Deep Learning Models for Brain Age Estimation

Lara Dular, Žiga Špiclin
University of Ljubljana, Faculty of Electrical Engineering, Laboratory of Imaging Technologies

Univerza *v Ljubljani*

BACKGROUND

Brain Age, t. i. estimation of chronological age from T1-weighted brain MR images using machine learning algorithms, shows great potential as a **biomarker of healthy brain aging**.

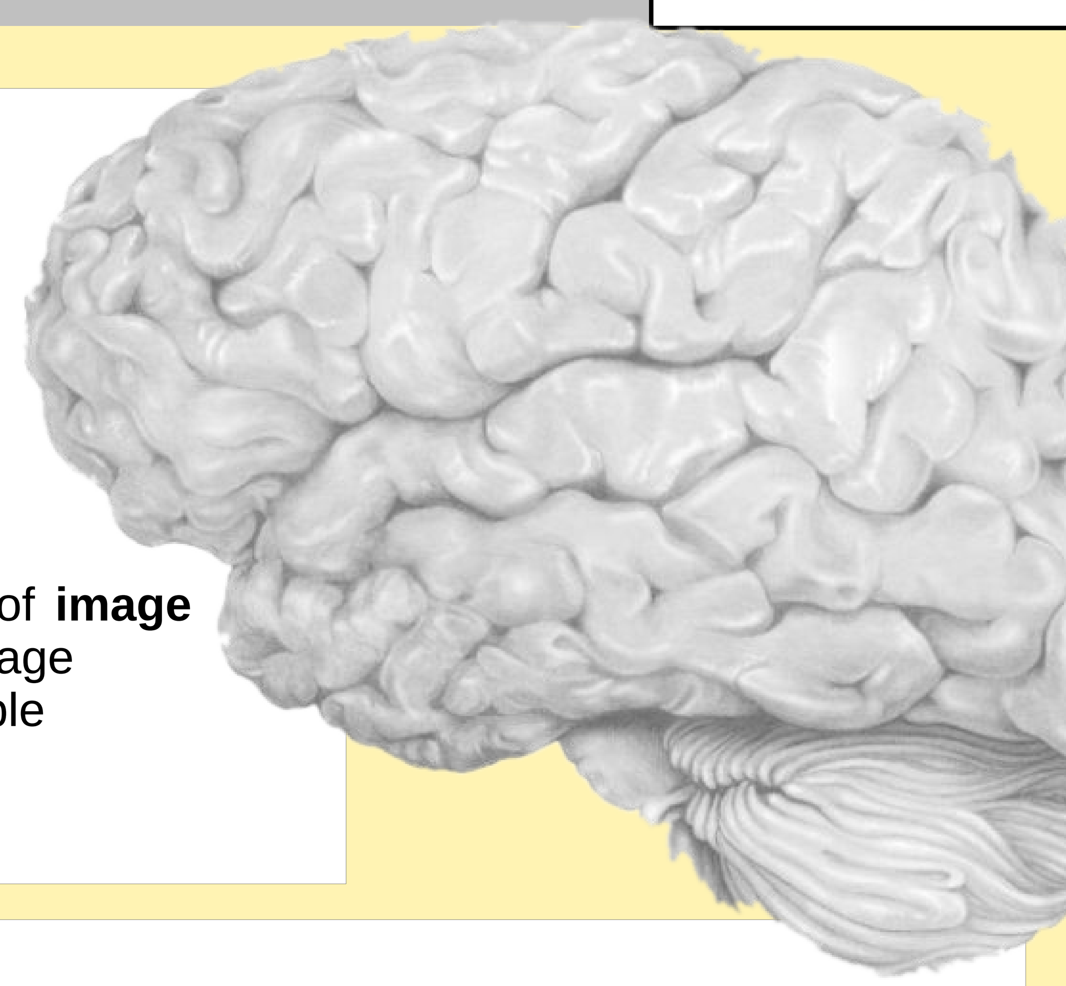
Large brain age gap may indicate accelerated brain aging. Significant differences were observed between healthy controls and neurologically impaired subjects, e.g. **Alzheimer's dementia.**

Earlier brain age estimation studies were based on traditional ML methods, however currently best predictions are known using Deep Learning methods, specifically **Convolutional Neural Networks (CNN).**

AIM

The aim of this study is to introduce and **comparatively evaluate deep learning algorithms** for brain age prediction on healthy subjects.

We rigorously and objectively test the impact of **image preprocessing** and **image representation** on age prediction accuracy on common publicly available datasets.



DATA & IMAGE PREPROCESSING

Datasets:
IXI, CamCAN, CC-359, FCON 1000, OASIS-2, ADNI 1, ABIDE I

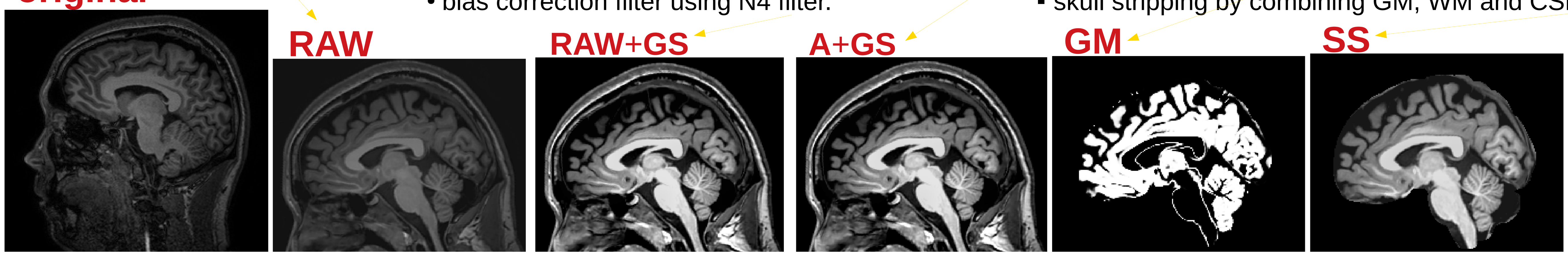
Description:
Healthy subjects 18-96 years
N = 2543:
2040 train, 250 test, 253 validation

Initial preprocessing:
- conversion to NifTI image format,
- rotation to RPI+ space,
- noise reduction using adaptive non-local means 3D filter.

Minimal preprocessing:
- rigid registration to MNI152 atlas,
- sinc resampling to 193×292×193 and 1 mm^3 spacing.

Rigid registration with gray-scale corrections:
- bias correction filter using N4 filter (for registration matrix calculation only),
- rigid registration to MNI152 atlas,
- sinc resampling to193×292×193 and 1 mm^3 spacing,
- bias correction filter using N4 filter.

Affine registration with gray-scale corrections:
- bias correction filter using N4 filter (for registration)
- affine registration to MNI152 atlas,
- sinc resampling to193×292×193 and 1 mm^3 spacing,
- bias correction filter using N4 filter,
- segmentation into GM, WM and CSF maps,
- skull stripping by combining GM, WM and CSF.

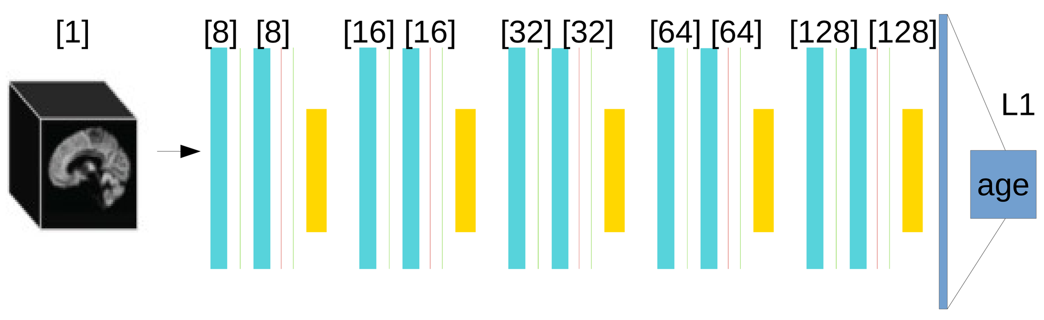


CNN MODELS

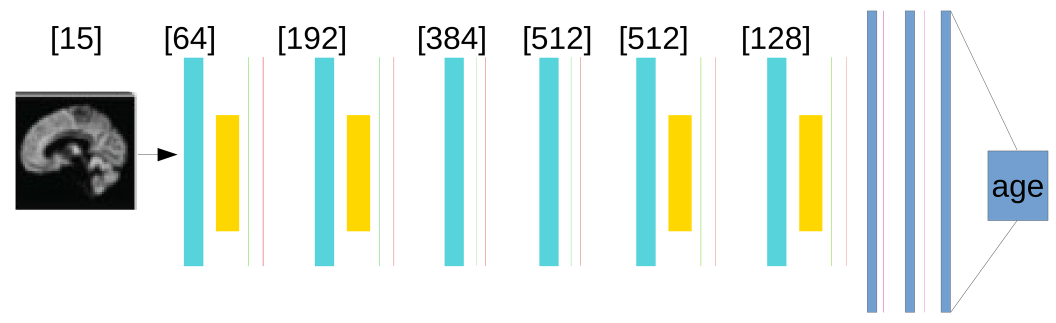
We **reimplement three CNN** for brain age prediction.

Each model architecture uses **different MRI representation** on input:

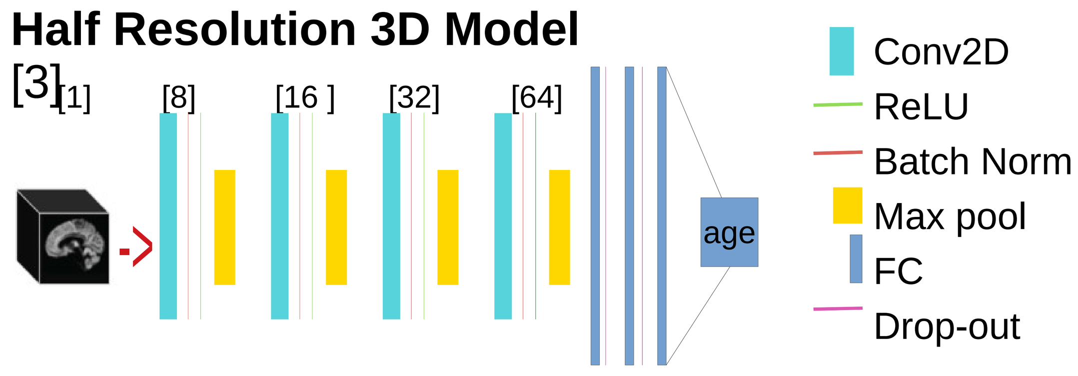
Full Resolution 3D Model [1]



Full Resolution 2D Model [2]



Half Resolution 3D Model [3]



CONCLUSIONS

Chosen experiment setting strongly affects the model's ability to accurately predict brain age.

The best image preprocessing approach was the same for all three tested architectures, namely using **A+GS**.

Comparable results can be achieved on both full resolution 3D images, as well as half resolution 3D images. 3Dmodels outperform 2D model.

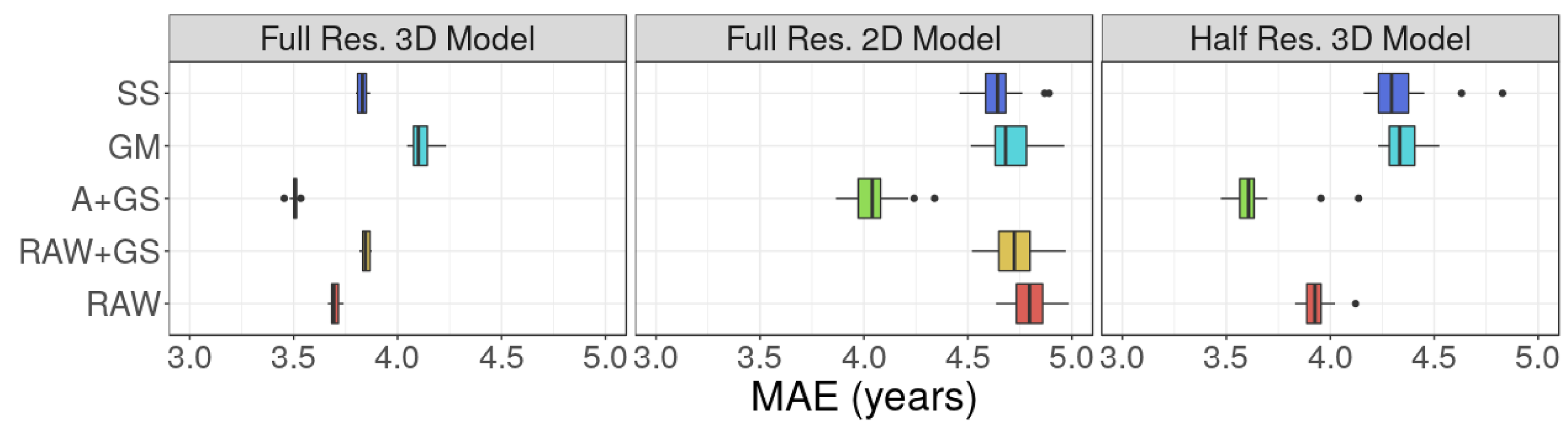
RESULTS

We re-implemented the **three CNN models**, which were trained and tested on the same datasets, preprocessed with **five preprocessing pipelines**. Extensive hyperparameter values were tested to achieve best results measured by **mean absolute error (MAE)** for y_i true age and y_i' age estimation

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i'|$$

All three models achieved the lowest MAE when trained on **affine aligned images with gray-scale corrections A+GS**.

Full resolution 3D model [1] resulted in least variable results across all preprocessing procedures.



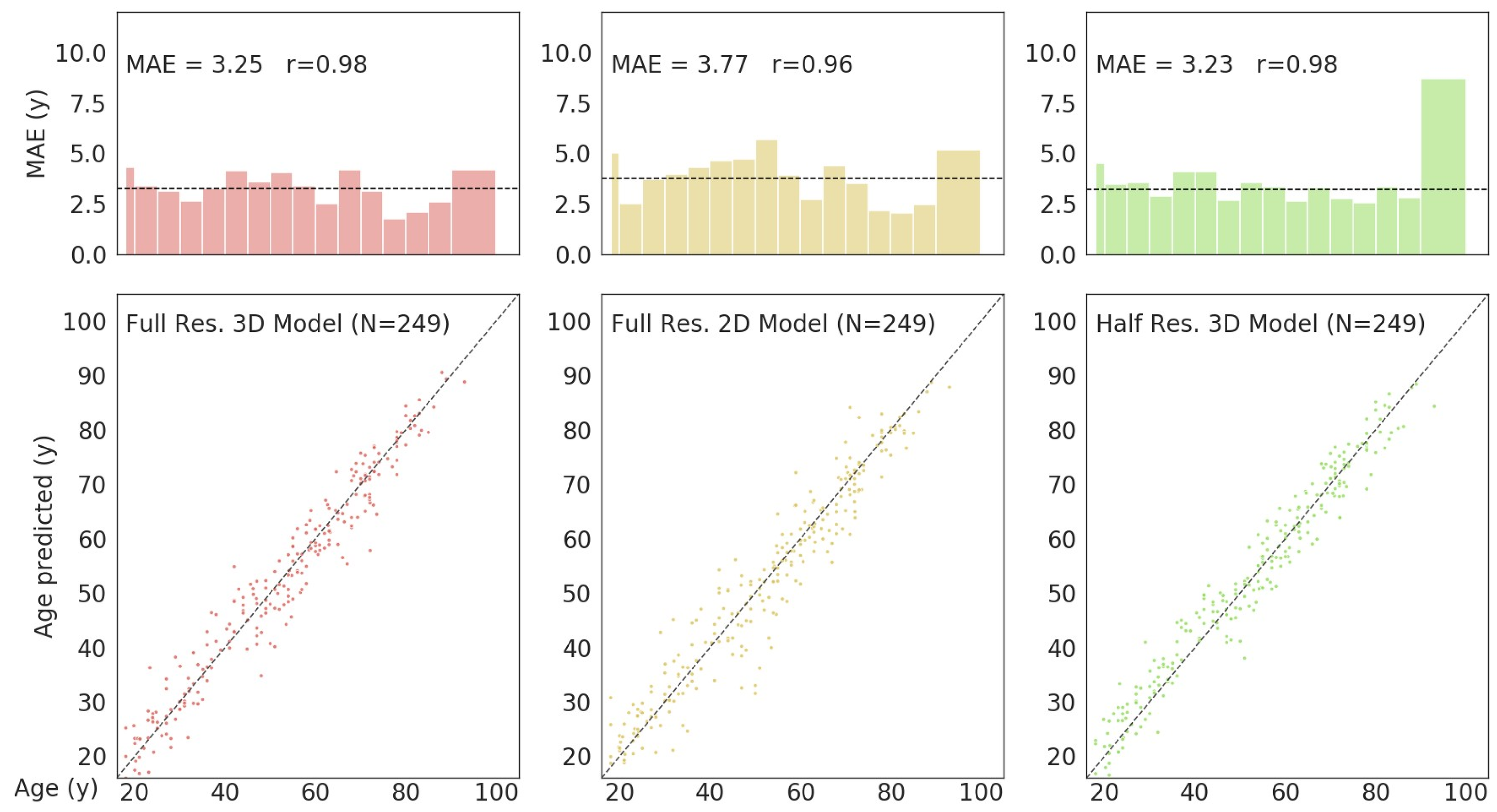
		Age	N	Preprocessing	MAE (med [min, max])	MAE (bias corr.)
Full res. 3D	Our study	18-96	2540	A+GS	3.24 [3.19, 3.29]	3.25 [3.21, 3.30]
	Cole et al. [1]	18-90	2001	GM	4.16	
Full res. 2D	Our study	18-96	2540	A+GS	3.99 [3.77, 4.18]	3.93 [3.79, 4.02]
	Huang et al. [2]	20-80	1099	RAW	4.0	
Half res. 3D	Our study	18-96	2540	A+GS	3.42 [3.22, 3.96]	3.34 [3.19, 3.47]
	Ueda et al. [3]	20-80	1101	RAW	3.67	

Comparing MAE on test set of last 20 epochs, we achieved **better or comparable results** for all three models.

Bias correction was preformed by fitting linear regression on validation set, generally achieving lower median and smaller interval range.

For all of the three models we observed and **increase** in MAE for ages from 35 to about 60, possibly due class under-representation.

We generally observed **systematic overestimation** of age for younger individuals and **underestimation** older individuals, most apparent for **GM** and **SS** preprocessing, which can in part be removed with bias correction.



REFERENCES

[1] J. H. Cole et al., “Predicting brain age with deep learning from raw imaging data results in a reliable and heritable biomarker,” NeuroImage, vol. 163, pp. 115–124, Dec. 2017, doi: 10.1016/j.neuroimage.2017.07.059.

[2] T. Huang et al., “Age estimation from brain MRI images using deep learning,” in 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017), Apr. 2017, pp. 849–852, doi: 10.1109/ISBI.2017.7950650.

[3] M. Ueda et al., “An Age Estimation Method Using 3D-CNN From Brain MRI Images,” in 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), Apr. 2019, pp. 380–383, doi: 10.1109/ISBI.2019.8759392.