Grey Matter Age prediction as a Biomarker for Risk of Dementia: A Population-based Study.
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INTRODUCTION

The gap between predicted brain age and chronological age may serve as a biomarker for dementia. We aimed to investigate the utility of this gap as a predictor for incident dementia, while using a deep learning approach for predicting brain age.

METHODS

Data was collected from 5656 subjects of the population-based Rotterdam Study, aged 45 years and older, including 159 incident dementia subjects[5]. We built a convolutional neural network (CNN) model to predict brain age, which had two inputs: grey matter (GM) 3D density maps extracted from magnetic resonance images (MRI), and gender to correct for sex differences in GM volume.

Prediction performance was measured in mean absolute error (MAE). Reproducibility was tested in intraclass correlation coefficient (ICC) on a subset of 80 subjects. We performed Cox proportional hazards regression to assess the association of the gap between chronological and brain age with incident dementia, adjusted for years of education, APoE4 gene carriership, GM and intracranial volume differences.

RESULTS

Data was split into training, validation and test sets (5865, 2353, 550 images; mean age: 66.09±10.76, 64.84±9.69, 64.85±10.82 years respectively). Incident dementia subjects were excluded during training of the CNN. MAE of brain age prediction was 4.45±3.59 years (Fig. 1). ICC was 0.97. Cox proportional hazards models showed that the age gap was significantly related to incident dementia (hazard ratio of 1.11; 95% confidence interval of 1.06-1.15). This association is reinforced by the Kaplan-Meier curves shown in Fig. 3.

CONCLUSIONS

We show that the gap between predicted and chronological brain age is an independent biomarker, associated with a risk of dementia development. This suggests that the age gap may be used for early-stage dementia risk screening.

References


Figure 1. The plot depicts chronological age (x-axis) and brain-predicted age (y-axis) with mean absolute error (MAE). Red dots indicate the test set subjects and the dashed line indicates the ideal case x=y.

Figure 2. Kaplan-Meier curves presenting the dementia-free probability over time for participants with different gap values, divided into quintiles. Low gap values correspond to chronological ages surpassing brain age, whereas high gap values correspond to chronological ages that are lower than the brain age.

Figure 3. Attention map overlaid on a brain template. A threshold of 0.65 has been applied to voxel values in the attention map to focus on more important regions.