Research on the intelligent diagnosis of dementia

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The Lancet Regional Health - Americas 2023;17: 100421

Published Online 28 December 2022
https://doi.org/10.1016/j.lana.2022.100421

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[4,5] 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.[3] 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 AD from FTD and 90% in differentiating FTD from healthy controls (HCs). Differently, in,[6] SVM achieved the best performance on the self-collected AD dataset. In,[7] the graph convolutional network (GCN) obtained better performance on their early AD dataset. The different performance of classifiers comes from their different feature learning ability, which renders them a research hotspot in intelligent diagnosis.

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 works[4,8] 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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that can affect the diagnosis performance. Maito et al.[3] 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.

References

1 Nativio R, Lan Y, Donahue G, et al. An integrated multi-omics approach identifies epigenetic alterations associated with Alzheimer's disease. *Nat Genet*. 2020;52:1024–1035. https://doi.org/10.1038/s41588-020-0696-0.

2 Ibáez A, Pina-Escudero SD, Possin KL, et al. Dementia caregiving across Latin America and the Caribbean and brain health diplomacy. *Lancet Health Longev*. 2021;2:e222–e231. https://doi.org/10.1016/S2666-7568(21)00031-3.

3 Maito MA, Santamaría-García H, Moguilner S, et al. Computational classification of Alzheimer's disease and frontotemporal dementia using routine clinical and cognitive measures across multicentric underrepresented samples. *Lancet Reg Health Americas*. 2022;17.

4 Song X, Zhou F, Frangi AF, et al. Multi-center and multi-channel pooling GCN for early AD diagnosis based on dual-modality fused brain network. *IEEE Trans Med Imaging*. 2022. https://doi.org/10.1109/TMI.2022.3187141.

5 Liu M, Li F, Yan H, et al. A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease. *Neuroimage*. 2020;208:116459. https://doi.org/10.1016/j.neuroimage.2019.116459.

6 Yang P, Zhou F, Ni D, et al. Fused sparse network learning for longitudinal analysis of mild cognitive impairment. *IEEE Trans Cybernetics*. 2021;51:233–246. https://doi.org/10.1109/TCYB.2019.2940526.

7 Song X, Zhou F, Frangi AF, et al. Graph convolution network with similarity awareness and adaptive calibration for disease-induced deterioration prediction. *Med Image Anal*. 2021;69:101947. https://doi.org/10.1016/j.media.2020.101947.

8 Guan H, Liu Y, Yang E, et al. Multi-site MRI harmonization via attention-guided deep domain adaptation for brain disorder identification. *Med Image Anal*. 2021;3:102076. https://doi.org/10.1016/j.media.2021.102076.

9 Yang E, Liu M, Yao D, et al. Deep Bayesian hashing with center prior for multi-modal neuroimage retrieval. *IEEE Trans Med Imaging*. 2020;40:503–513. https://doi.org/10.1109/TMI.2020.3030752.

10 Pan Y, Liu M, Xia Y, et al. Disease-image-specific learning for diagnosis-oriented neuroimage synthesis with incomplete multi-modality data. *IEEE Trans Pattern Anal*. 2022;44:6839–6853. https://doi.org/10.1109/TPAMI.2021.3091214.