of dementia with Lewy bodies: Fourth consensus report of the DLB Consortium. Neurology, 89(1), 88-100.
- Van der Zande, J. J., Gouw, A. A., Van Steenoven, I., Scheltens, P., Stam, C. J., & Lemstra, A. W. (2018). EEG characteristics of dementia with Lewy bodies Alzheimer's disease and mixed pathology. Frontiers in Aging Neuroscience, 10,

CONTACT



jhrin@imedisync.com

eungwankang@imedisync.com

iMediSync Inc.

