# Screening of Mild Cognitive Impairment Subtypes Through the Training of 1D Convolutional Neural Network with QEEG Features

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***Classifier of MCI subtype based on LBD component using QEEG-based deep learning model***

## INTRODUCTION

- The pre-clinical stage of dementia, mild cognitive impairment (MCI) carries various pathological pathways and respective prognoses.
- The two foremost causes of MCI and dementia are Alzheimer's disease (AD) and Lewy body disease (LBD) respectively, and large-scale autopsy studies show that 43-53% of cases have two or more neurodegenerative diseases[1].
- In particular, AD patients with LBD show more rapid cognitive decline and disease progression than patients with AD alone[1][3].
- Hence, correct identification of AD and LBD in MCI patients plays a crucial role in effective designing of treatment methods.
- We utilized quantitative electroencephalography (QEEG) to generate a classifier that discriminates the degree of LBD in MCI.

## METHODS

- A total of 180 MCI patients' EEG data were aggregated into 3 groups, pure AD (n=29), pure LBD(n=88), and mixed (n=63). The mixed type was further subdivided into main AD (n=31) and Mixed (n=29)and main LBD(n=3) groups, in accordance with AD/LBD tendency exhibited by the patients.
- The clinical labelling was brought by the experienced experts of Yonsei Severance hospital, South Korea.
- 1D SE-ResNet-based classification model (Figure1) was established for quantitative investigation of AD and LBD propensity.
- The power spectrum density (PSD) in dB/Hz scale were computed from the EEG data that was measured in 19-channels from subjects' scalps at sites corresponding to the international 10-20 system and 19-channels PSD data were taken as the input of the classification models.
- Due to the small number of data, augmentation was applied to the training data. The augmentation method is illustrated in Figure 2. Initially, the EEG data is segmented into 4-second epochs through cropping. Subsequently, the absolute PSD is calculated for each epoch, and a random selection of PSD data is made. The chosen PSD data is then averaged and transformed to the dB/Hz scale.
- The final dataset was split into 8 to 1 to 1 ratio (Train n=5968: 2274 pure AD + main AD; 3694 pure LBD + main LBD, Validation n=40: 3 pure AD + 3 main AD; 8 Pure LBD + 26 Mixed, Test n=18: 3 pure AD + 3 main AD; 9 pure LBD + 3 Mixed).

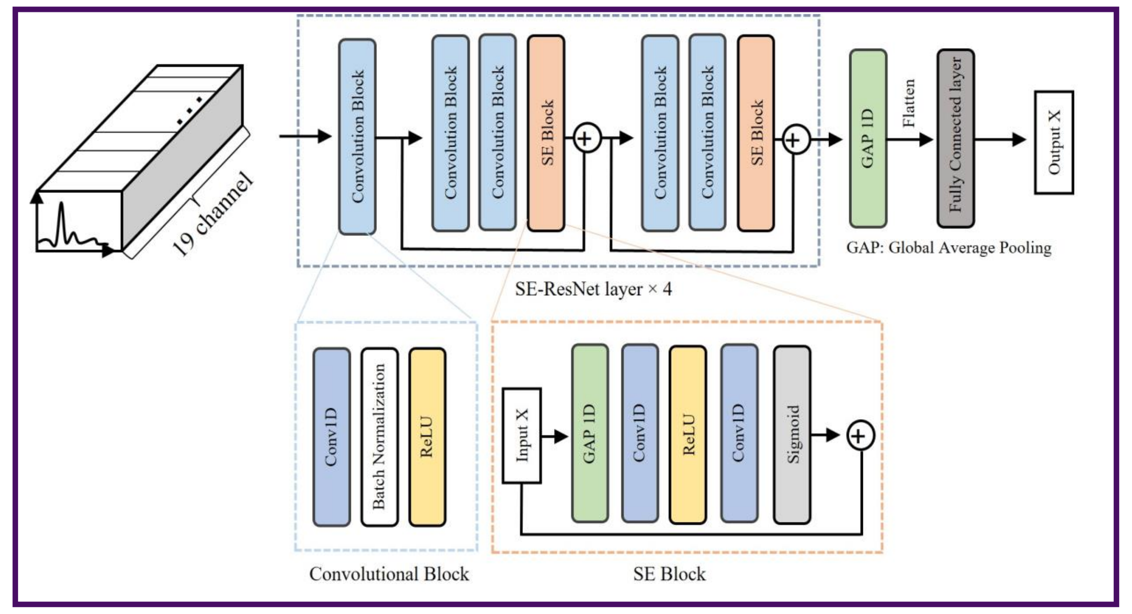


Figure 1. 1D SE-ResNet model architecture

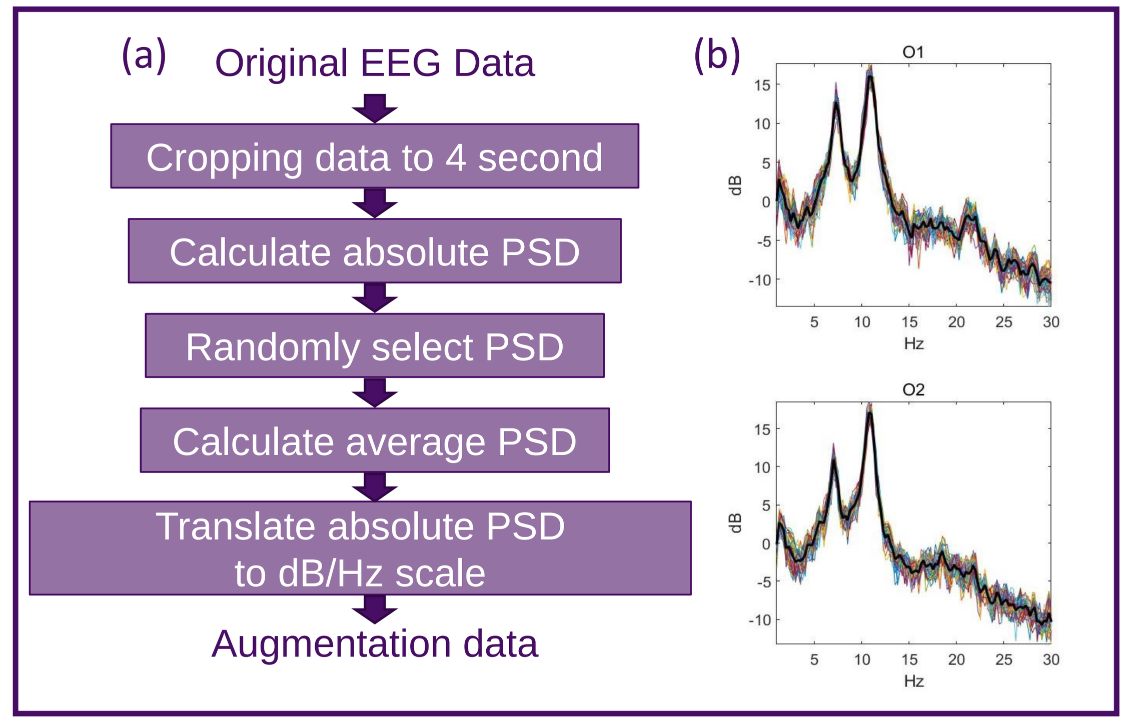


Figure 2. (a) Flowchart of data augmentation (b) Augmentation result of one sample data (black bold line : mean of generated data)

| | Original data | augmentation |
|---|---|---|
| Pure AD | 23 | 1084 |
| Main AD | 25 | 1190 |
| Main LBD | 3 | 153 |
| Pure LBD | 71 | 3541 |
| Total | 122 | 5968 |

Table1. The number of train data (EEG data)

## RESULTS

- The confusion matrix of classification models are shown in Table2.Validation results of 83.3% AD sensitivity and 70.6% LBD sensitivity. And test results were at 83.3% accuracy, 83.3% AD sensitivity and 83.3% LBD sensitivity.

| Validation | pred LBD(-) | pred LBD(+) | Test | pred LBD(-) | pred LBD(+) |
|---|---|---|---|---|---|
| pure AD | 3 | 0 | pure AD | 3 | 0 |
| main AD | 2 | 1 | main AD | 2 | 1 |
| Mixed | 8 | 18 | Mixed | 1 | 2 |
| pureLBD | 2 | 6 | pureLBD | 1 | 8 |

Table 2. confusion matrix of Validation & Test results

- Based on the XAI results shown in Figure 3, the classifier model exhibits significant attention to the Delta band (1-4Hz) for prediction, followed by theta and alpha bands in terms of weighting.
  MCI-LBD tends to show a relatively slower qEEG main frequency compared to MCI-AD [2], and our model also appears to pay attention to this reasonable aspect.

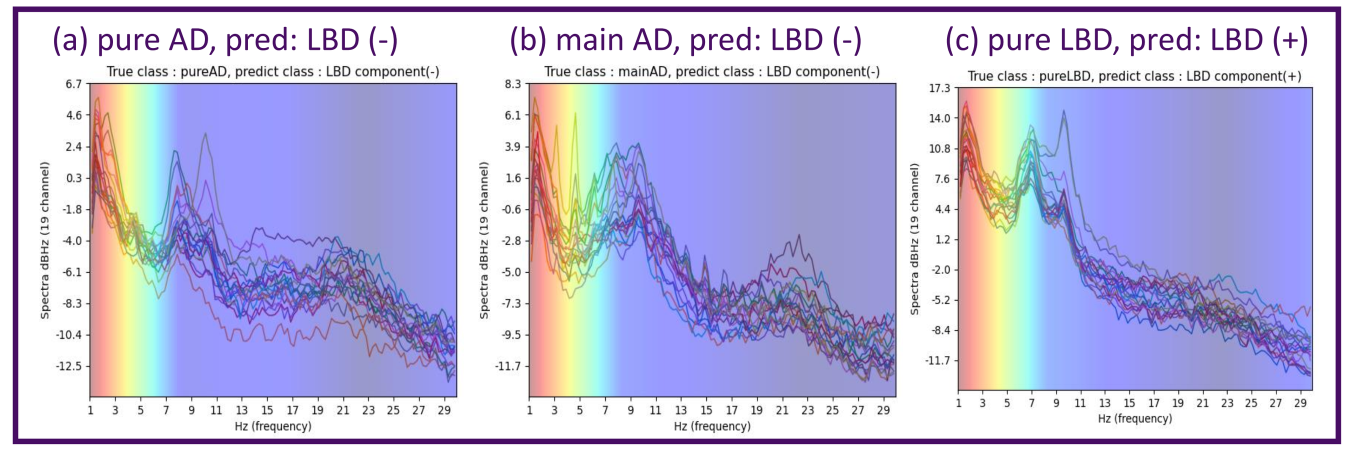


Figure 3. XAI(method= Grad Cam) result of AD/LBD tendency classifier model; (a) XAI result of true class-pureAD (b) class – mainAD (c) class- pureLBD

## CONCLUSIONS

- QEEG-based deep learning classifier developed in this study successfully distinguished the degree of LBD in MCI patients.
- Our model can help identify subtype-specific spectral trends, which could also make contributions in the establishment of effective treatment methods for MCI.

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