## Research on the intelligent diagnosis of dementia

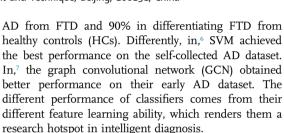
Xuegang Song,<sup>a</sup> Peng Yang,<sup>a</sup> Hongbin Han,<sup>b,c,d,\*</sup> and Baiying Lei<sup>a,\*\*</sup>

<sup>a</sup>National-Regional Key Technology Engineering Laboratory for Medical Ultrasound, Guangdong Key Laboratory for Biomedical Measurements and Ultrasound Imaging, School of Biomedical Engineering, Health Science Centre, Shenzhen University, Shenzhen, 518060, China

<sup>b</sup>Department of Radiology, Peking University Third Hospital, Beijing, 100191, China <sup>c</sup>Institute of Medical Technology, Peking University Health Science Center, Beijing, 100191, China <sup>d</sup>NMPA Key Laboratory for Evaluation of Medical Imaging Equipment and Technique, Beijing, 100191, China

As the seventh leading cause of death worldwide, dementia is a syndrome that mainly affects cognitive function. Since its treatment is quite difficult, the accurate dementia diagnosis is of great significance. The traditional diagnostic procedures include cognitive and neurological tests, such as brain scans, psychiatric evaluations, genetic tests, and blood tests. Where brain scans (i.e., magnetic resonance imaging (MRI) and positron emission tomography (PET)) and genetic tests are usually expensive and unavailable.1 For those that live in developing regions facing high social and economic burdens of dementia and caregiving, it is difficult to get the timely diagnosis and proper treatment.2 In The Lancet Regional Health - Americas, Maito et al.3 study the dementia diagnosis in Latin America. In this study, the authors differentiate Alzheimer's disease (AD) from frontotemporal dementia (FTD) patients via acquired low-cost clinical and cognitive measures with successful diagnosis performance. With the development of the computer technology, intelligent diagnosis based on machine learning has attracted growing attention as it is desired to relieve the pressure on the medical system<sup>4,5</sup> by reducing radiologists' workload. Where designing appropriate classifiers, studying multi-site datasets, and fusing multimodal data are main research hotspots.

The popularly used classifiers include multiple layer perception (MLP), logistic regression (LR), random forest (RF), and support vector machine (SVM). They usually show different performances on different diagnosis tasks or datasets. As the preliminary research on the pathogenesis, the subjective diagnostic bias of physicians, and insufficient data, the diagnosis performance of dementia is usually limited. This results that most works devoted to binary classification. Maito et al.<sup>3</sup> studied the above classifiers and compare their performance on their dataset. It shows that the RF model achieved the best discriminative power with accuracy reaching 93.2% in differentiating



Collecting data from different hospitals significantly increases the number of samples, which benefits to train the classifier. However, the heterogeneity between multi-site datasets limits the performance to some extent.8 The heterogeneity is produced by diverse imaging conditions and subjective criteria, which affects the generalisation ability of the classifier. Many studies have devoted to multi-site learning, such as the works4.8 that studied the multi-site classifier to adapt the heterogeneity between multi-site neuroimaging data. Maito et al.3 collected clinical data from 11 centres across five Latin America countries, including a total of 1794 participants with low-cost clinical and cognitive measures. The authors declared they will analyse the differences between multi-site datasets and design a corresponding multi-site classifier to adapt to the difference in their further work, which is also of great significance. Generally speaking, quality assessment, difference analysis, abnormality detection, and multi-site classifier are the main research points of multi-site learning.

Collecting multi-modal data and studying the biomarkers from multiple aspects have a great potential to improve diagnosis performance.9,10 But it is usually subjected to data imbalance and modal absence. Maito et al.3 collected a large amount of data including cognitive screening (Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and Addenbrooke's cognitive examination (ACE)), executive functions (IFS), social cognition (Mini-SEA), functional status (Pfeffer FAQ and Barthel index), neuropsychiatric symptoms (NPI), and corresponding demographic data (i.e., birth, country, years of education, and sex). This work harmonised the available data by using equivalence tables, completed missing data and then analysed them, showing that the measures of social cognition, neuropsychiatric symptoms, executive functioning performance, and cognitive screening are highly related to the disease. Age, educational attainment, and sex are also associated factors



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<sup>\*</sup>Corresponding author. Department of Radiology, Peking University Third Hospital, Beijing, China.

<sup>\*\*</sup>Corresponding author. School of Biomedical Engineering, Health Science Centre, Shenzhen University, Shenzhen, China.

*E-mail addresses:* hanhongbin@bjmu.edu.cn (H. Han), leiby@szu.edu.cn (B. Lei).

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that can affect the diagnosis performance. Maito et al.<sup>3</sup> found functional tests show different diagnosis abilities, where the ranking of conventional cognitive tests (social cognition > executive functioning > neuropsychiatric symptoms > cognitive screening) helped to discriminate between AD and FTD patients. This work also revealed that Mini-SEA, NPI, IFS, and MMSE are the best predictors to differentiate HCs vs. AD and HCs vs. FTD. Compared to HCs, patients with AD and FTD tend to have impairment in cognitive processes, social cognition, and neuropsychiatric symptoms. These findings can help physicians in low-resource regions to better understand and diagnose dementia.

## Contributors

Xuegang Song and Peng Yang drafted the article, Hongbin Han and Baiying Lei revised it. All authors contributed to the final approval of the paper.

## Declaration of interests

The authors declare that they have no competing interests.

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