DOI: 10.1002/alz.078606

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POSTER PRESENTATION

Alzheimer's & Dementia®
THE JOURNAL OF THE ALZHEIMER'S ASSOCIATION

NEUROIMAGING

A high-dimensional incomplete-modality transfer learning method for early prediction of Alzheimer's disease

Dohyun Ku[1] | Zhiyang Zheng[1] | Lingchao Mao[1] | Rui Qi Chen[1] | Yi Su[2] | Kewei Chen[2] | David Weidman[2] | Teresa Wu[3] | Fleming Lure[4] | ShihChung Lo[5] | **Jing Li**[6]

[1]Georgia Institute of Technology, Atlanta, GA, USA

[2]Banner Alzheimer's Institute, Phoenix, AZ, USA

[3]ASU-Mayo Center for Innovative Imaging, Tempe, AZ, USA

[4]MS Technologies, Washington DC, DC, USA

[5]MS Technologies Corp., Rockville, MD, USA

[6]Georgia Institute of Technology, Atlanta, AZ, USA

Correspondece
Jing Li, Georgia Institute of Technology, Atlanta, AZ, USA.
Email: jli3175@gatech.edu

Abstract

Background: Prediction of Alzheimer's disease (AD) risk for individuals with mild cognitive impairment (MCI) provides an opportunity for early intervention. Neuroimaging of different types/modalities has shown promise, but not every patient has all the modalities due to the cost and accessibility constraints. To integrate incomplete multi-modality datasets, we previously developed a machine learning (ML) model called incomplete-modality transfer learning (IMTL). We extended the capacity of IMTL to handle high-dimensional feature sets, namely, HD-IMTL, to further improve accuracy and robustness.

Method: Our dataset included 1319 T1-MRI scans from MCI patients in ADNI; among them, 1002 had FDG-PET and 612 had amyloid-PET. 156 regional volumetric and thickness features were computed from MRI and 83 and 83 regional SUVR features from FDG-PET and amyloid-PET, respectively. The dataset is randomly split into training and test sets. The goal of HD-IMTL was to jointly train 4 ML models to predict MCI conversion to AD in 36 months, with each model based on a certain combination of available modalities, namely, MRI, MRI+FDG, MRI+amyloid, and MRI+FDG+amyloid. These correspond to patient sub-cohorts that differ in their access to imaging modalities. To handle high-dimensional features, we employed feature screening to remove uninformative features, performed modality-wise partial least squares (PLS) to condense remaining features into PLS components, and used correlation tests to select components. To jointly train the 4 ML prediction models, IMTL was used, which is a generative model that uses expectation-maximization (EM) in joint parameter estimation to facilitate transfer learning. To account for sample imbalance in training, the Synthetic Minority Over-sampling Technique (SMOTE) was used. The trained models were applied to the test set. 20 training/test splits were repeated and AUCs on the test set were averaged. For comparison, three existing ML models for incomplete-modality fusion were applied to the same dataset.

Result: The AUCs by HD-IMTL were 0.802, 0.840, 0.868, and 0.880 for sub-cohorts with MRI, MRI+FDG, MRI+amyloid, and MRI+FDG+amyloid, respectively. The AUCs

by existing methods were lower, with ranges of 0.749-0.793, 0.769-0.826, 0.816-0.863, and 0.832-0.868.

Conclusion: HD-IMTL demonstrated high accuracy in predicting MCI conversion to AD for patients with varying access/availability of imaging modalities.