Parcel-wise stacking ensemble provides improved age prediction and brain-aging insights

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Introduction

- Brain-age prediction (BAP) using structural MRI has a great potential for studying healthy aging and disease [1].
- Both high accuracy and data privacy are desirable.
- We propose a stacking ensemble model (SEM) [2] which takes the advantage of the most informative voxels.

Material

- T1w MRI scans of healthy subjects from IXI [3], eNKI [4], CamCAN [5] and 1000Gehirne [6].
  (each n>500, total N=3103, 18-90 age range).
- Preprocessing: Voxel Based Morphometry CAT 12.8→ gray-matter volume (GMV).
- 873-parcel atlas to group GMV voxels

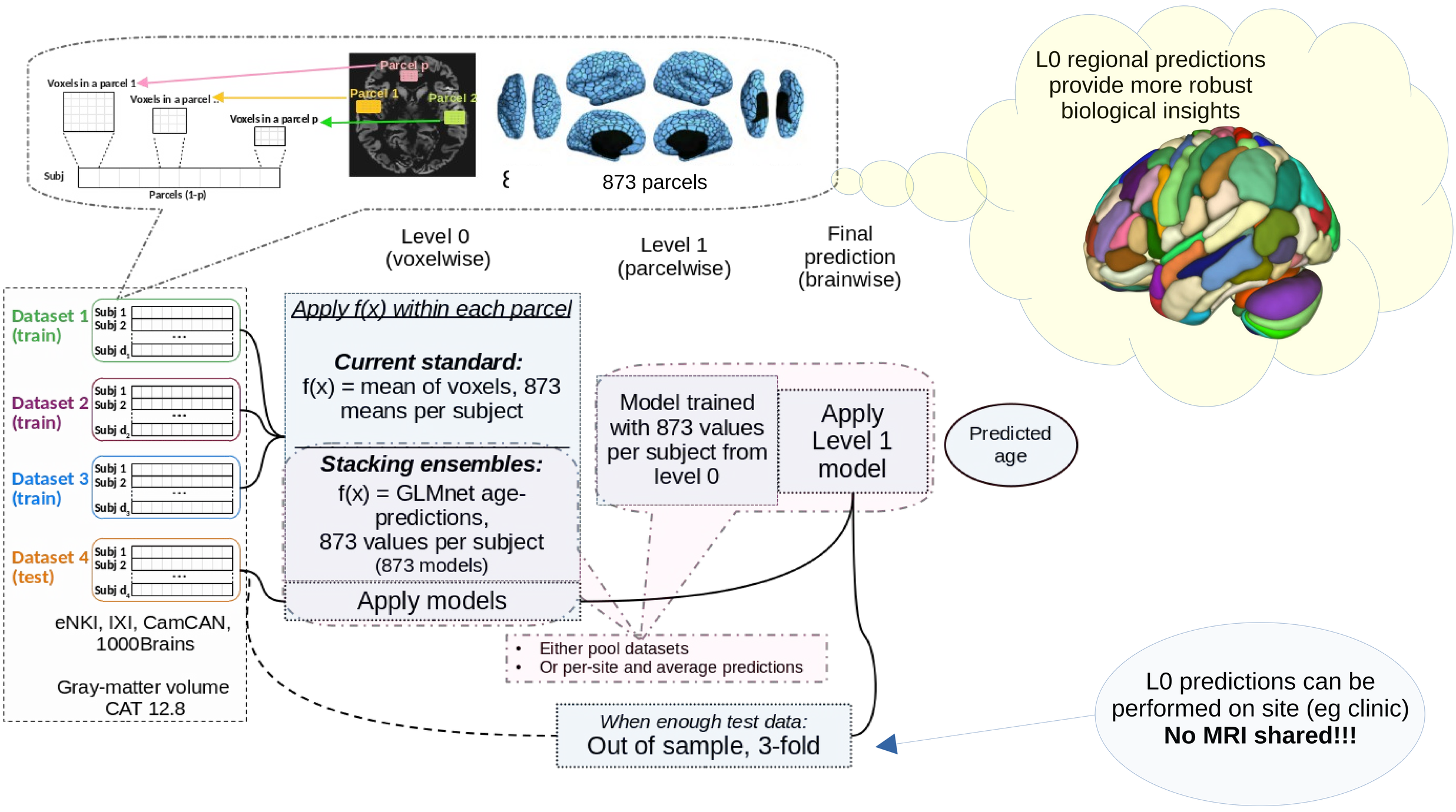
Methods

- Two-level stacking ensemble model.
  - Level 0 → A GLMnet model predicting age for each parcel with voxel-wise GMV as features.
  - Level 1 → A GLMnet model predicting age for an individual with predictions out-of-sample (3-fold cross-validation) from all L0 models as features.

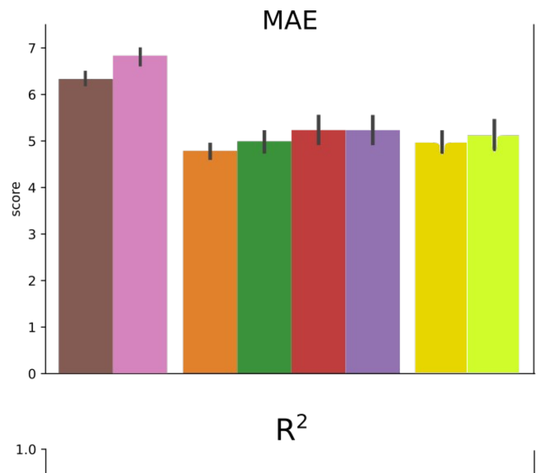
We explored two different ways to train models at L0 and L1 and several combinations between them providing different levels and types of privacy:
i) using pooled data from different sites, and
ii) treating each site separately and then averaging their predictions

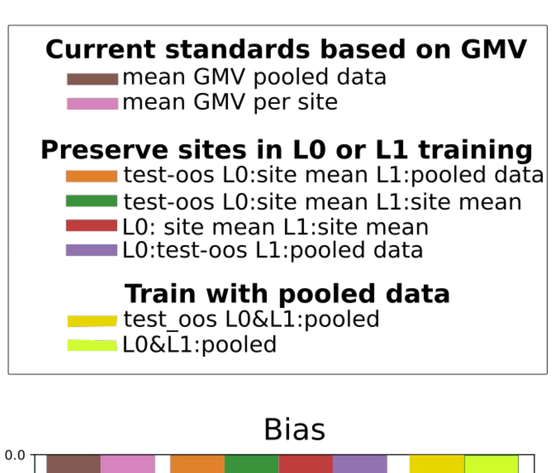
Additionally, to test the case where enough data is available at the test site, we estimated L0-level OOS predictions on the test data. These were then used to obtain predictions using L1 models.

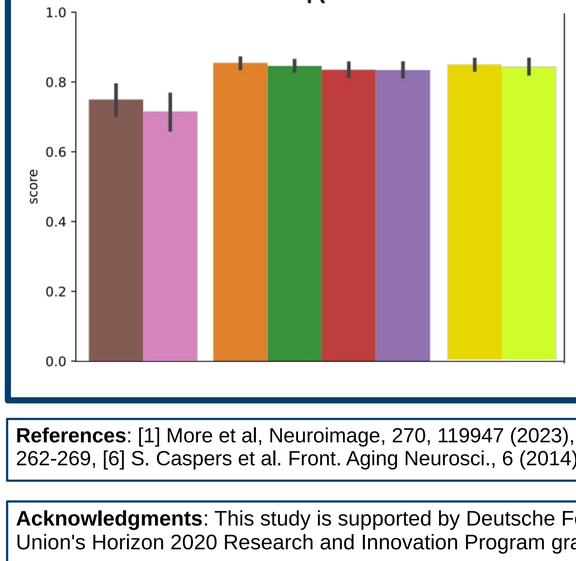
To compare with current standards we also tested models using average GMV in each parcel as inputs of L1. Performance was estimated using leave-one-site-out analysis.

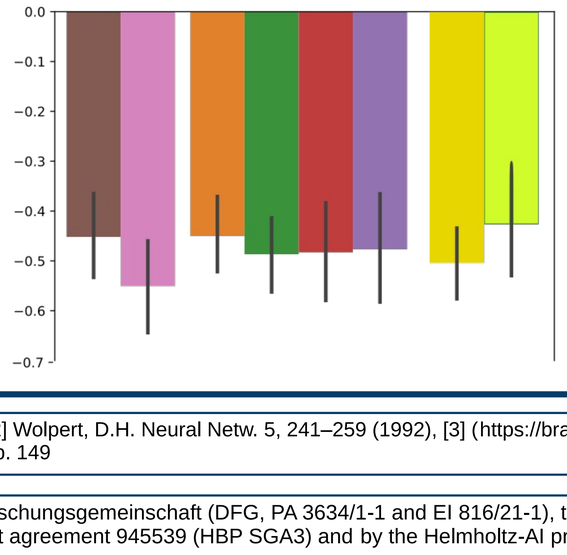


Results & Conclusions



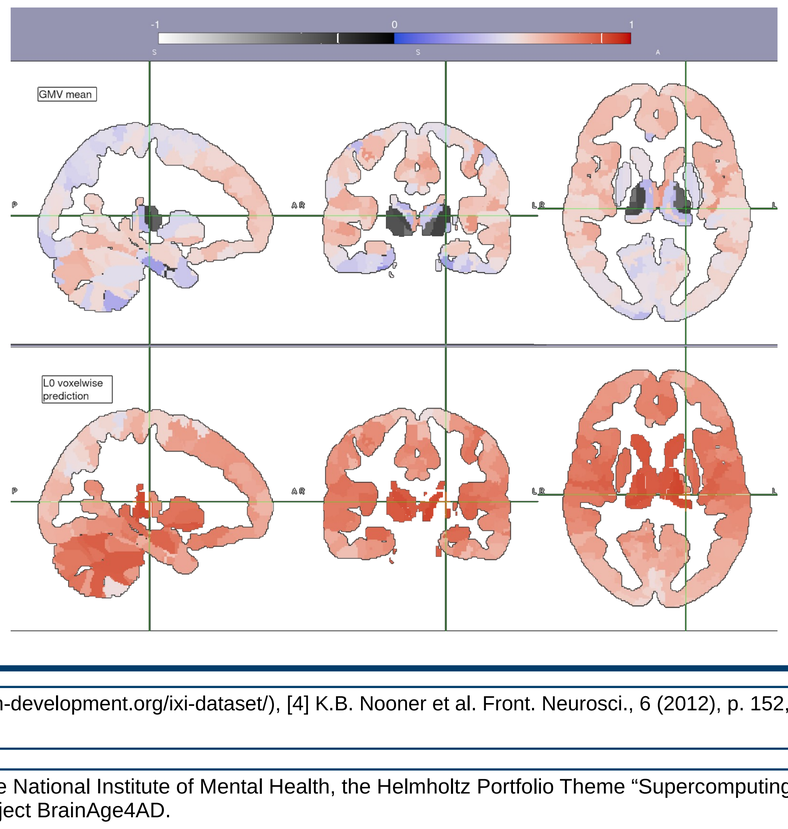






Brain maps

Pearson's r (* -1) Age-mean regional GMV (upper) & Pearson's r Age-regional L0 prediction (lower), across subjects



- **Improved performance in all metrics!**
- **Additional biological insights**

References: [1] More et al, Neuroimage, 270, 119947 (2023), [2] Wolpert, D.H. Neural Netw. 5, 241–259 (1992), [3] (https://brain-development.org/ixi-dataset/), [4] K.B. Nooner et al. Front. Neurosci., 6 (2012), p. 152, [5] J.R. Taylor et al. Neuroimage, 144 (Pt B) (2017), pp. 262-269, [6] S. Caspers et al. Front. Aging Neurosci., 6 (2014), p. 149

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