

Extending the Reach of a Brain Age Model: Preserving Knowledge Across the Lifespan and Scanners

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OBJECTIVE

- ❑ Fine-tuning a UKBB-trained brain age model to expand age span and scanner compatibility, mitigating base-data bias and catastrophic forgetting.

BACKGROUND

- ❑ **Data Constraints:** Access to large-scale, high-quality medical imaging datasets remains heavily restricted by high costs and privacy concerns.
- ❑ **The UKBB Trade-off:** While the UK Biobank (UKBB) provides the scale needed for robust brain age modeling, it suffers from a narrow age range and uniform scanner protocols.
- ❑ **The Fine-Tuning Risk:** Adapting UKBB-trained models to smaller, external cohorts can easily amplify or inherit original base-model biases.
- ❑ **The Need for Mitigation:** Overcoming these limitations requires targeted regularization and data-balancing strategies to ensure generalizability without catastrophic forgetting.

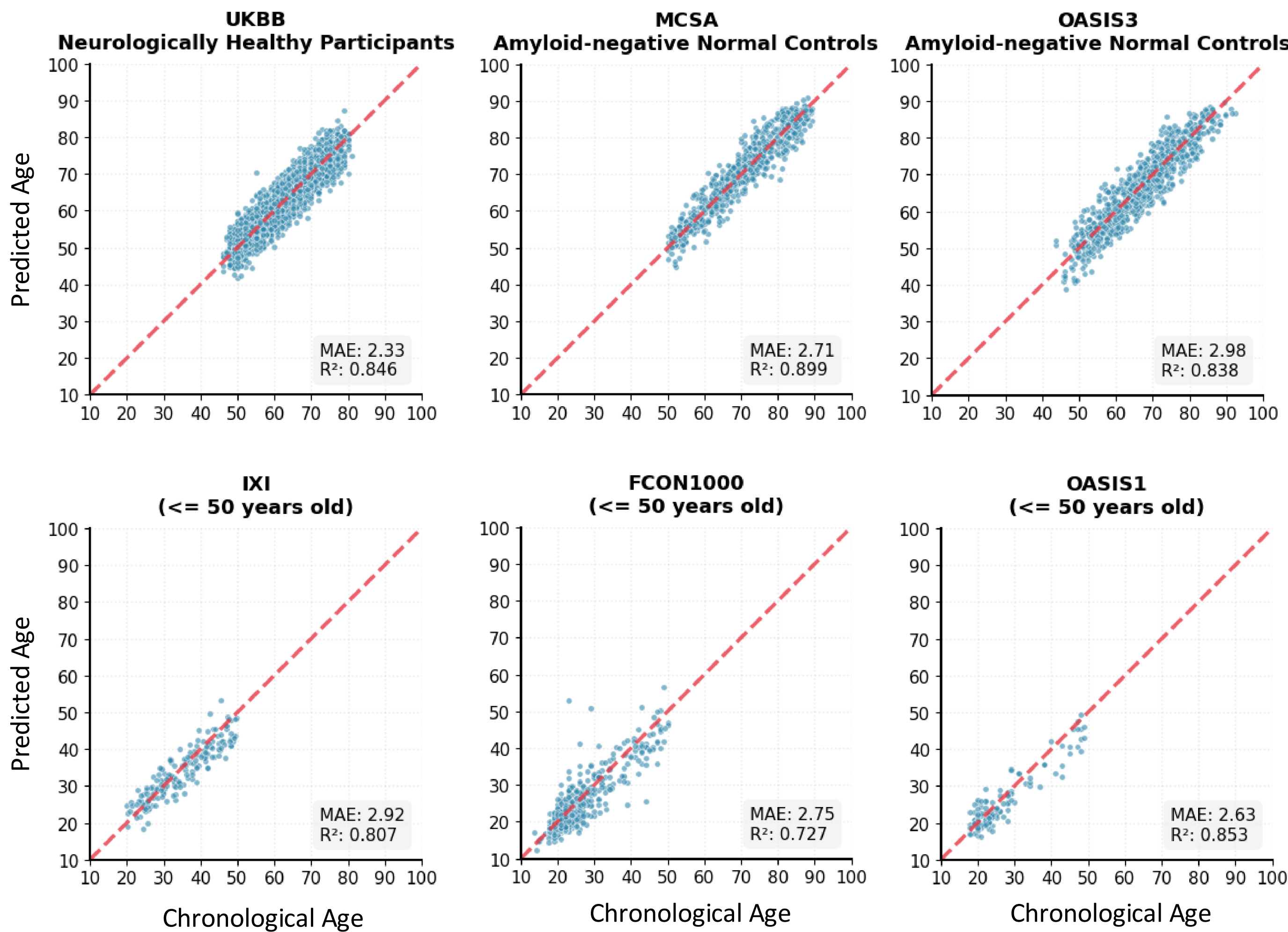
DATA

Demographic info of various datasets utilized in this study.

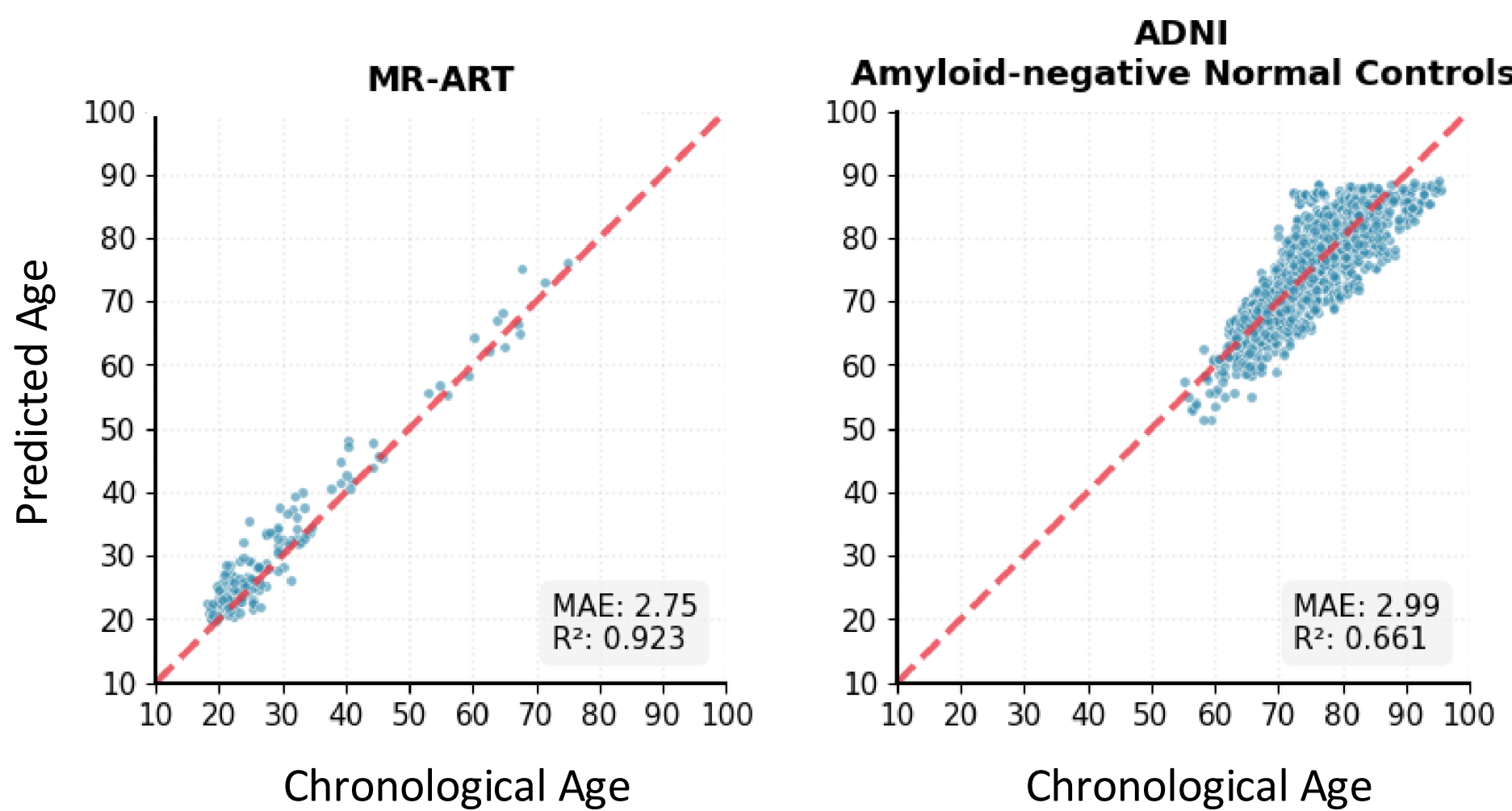
Cohort	Size	Age range
UKBB	26,512	44 – 82 y
MCSA	1,297	49 – 89 y
OASIS-3	2,035	43 – 92 y
FCON1000	991	13.41 – 50.0 y
IXI	290	19.98 – 49.92 y
OASIS-1	203	18 – 49 y

RESULTS

VALIDATION

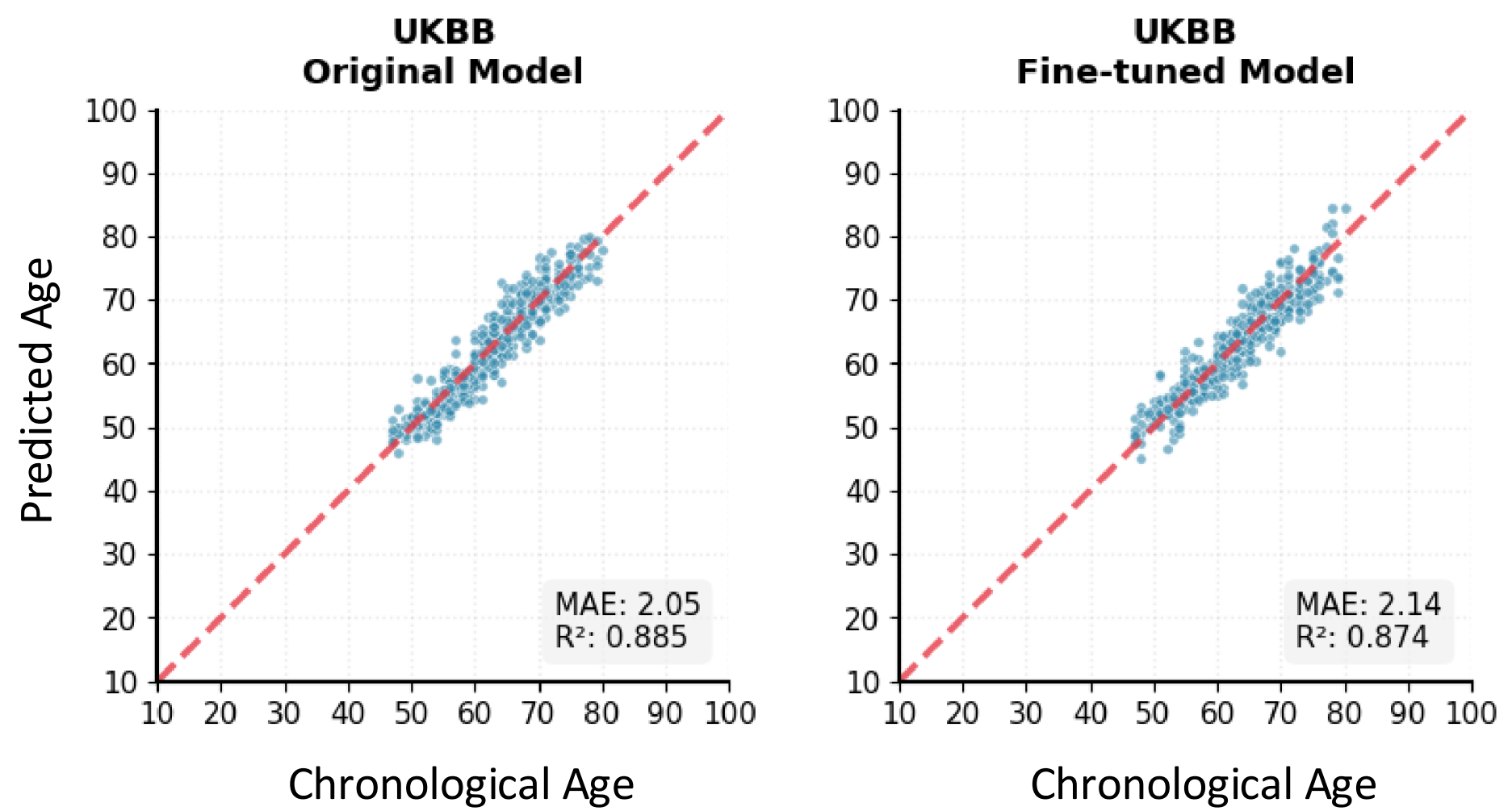


EXTERNAL TEST



Similar
to validation
results!

KNOWLEDGE PERSERVATION



< 5%
performance
degradation

METHODS

TRAINING

- ❑ We trained¹ an ensemble of three separate regularized deep models on neurologically healthy UKBB participants (n=26,512, aged 44-82).

FINE-TUNING

- ❑ Replaced linear head with a two-layer MLP (64 hidden neurons).
- ❑ Fine-tuned on healthy, amyloid-negative cohorts (MCSA, OASIS1/3, FCON1000, IXI) with expanded age ranges.
- ❑ Mitigated dataset and age imbalances using oversampling and Label Distribution Smoothing (LDS)².
- ❑ Applied Elastic Weight Consolidation (EWC)³ to prevent catastrophic forgetting.

EVALUATION

- ❑ Tested on independent unseen cohorts: ADNI (elderly) and MR-ART (young).
- ❑ Tested on a held-out UKBB set to measure knowledge retention.

REFERENCES

- 1) Rajabli, R., et al. (2025). Brain age prediction: Deep models need a hand to generalize. Human Brain Mapping, 46(11), e70254. <https://doi.org/10.1002/hbm.70254>
- 2) Yang, Y., Zha, K., Chen, Y.-C., Wang, H., & Katabi, D. (2021). Delving into Deep Imbalanced Regression. Proceedings of the 38th International Conference on Machine Learning, 11842–11851. <https://doi.org/10.48550/arxiv.2102.09554>
- 3) Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A. A., et al. (2017). Overcoming catastrophic forgetting in neural networks. Proceedings of the National Academy of Sciences, 114(13), 3521–3526. <https://doi.org/10.1073/pnas.1611835114>