Intuitive visualization for convolutional neural networks detecting brain diseases in MRI scans

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Intuitive visualization for convolutional neural networks detecting brain diseases in MRI scans

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Introduction

- Although deep learning approaches achieve high diagnostic accuracy to automatically detect neurodegenerative diseases -such as Alzheimer's disease- based on MRI and PET, they are currently not part of clinically applied diagnostic systems.
- The main reason for this lack of clinical use is the shortcoming in proper methods for model comprehensibility and interpretability for clinical users.

Aim of the study:

i. Development of a convolutional neural network (CNN) model to achieve competitive diagnostic accuracy for detecting Alzheimer's disease in patients with dementia and mild cognitive impairment (MCI).

ii. Intuitive visualization to aid model comprehensibility and clinical utility using class activation mapping approaches to highlight contributing brain regions.

Methods

- MRI data from the *Alzheimer's Disease Neuroimaging Initiative* (ADNI) (Tab.1) were used for model training by applying a six-fold cross-validation scheme.
- Only patients with positive amyloid-β biomarker and controls with negative finding were included to improve the diagnostic confidence of the training sample.
- Twelve coronal slices covering the hippocampus area were selected, corrected for effects of age and gender using linear regression, and fed into the CNN model as separate channels (Fig.1).
- MRI data from the *DZNE – Longitudinal Cognitive Impairment and Dementia Study* (DELCODE) (Tab.1) were used as independent validation set.

Table 1 Sample characteristics.

		Male/Female	Age	Years of education	MMSE
Training & cross-validation set	**ADNI (N=294)**				
	HC (n=126)	65/61(48.4%)	72.7±6.4	16.8±2.5	29.1±1.2
	MCI (n=93)	50/43(46.2%)	72.3±7.4	16.4±2.8	27.1±1.9
	AD (n=75)	40/35(46.7%)	75.0±8.5	15.6±2.8	22.9±2.1
Independent validation set	**DELCODE (N=332)**				
	HC (n=182)	75/107(58.8%)	69.0±5.3	14.8±2.7	29.4±0.9
	MCI (n=89)	54/35(39.3%)	72.3±5.1	14.0±3.0	28.0±1.7
	AD (n=61)	27/34(55.7%)	74.0±6.4	13.3±3.3	23.5±3.3

Abbreviations: AD – Alzheimer's dementia, MCI – mild cognitive impairment, HC – healthy controls, MMSE – mini mental status examination.

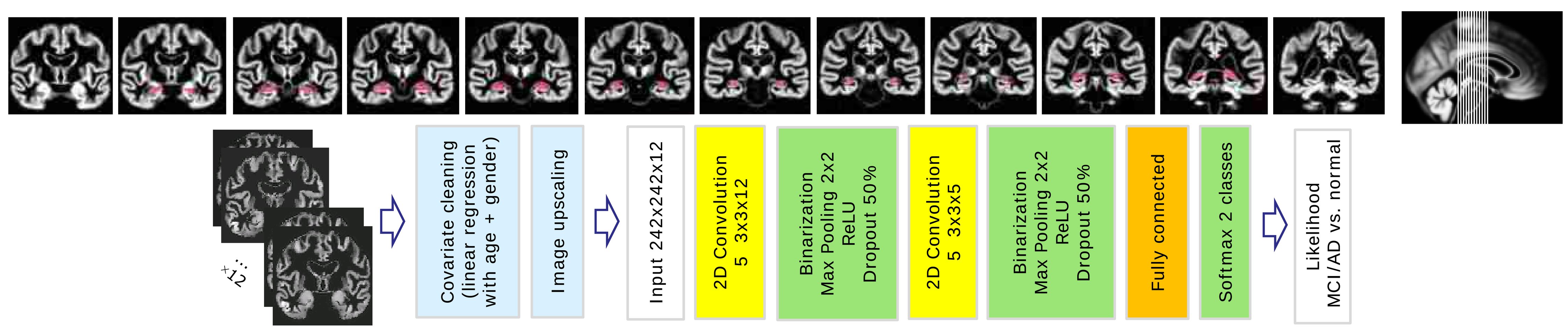

Figure 1 Input data (top) and deep learning model layout (bottom). Twelve coronal slices covering the hippocampus enter the model as separate input channels.

Results

- Area under the curve and diagnostic accuracy are given in Fig.2.
- Group mean CNN activation maps indicate hippocampal areas as most informative for the model (Fig.3 left).
- Individual subject's activation maps show more distributed cortical and subcortical regions to contribute to the model's decision (Fig.3 right).

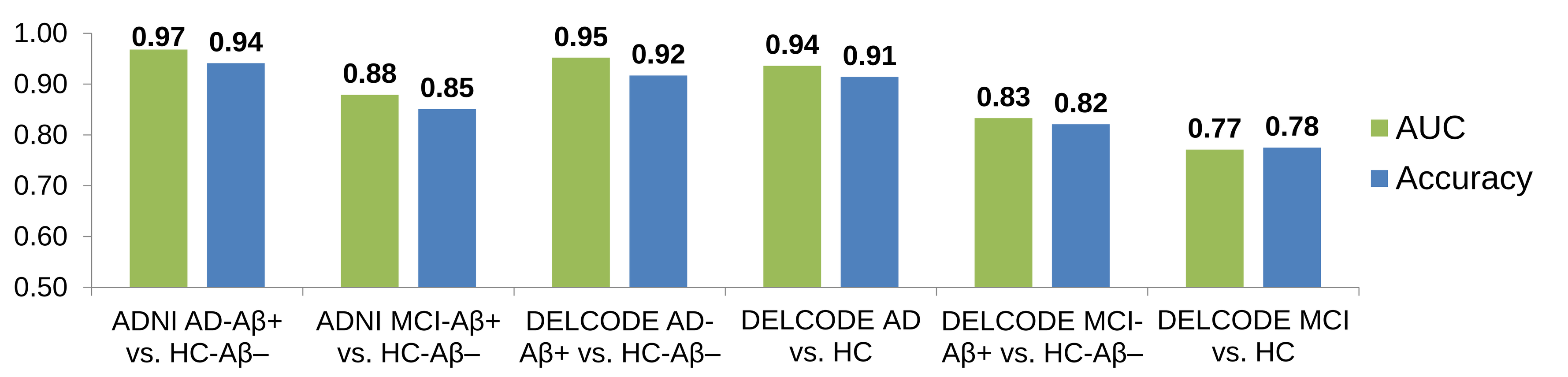

Figure 2 Area under the curve (AUC) and diagnostic accuracy.

Abbreviations: AD – Alzheimer's dementia, MCI – mild cognitive impairment, HC – healthy controls, Aβ+/- – amyloid-β biomarker positive/negative.

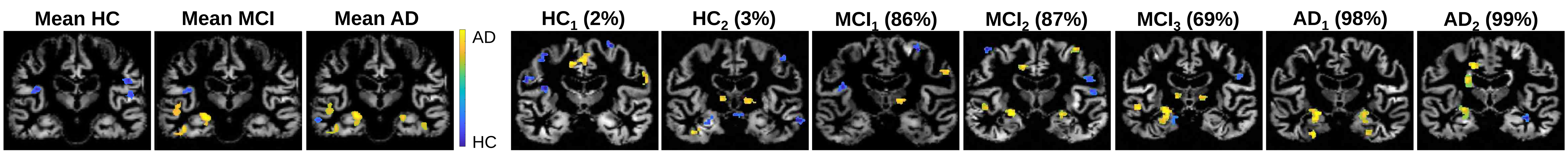

Figure 3 Group average (left) and individual subject's activation maps (right) as well as likelihood scores for Alzheimer's disease returned by the CNN model.

Discussion and conclusion

- Results applying 2D convolutional layers provide high diagnostic accuracy and promising results for the visualization of individual subject's CNN activity maps.
- Extension of the CNN toolbox for 3D convolutional layers recently became available in MATLAB R2019a and will provide activation maps with higher spatial information.
- Prospectively, we will focus on generating textual explanations from the input images [1] to enhance model interpretability and clinical utility.

References

1. Hendricks, et al. *Generating Visual Explanations*. ECCV (2016).

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