Machine Learning in Alzheimer's Disease and Aging Neuroimaging

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MACHINE LEARNING AD MRI

A wealth of machine learning algorithms have been applied to Alzheimer's disease clinical and imaging data in the past few years. My lab has developed and trained 3D CNN models on AD dementia using minimally processed T1-weighted structural data. With a focus on regional vulnerability using class activation techniques and slice/lobar analyses, these techniques have created models to which we can forward classify AD dementia with high accuracy using a system that targets the anterior hippocampal formation.

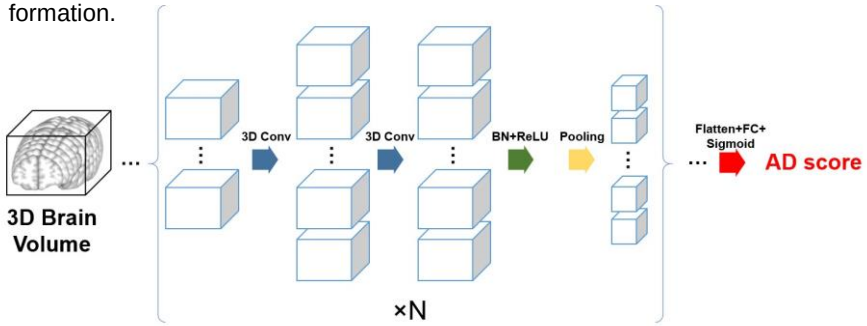


Figure 1: 3D CNN trained on AD (n=1874) and normal (n=2817) from ADNI. Model uses natural data-augmentation by including multiple scans from the same subjects, while preserving each group.

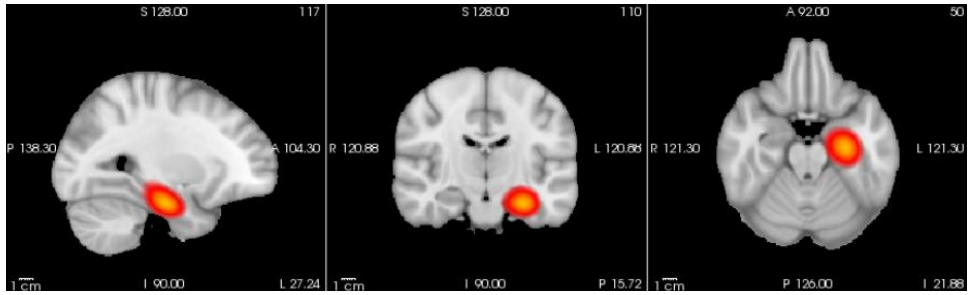


Figure 2: Class activation mapping implicates the left anterior hippocampal formation as the most predictive region for AD diagnosis.

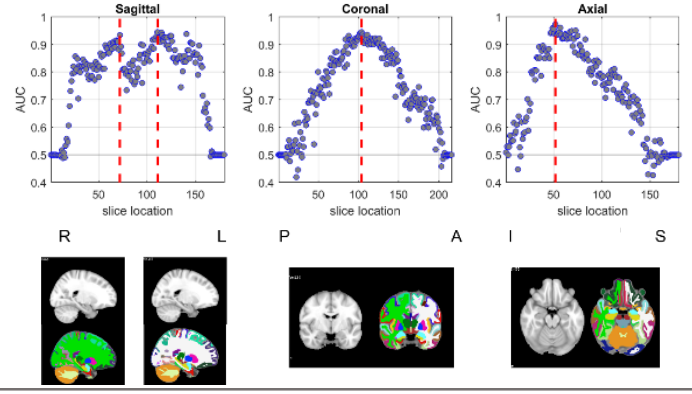
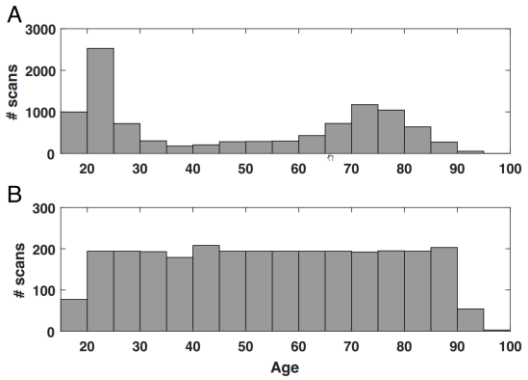


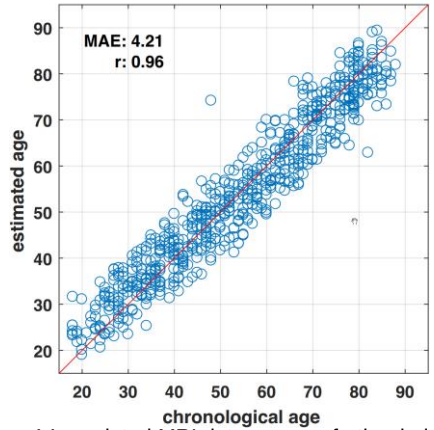
Figure 3: 2D slab analysis (3 slice thick slabs across each plane) implicate similar regions in each plane. Theoretically, this model demonstrates dimensionality reduction with still appreciably accurate results.

Feng et al. bioRxiv 456277

AGE PREDICTION AND DEVIATION IN STRUCTURAL MRI

We have further applied a similar model of AD prediction to a healthy aging model. Deviations from normal aging may be valuable in several different domains. The importance of this work comes from the large (n>30,000) MRI freely available from which to draw from and develop a balanced dataset.





Figures 4 and 5: (L top) Culled dataset of 10,158 MRIs from 14 unrelated MRI data sources further balanced (L bottom) to create a training model of 2,852 MRI scans on which to train aging. (R) Mean absolute error of our model in an independent (hold-out) testing set.

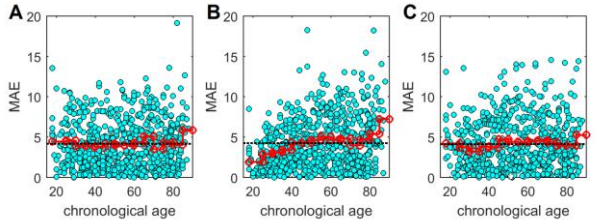


Figure 6: (L) Error estimation on a balanced dataset (M) Error on an unbalanced dataset (R) Error with sample re-weighting

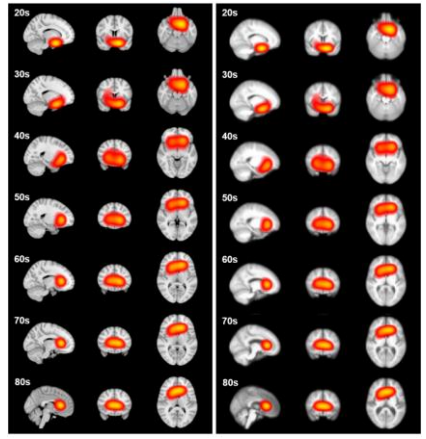


Figure 7: (R) Class activation maps (CAM) show an inferior to superior drift in which group of voxels are most predictive in the contribution of age estimation. CAM interpretation may be a useful aid in interpreting results from these models in the future. While this reflects a more diverse population of subjects, deviations from these patterns on an individual basis may be useful in assessing volumetric differences when prediction is poorly estimated.

Feng et al. arXiv:1907.00943

Disclosures: Imij Technologies

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