

PREDICTING BRAIN AMYLOIDOSIS WITH PLASMA B-AMYLOID42/40 AND MRI-BASED MORPHOMETRY FEATURES

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1. OBJECTIVE

Biomarker assisting early detection and intervention in Alzheimer’s disease (AD) may be the key to therapeutic breakthroughs. One of the presymptomatic hallmarks of AD is the accumulation of beta-amyloid (A β) plaques in the human brain. However, current methods to detect brain A β pathology are either invasive (lumbar puncture) or quite costly and not widely available (amyloid PET). The blood-based biomarker, like plasma A β 42/A β 40, enables more rapid and inexpensive screening of potential participants for brain amyloidosis [1]. Additionally, our recent research has demonstrated that MRI-based hippocampal multivariate morphometry statistics (MMS) can be an effective neurodegenerative biomarker for predicting brain amyloid deposition [2]. In this study, we demonstrate that the combination of these two state-of-the-art biomarkers could achieve superior performance in predicting the brain A β burden assessed based on amyloid PET.

2. METHODS

In Fig. 1, MMS are first extracted from MR images. As MMS have a larger dimension than the sample size, we used our previously introduced sparse coding algorithm, Patch Analysis-based Surface Correntropy-induced Sparse coding and max-pooling (PASCs-MP), to generate a low-dimensional representation of hippocampal morphometry for each subject. We randomly but consistently over subjects select patches of MMS on the hippocampal surface. Then, sparse-coding and max-pooling are used to generate representations for these subjects. Finally, we train binary random forest classifiers on the representations and the measures of plasma A β 42/40 from the people with different PET-based brain A β positivity status and evaluate these classifiers with 10-fold cross-validation.

3. EXPERIMENTAL RESULTS

From the Alzheimer’s Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu), we identified 198 subjects with matching plasma A β 42/40 measures, florbetapir PET and T1-MRI scans, 98 subjects were amyloid positive and 100 were amyloid negative based on florbetapir PET and previously discussed processing pipeline and positivity threshold [1]. And plasma A β 42/40 was measured as [3].

We trained random forest classifiers on this dataset with different features, including plasma A β 42/40, MMS separately or jointly. For each experiment, we performed 10-

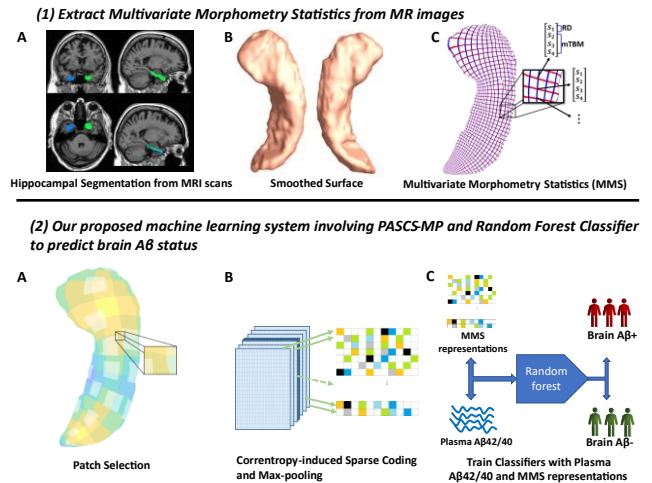


Fig. 1. Overview of the framework

fold cross-validation five times, and the average results (sensitivity, specificity and accuracy) are shown in Table 1.

Table 1. Classification Results.

	SPE	SEN	ACC
Plasma A β	0.70 \pm 0.01	0.73 \pm 0.01	0.72 \pm 0.00
MMS	0.86 \pm 0.01	0.75 \pm 0.02	0.80 \pm 0.01
MMS + A β	0.92 \pm 0.01	0.83 \pm 0.03	0.87 \pm 0.01

Values are mean \pm standard deviation where applicable.

4. CONCLUSION

Although plasma A β has been shown to be an adequate test to screen cognitively normal individuals for brain amyloidosis, combining it with our MRI-based hippocampal multivariate morphometry statistics may further improve the diagnosis accuracy of brain amyloidosis.

5. REFERENCES

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