Multimodal EEG-MRI in the diagnosis of mild cognitive impairment with Lewy bodies

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1. Background

- Differentiating mild cognitive impairment with Lewy bodies (MCI-LB) from mild cognitive impairment with Alzheimer's disease (MCI-AD) is challenging, due to an overlap in clinical presentation.
- Quantitative electroencephalography (qEEG) has modest diagnostic utility as a biomarker for MCI-LB, while the diagnostic utility of structural MRI (sMRI) and visual EEG assessment is uncertain.

2. Aims

- To train machine learning classifiers on combinations of qEEG, sMRI and visual EEG features to discriminate MCI-LB from MCI-AD.
- To determine the predictive value of individual features in the classifiers.

3. Hypothesis:

A multimodal classifier including qEEG, visual EEG and sMRI features would improve diagnostic utility compared to qEEG features alone in differentiating MCI-LB from MCI-AD.

4. Methods

- Resting state, eyes closed EEG and T1 weighed sMRI data from 37 MCI-LB and 36 MCI-AD patients were analysed. Random forest classifiers were trained in MATLAB R2017a on a combination of qEEG, visual EEG and sMRI features, as shown in Figure 1:

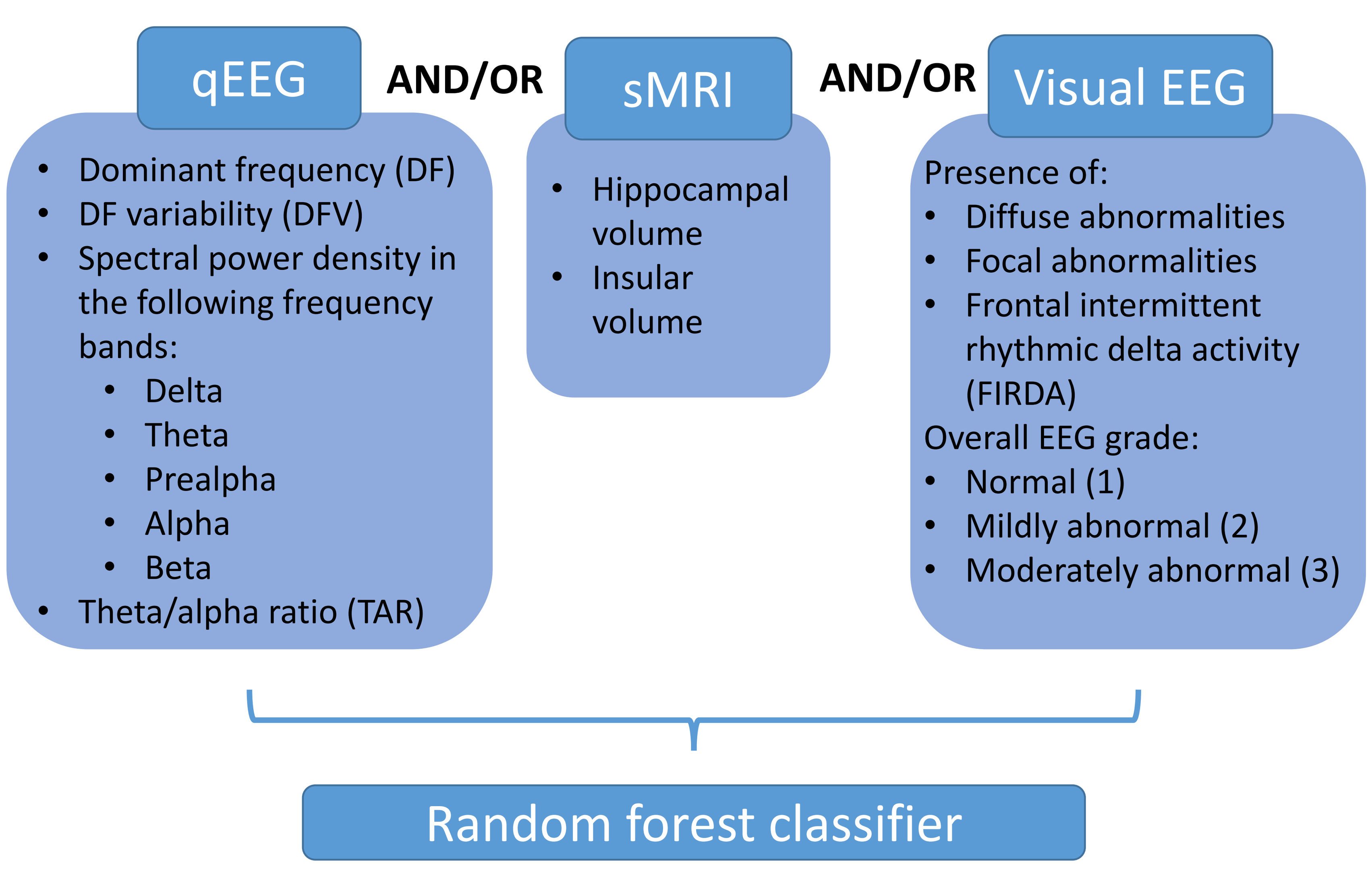

Figure 1: Features used to train the random forest classifier.

- **qEEG** analysis was carried out on 45 x 2 second artefact-free epochs with EEGLAB (v14). **Visual** assessments were done on only leads present in the 10-20 system and filtered between 1 and 40 Hz to exclude artefacts. **sMRI** features were computed with voxel-based morphometry in SPM12.
- Random forest classifiers were trained with a bootstrapped aggregated ensemble of 500 classification trees, with maximum splits = 72 and 10 - fold cross-validation.
- Classifiers were trained 100 times, then the mean sensitivity, specificity, accuracy and receiver operating curve were calculated.

5. Results

Machine learning classifiers

- All classifiers showed similar diagnostic performance, as evaluated by classification accuracy, sensitivity, specificity (Table 1) and area under the receiver operating characteristic curve (Figure 2).

Classifier	Accuracy	Sensitivity	Specificity
qEEG only	64.1 (2.89)	63.8 (3.86)	64.3 (3.77)
qEEG + sMRI	64.4 (2.56)	62.3 (3.26)	66.5 (3.88)
qEEG + visual	66.5 (2.58)	64.8 (3.44)	68.2 (3.45)
qEEG + sMRI + visual	65.3 (2.37)	62.5 (3.44)	68.2 (2.96)

Table 1: Diagnostic performance for random forest classifiers trained on different feature groups. Values shown are mean (standard deviation) over 100 runs.

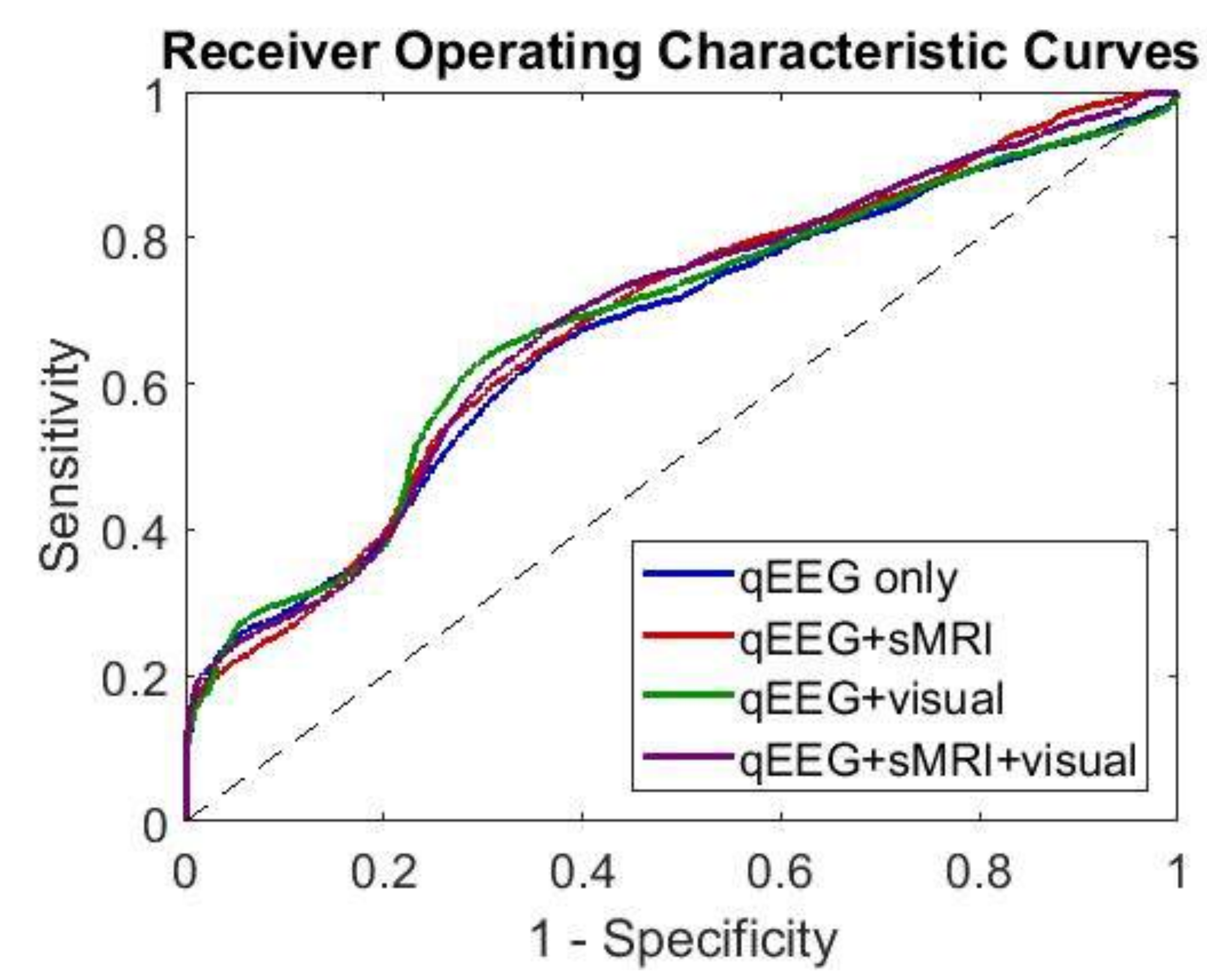

Figure 2: Receiver operating characteristic curves for random forest classifiers.

Predictor importance scores

- Beta power had the highest predictor importance score, followed by alpha power, TAR, DFV, prealpha power and DF in the combined qEEG + sMRI + visual classifier.
- Discriminative power of the classifiers was driven mostly by qEEG features, as shown in Figure 2.

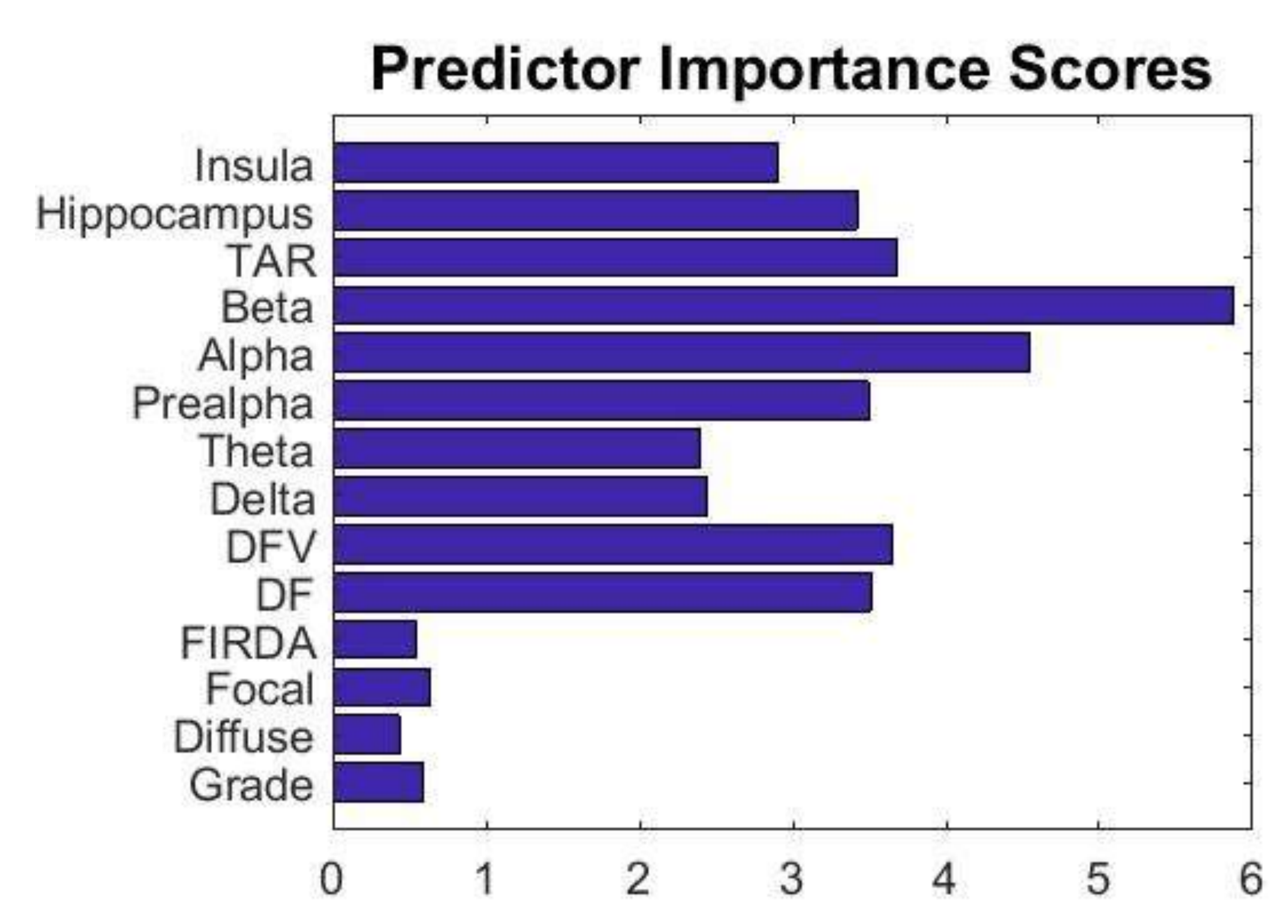

Figure 3: Predictor importance scores for each feature in the qEEG + sMRI + visual classifier.

6. Conclusion:

The use of sMRI and visual EEG features does not enhance the diagnostic utility of qEEG features alone in machine learning-aided differential diagnosis of MCI-LB from MCI-AD. However, the diagnostic utility of qEEG features alone is only modest, which may limit its application in clinical practice.

7. Acknowledgements

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