Combining Radiomics and Diffusion-MR to Unveil the Ageing Brain

Agnese Robustelli Test

UNIVERSITÀ DI PAVIA

INFN Istituto Nazionale di Fisica Nucleare

NIH National Institute on Aging

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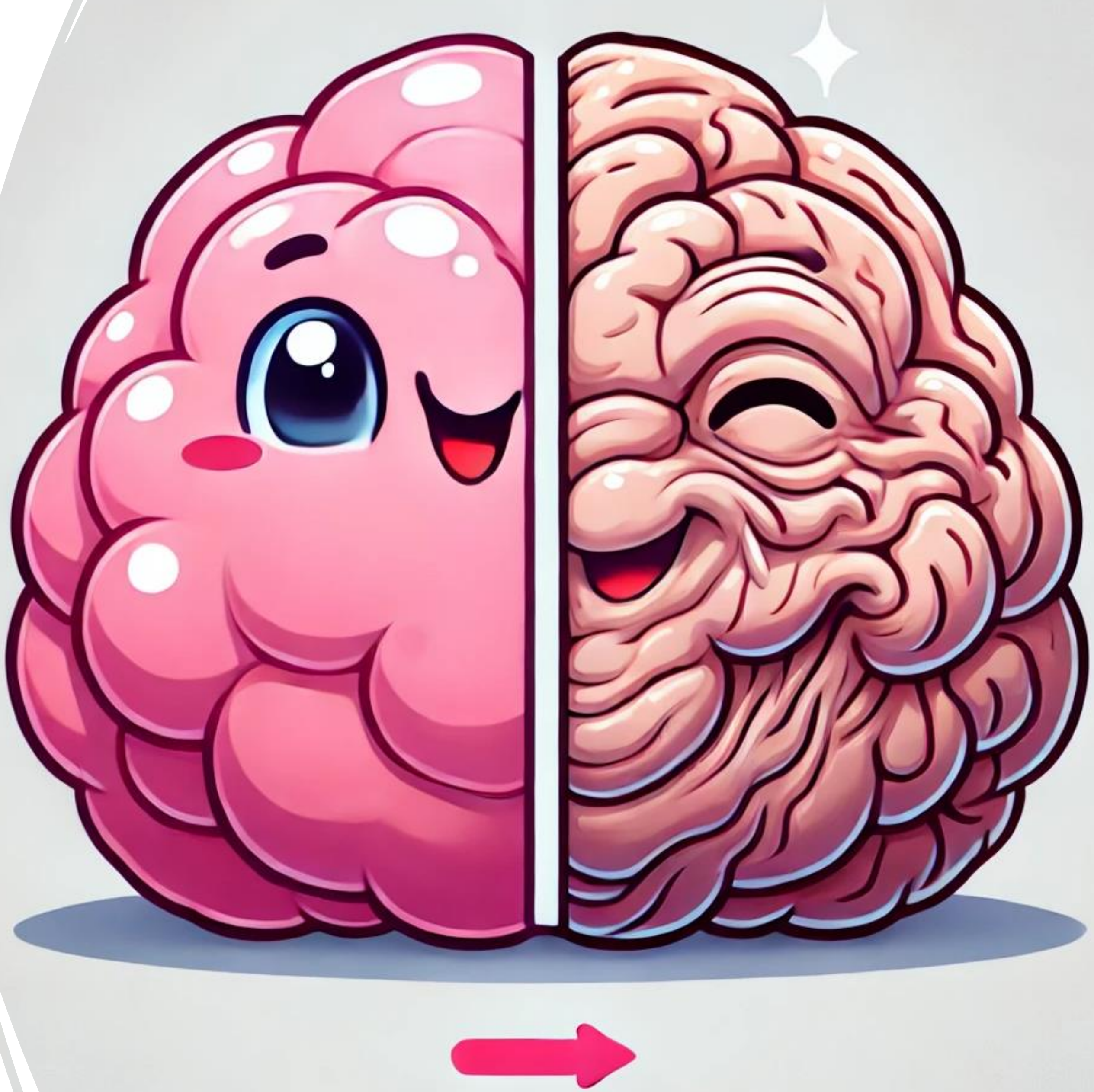
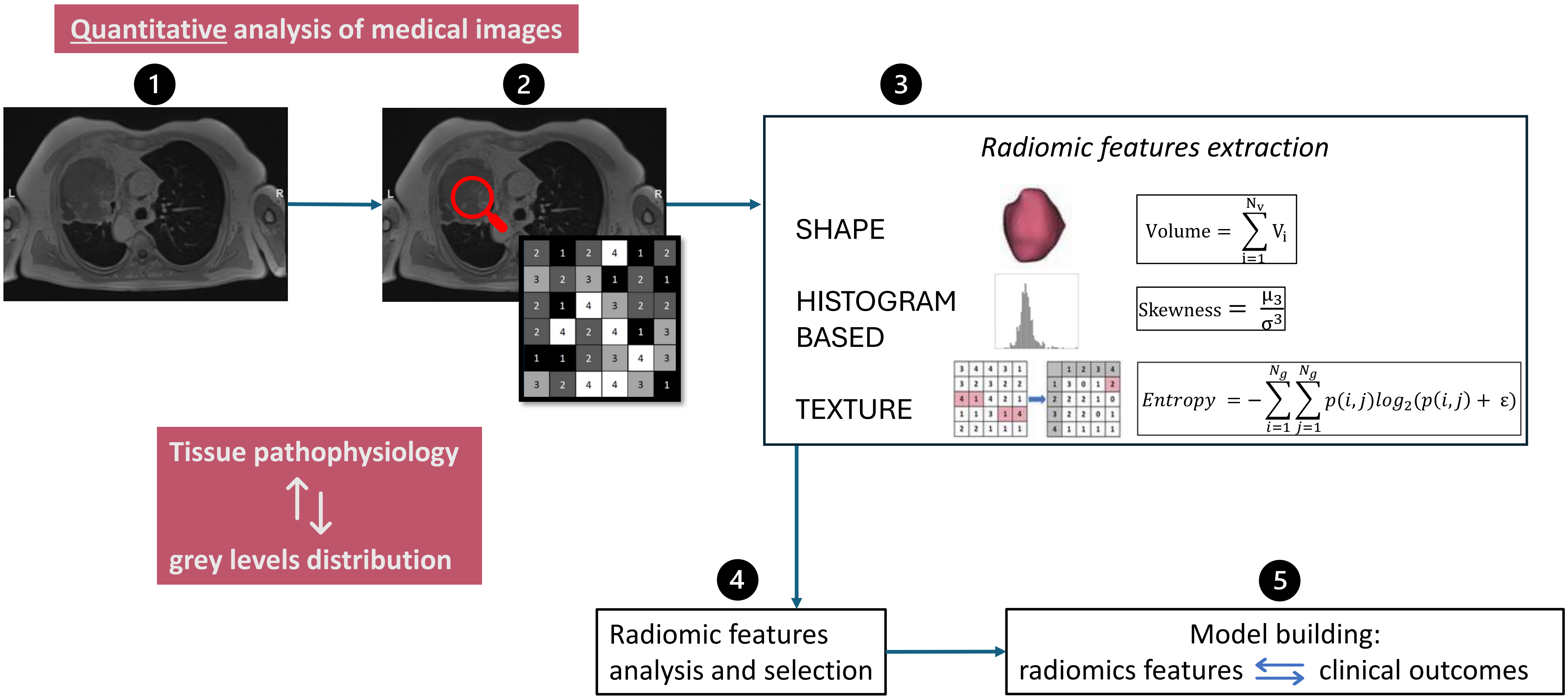


RADIOMICS



Quantitative analysis of medical images
1
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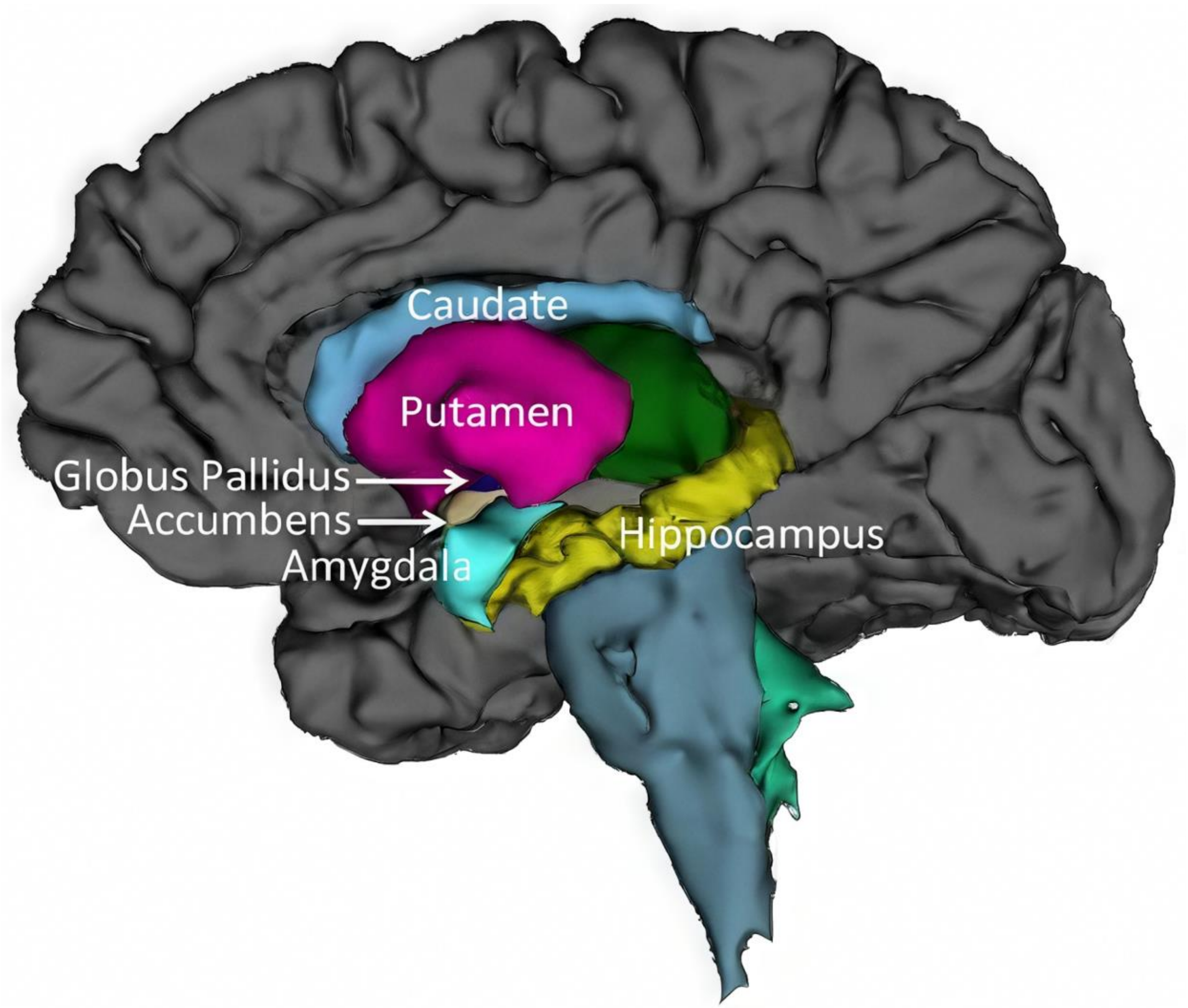
R
2 1 2 4 1 2
3 2 3 1 2 1
2 1 4 3 2 2
2 4 2 4 1 3
1 1 2 3 4 3
3 2 4 4 3 1
Radiomic features extraction
SHAPE
$\text{Volume} = \sum_{i=1}^{N_v} V_i$
HISTOGRAM BASED
$\text{Skewness} = \frac{\mu_3}{\sigma^3}$
TEXTURE
$Entropy = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\log_2(p(i,j) + \varepsilon)$
Tissue pathophysiology
grey levels distribution
4
Radiomic features analysis and selection
5
Model building:
radiomics features clinical outcomes

COHORT

30 healthy subjects
Age range: [23, 77] years

Accumbens
Amygdala
Caudate
Globus Pallidus
Hippocampus
Inferior Occipital Gyrus
Middle Occipital Gyrus
Post Central Gyrus
Precentral Gyrus
Putamen



ACQUISITIONS

Diffusion-weighted signal

Mean Isotropic Diffusivity (D_{iso})
Squared normalized Anisotropy (D_{Δ}^{2})

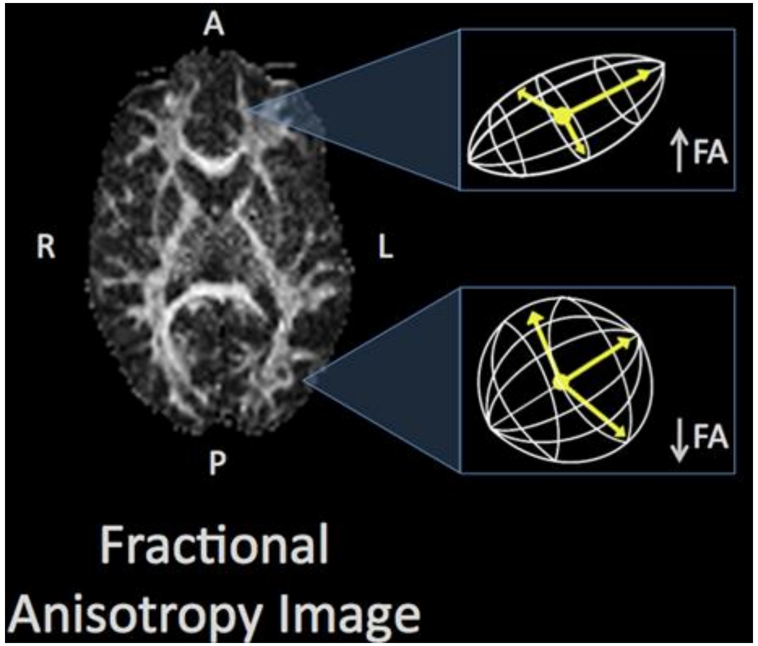
Relaxometry

Spin-Lattice Relaxation (m_{R1})
Spin-Spin Relaxation (m_{R2})

ACQUISITIONS

Diffusion-weighted signal

Mean Isotropic Diffusivity (D_{iso})
Squared normalized Anisotropy (D_{Δ}^{2})



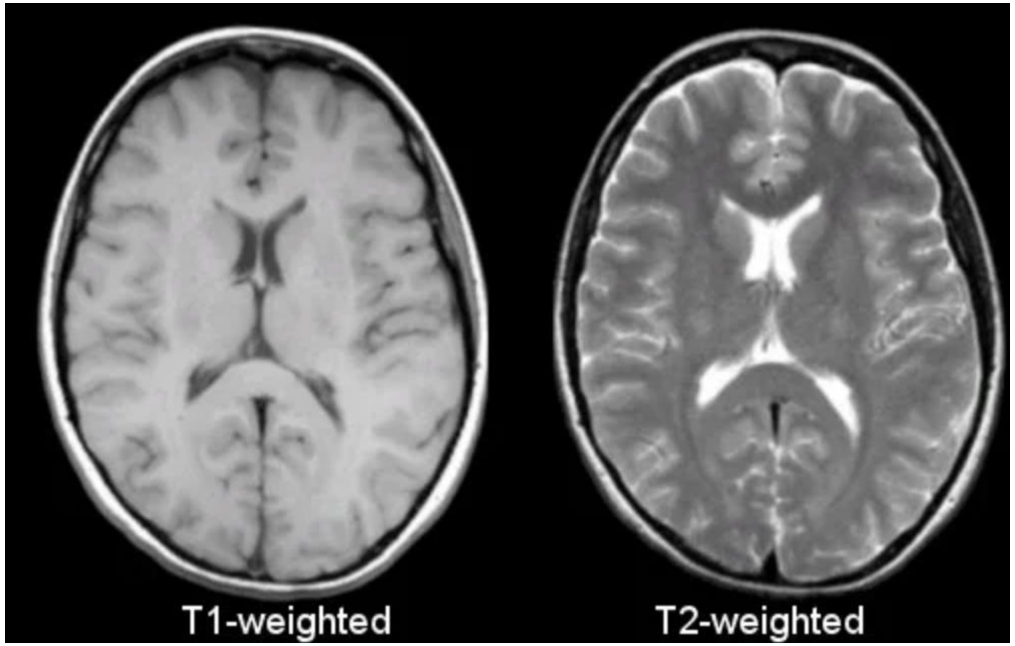
$$D_{\mathrm{iso}}(\omega) = \frac{\boxed{D_{\parallel}}(\omega) + 2\boxed{D_{\perp}}(\omega)}{3}$$

Axial diffusivity
Radial diffusivity

$$D_{\Delta}^{2}(\omega) = \frac{\left(D_{\parallel}(\omega) - D_{\perp}(\omega)\right)^{2}}{\left(D_{\parallel}(\omega) + 2D_{\perp}(\omega)\right)^{2}}$$

Relaxometry

Spin-Lattice Relaxation (m_{R1})
Spin-Spin Relaxation (m_{R2})



ACQUISITIONS

Diffusion-weighted signal

Mean Isotropic Diffusivity (D_{iso})
Squared normalized Anisotropy (D_{Δ}^2)

Relaxometry

Spin-Lattice Relaxation (m_{R1})
Spin-Spin Relaxation (m_{R2})

+

Bin1 range:
D_{iso} < 2.5 $\mathrm{\mu m}^2$/ms, D_{Δ}^2 > 0.25

Bin2 range:
D_{iso} < 2.5 $\mathrm{\mu m}^2$/ms, D_{Δ}^2 < 0.25

Bin3 range:
D_{iso} > 2.5 $\mathrm{\mu m}^2$/ms, D_{Δ}^2 full range

ACQUISITIONS

Diffusion-weighted signal

Mean Isotropic Diffusivity (D_{iso})
Squared normalized Anisotropy (D_{Δ}^2)

Relaxometry

Spin-Lattice Relaxation (m_{R1})
Spin-Spin Relaxation (m_{R2})

+

Bin1 range:
$D_{iso} < 2.5\ \mu m^2/ms$, $D_{\Delta}^2 > 0.25$

White Matter

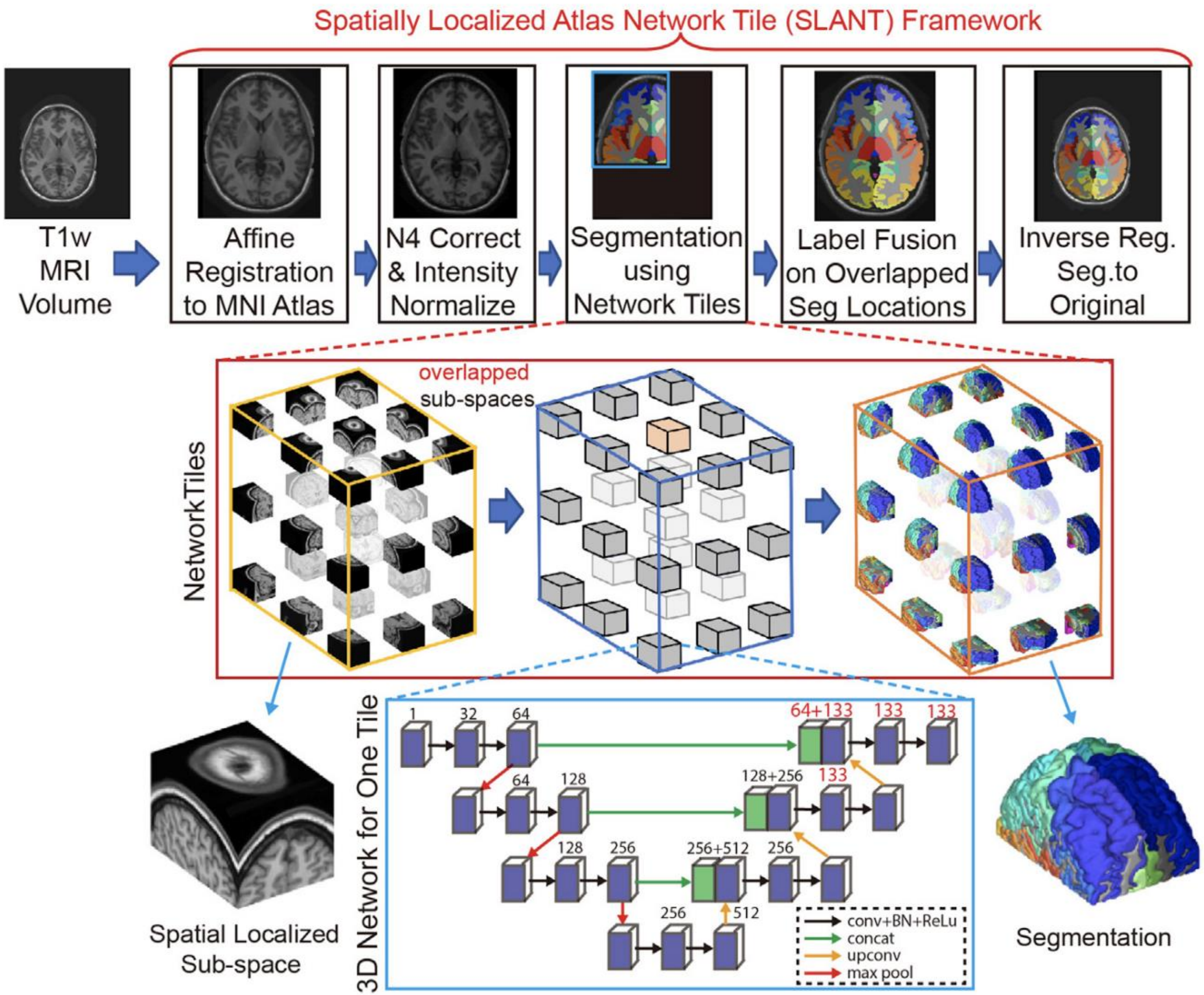
Bin2 range:
$D_{iso} < 2.5\ \mu m^2/ms$, $D_{\Delta}^2 < 0.25$

Gray Matter

Bin3 range:
$D_{iso} > 2.5\ \mu m^2/ms$, D_{Δ}^2 full range

Cerebrospinal Fluid

SEGMENTATION



TO SUM UP

Diffusion-weighted signal

Relaxometry

13 MRI acquisitions, 10 brain regions, 30 healthy subjects

ANALYSIS

Images pre-processing:
Z-score method

$$Z = \frac{X - \mu}{\sigma}$$

Radiomic features:
- 104 IBSI-compliant features
- PyRadiomics 3.0.1

Feature selection:
Spearman correlation coefficient,
p-value $\leq 0{,}05$
(Benjamini-Hochberg correction)

$$\rho = 1 - \frac{6\sum \boxed{d_i^2}}{\boxed{n}(n^2 - 1)}$$

d_i: difference between the two ranks of each observation
n: number of observations

RESULTS

Metrics with more features age-related:

1. Caudate (m_{R2bin2}: 77 , D^2_{Δ}: 69)
2. Putamen (m_{R2bin2}: 68 , D^2_{Δ}: 61)
3. Accumbens (m_{R2bin1}: 56)

Age related volume shrinkage in Caudate and Putamen

Structural and functional changes affect the Accumbens

m_{R2bin2}- Caudate axial view

23 years

77 years

25 years

73 years

RESULTS

Region less affected by age:
Amygdala, 11/13 MRI-metrics with 0 features age-informative

Healthy ageing does not markedly impair Amygdala structural integrity

RESULTS

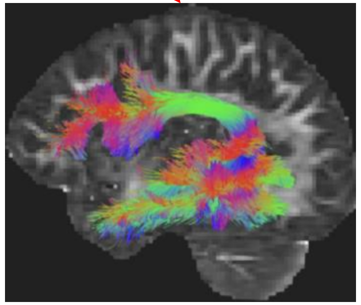
Region less affected by age:
Amygdala, 11/13 MRI-metrics with 0 features age-informative

Healthy ageing does not markedly impair Amygdala structural integrity

More informative MRI metrics:
m_{R2bin1}, m_{R2bin2}, D_{Δ}^{2}

White Matter

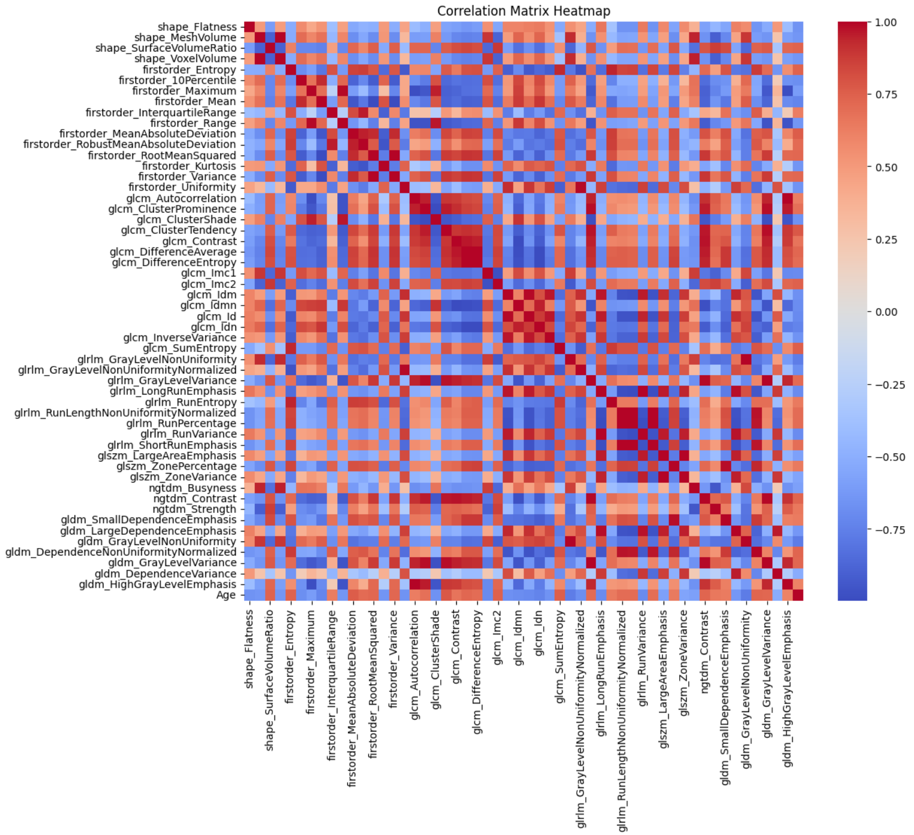
Gray Matter



Brain microstructure

NEXT STEPS

Radiomics-based Regression

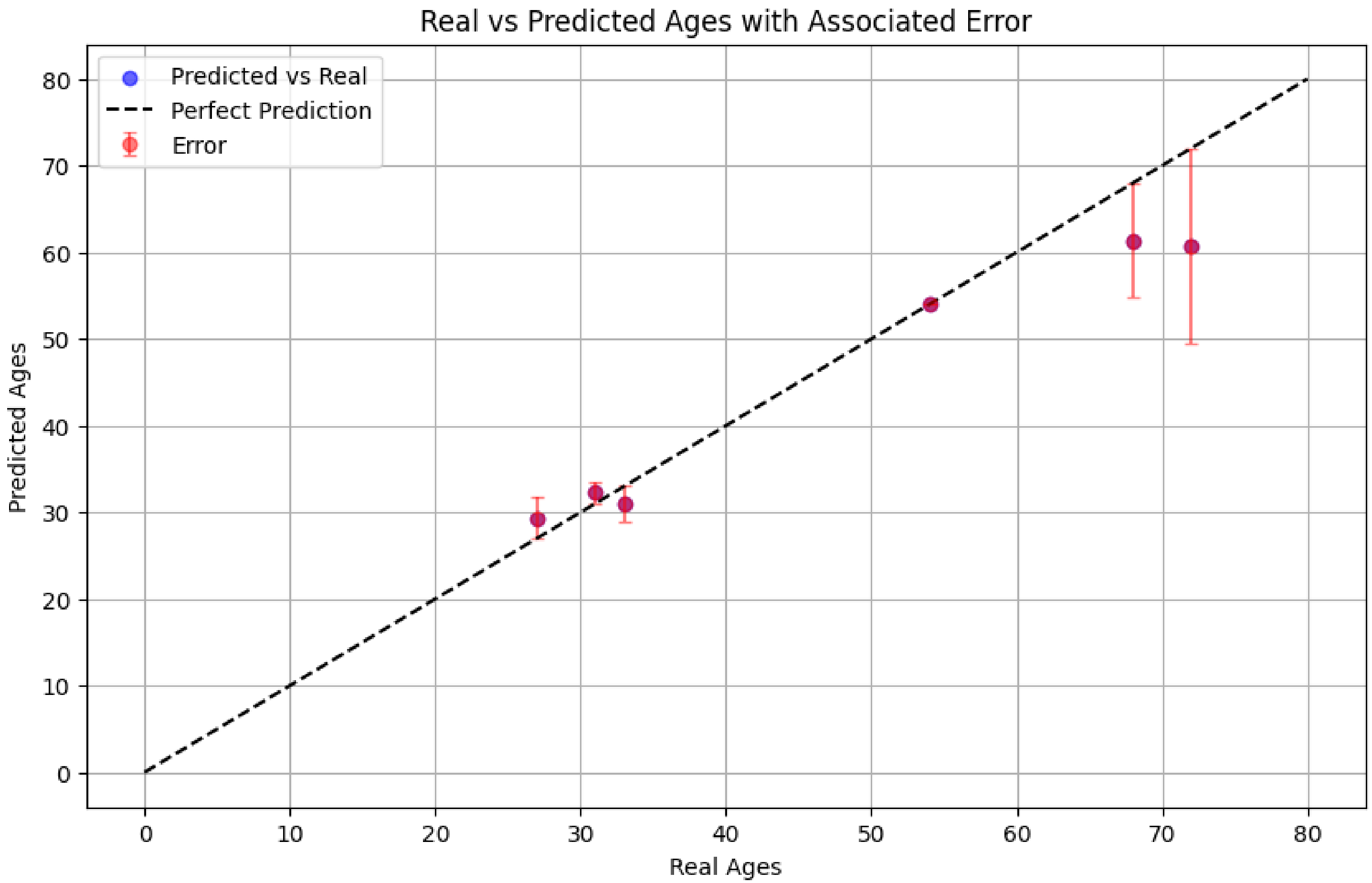


Drop related features

PCA

Preliminary results

(PCA + Random Forest Regressor)



NEXT STEPS

Radiomics-based Regression

Explainable machine learning radiomics model for Primary Progressive Aphasia classification

Benedetta Tafuri[1,2*], Roberto De Blasi[2], Salvatore Nigro[2†] and Giancarlo Logroscino[1,2†] on behalf of the Frontotemporal Lobar Degeneration Neuroimaging Initiative

SHAP
LIME

NN-based Regression

MULTI-BRANCH DEFORMABLE CONVOLUTIONAL NEURAL NETWORK WITH LABEL DISTRIBUTION LEARNING FOR FETAL BRAIN AGE PREDICTION

Lufan Liao[1,2], Xin Zhang[1,2], Fenqiang Zhao[2], Jingjiao Lou[2], Li Wang[2], Xiangmin Xu[1], He Zhang[3], Gang Li[2*]*

ELSEVIER
Medical Image Analysis
Volume 51, January 2019, Pages 89-100

3D regression neural network for the quantification of enlarged perivascular spaces in brain MRI

ELSEVIER
Contents lists available at ScienceDirect
NeuroImage
journal homepage: www.elsevier.com/locate/neuroimage

Learning patterns of the ageing brain in MRI using deep convolutional networks

Check for updates

Nicola K. Dinsdale[a,1,*], Emma Bluemke[b,1], Stephen M. Smith[a], Zobair Arya[a], Diego Vidaurre[a,c], Mark Jenkinson[a], Ana I.L. Namburete[b]

Grad-CAM

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Acknowledgments:

- *Prof. Alessandro Lascialfari, Prof. Manuel Mariani, Dr. Francesca Brero*
- *Prof. Daniel Topgaard, Dr. Dan Benjamini, Dr. Eppu Manninen, Dr. Shunxing Bao, Dr. Bennett A. Landman*

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