

Machine Learning-based Amyloid Pathology Screening Model Using QEEG Sensor Level Imaginary Coherence



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Introduction

 \bullet β -Amyloid is a peptide found in patients with Alzheimer's disease, which from amyloid plaques in the brain.

• The composition and population of β -Amyloid peptides correlates to the clinical status of the patients.

• Thus, detection of the β -Amyloid peptide is crucial for early screening and prevention of Alzheimer dementia.

• Amyloid Positron Emission Tomography (Amyloid PET) employing 18-F labelled radiopharmaceuticals is popularly adopted for screening of the peptide/plaques.

• There are several disadvantages of Amyloid PET, the imaging process exposes the patient to a high dose of harmful ionizing radiation and could be very costly.

 \bullet This research aims to develop a novel $\beta\mbox{-}Amyloid$ screening method overcoming the disadvantages.

Methods

• The EEG signal employed in this research has been measured at 19 electrode locations in correspondence to the 10-20 system.

• iSyncBrain® platform was used for preprocessing procedures, which includes Independent Component Analysis (ICA) and bad epoch rejection.

• Preprocessed signals were then band pass filtered into eight different frequency bands: Delta (1-4Hz); Theta (4-8Hz); Alpha1 (8-10Hz); Alpha2 (10-12Hz); Beta1 (12-15Hz); Beta2 (15-20Hz); Beta3 (20-30Hz); Gamma (30-45Hz).

• Signals which fall under Delta and Gamma frequency bands were excluded from the scope of interest due to a high chance of noise contamination.

• The imaginary coherences were selected as feature values which represent phase differences among the signals at locations specified by the 10-20 system.

• The feature values were then normalized at each frequency bands.

• Sensor-level imaginary coherence feature map (see figure 1 below) was yielded through horizontal concatenation of the normalized matrices.



Figure 1: The sensor level imaginary coherence feature map employed for training/testing of the model

- The class labelling was done through Amyloid PET results.
- \bullet Data augmentation was performed on $\beta\text{-Amyloid}$ positive class through splitting of the data in time series, with the aim to overcome the class imbalance.
- Sensor-level imaginary coherence feature maps were produced for each subjects, comprising the augmented dataset.
- \bullet The final training dataset consists of 138 β -Amyloid positive data and 143 β -Amyloid negative data.

 \bullet The final test dataset consists of 61 $\beta\text{-Amyloid}$ positive data and 33 $\beta\text{-Amyloid}$ negative data.

Results

	Pred Amyloid +	Pred Amyloid -
Real Amyloid +	57	4
Real Amyloid -	2	31

Table 1: Confusion matrix for test set classification

• The β -Amyloid screening model adopting machine learning algorithm has yielded test sensitivity at 0.934 and specificity at 0.939.

• 5-fold cross validation was performed on the training dataset, which returned the sensitivity at 0.884 and specificity at 0.923.

Conclusions

• The machine learning model developed in this research achieved outstanding classification results.

• Such QEEG based model may sufficiently replace Amyloid PET for screening of the β -Amyloid plaque, resolving previously discussed disadvantages.

• Sensor level imaginary coherences are statistically more robust than source level imaginary coherences, free from errors accumulated during source location calculation process.

• Therefore, correct and appropriate application of the sensor level imaginary coherences may aid screening of several other neurological diseases.

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