Medical/Bio Research Topics Ⅱ: Week 15 (10.12.2024)

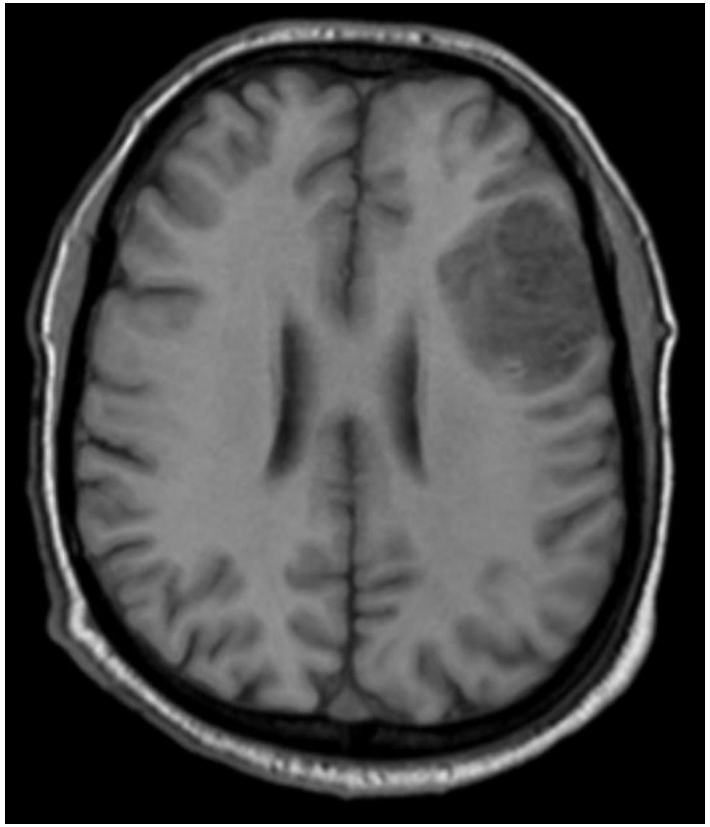
Comprehensive Assessment and Course Summary

종합 평가 및 과정 요약

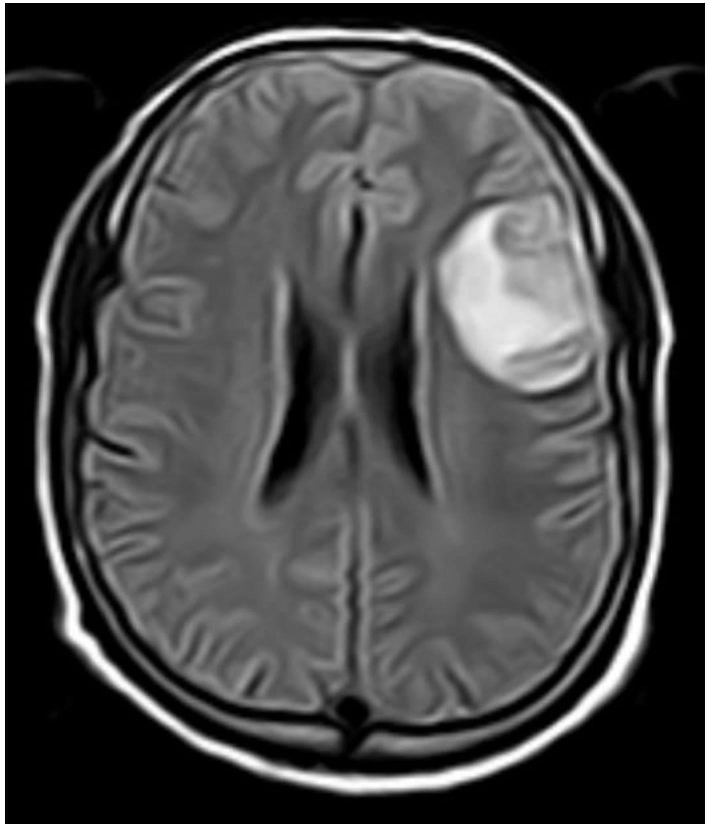
Practical Implementation of AI Models (1): Stroke Lesion Segmentation

- Stroke lesion
  - Area of damaged brain tissue caused by interrupted blood flow (stroke)
  - Types:
    - Ischemic lesions: caused by blocked blood vessels
    - Hemorrhagic lesions: caused by bleeding in the brain

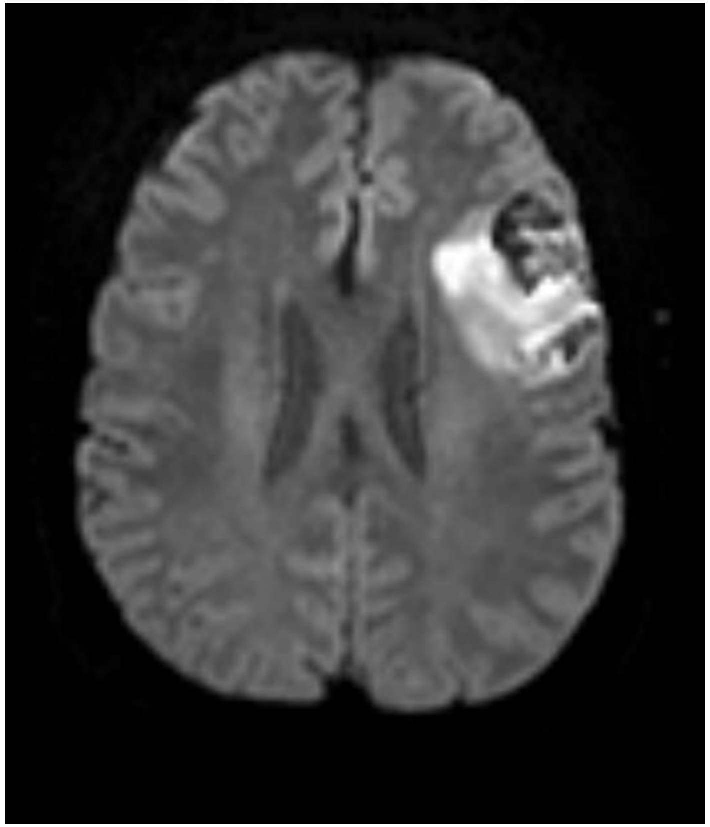
- Characteristics:
  - Appears as abnormal tissue on brain scans
  - Can vary in size and location
  - May be visible on CT or MRI
  - Can be acute (new) or chronic (old)
- Clinical significance:
  - Indicates the location and extent of stroke damage
  - Helps determine stroke severity
  - Used to predict potential recovery outcomes
  - Guides treatment decisions



T1-weighted



FLAIR



Diffusion-weighted

[https://www.mayoclinic.org/diseases-conditions/stroke/diagnosis-treatment/drc-20350119]

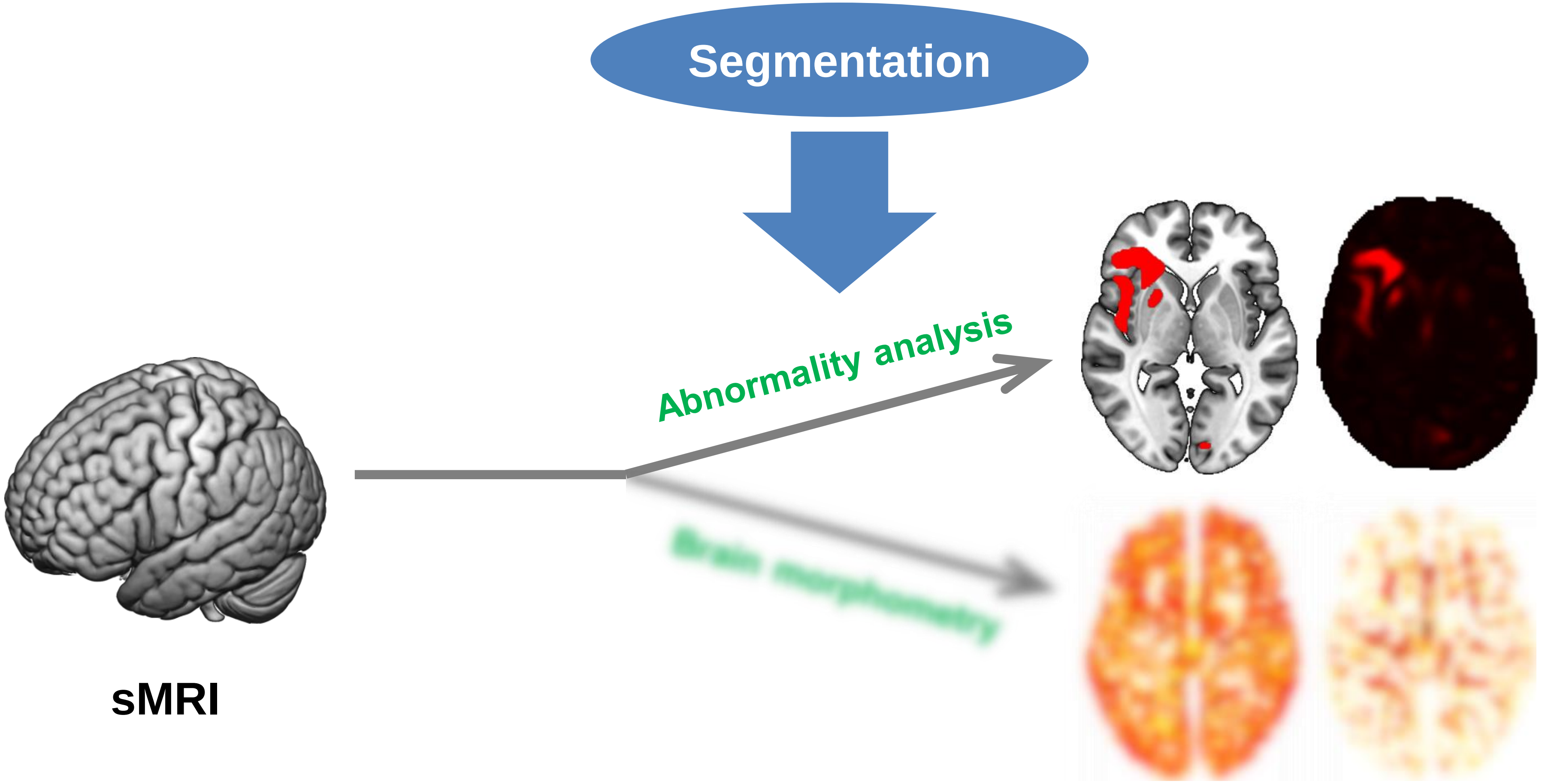
Stroke lesion displayed as altered signals in MRI

- Stroke lesion segmentation
  - Process of identifying and delineating (outlining) stroke lesions
  - Key purpose: separating stroke lesions from healthy brain tissue
  - Critical in stroke rehabilitation research
    - For the quantification of lesion burden
    - For accurate image processing
  - Still faces challenges and difficulties primarily due to variations of lesions in terms of shape, size, and location
  - Manual segmentation remains the gold standard, but it is time-consuming, subjective, and requires neuroanatomical expertise

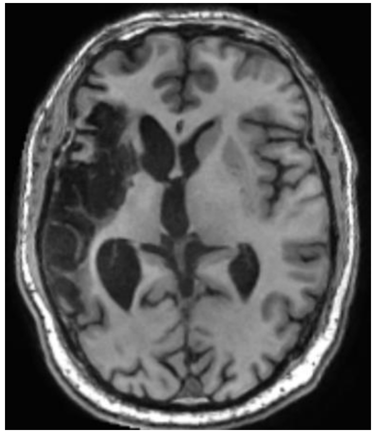
- Anatomical Tracings of Lesions After Stroke (ATLAS) v2.0

[https://fcon_1000.projects.nitrc.org/indi/retro/atlas.html]

  - Released in 2021 by expanding upon and replacing ATLAS v1.2 released in 2018
  - Includes T1-weighted structural MRI (sMRI) scans and manually segmented lesion masks (n = 1,271)
- Practice dataset
  - ATLAS v2.0 dataset for training (n = 655)
    - T1-weighted sMRI scans and lesion masks
    - Training set: n = 600
    - Test set: n = 55


Segmentation
Abnormality analysis
Brain morphometry
sMRI

T1-weighted MRI scan



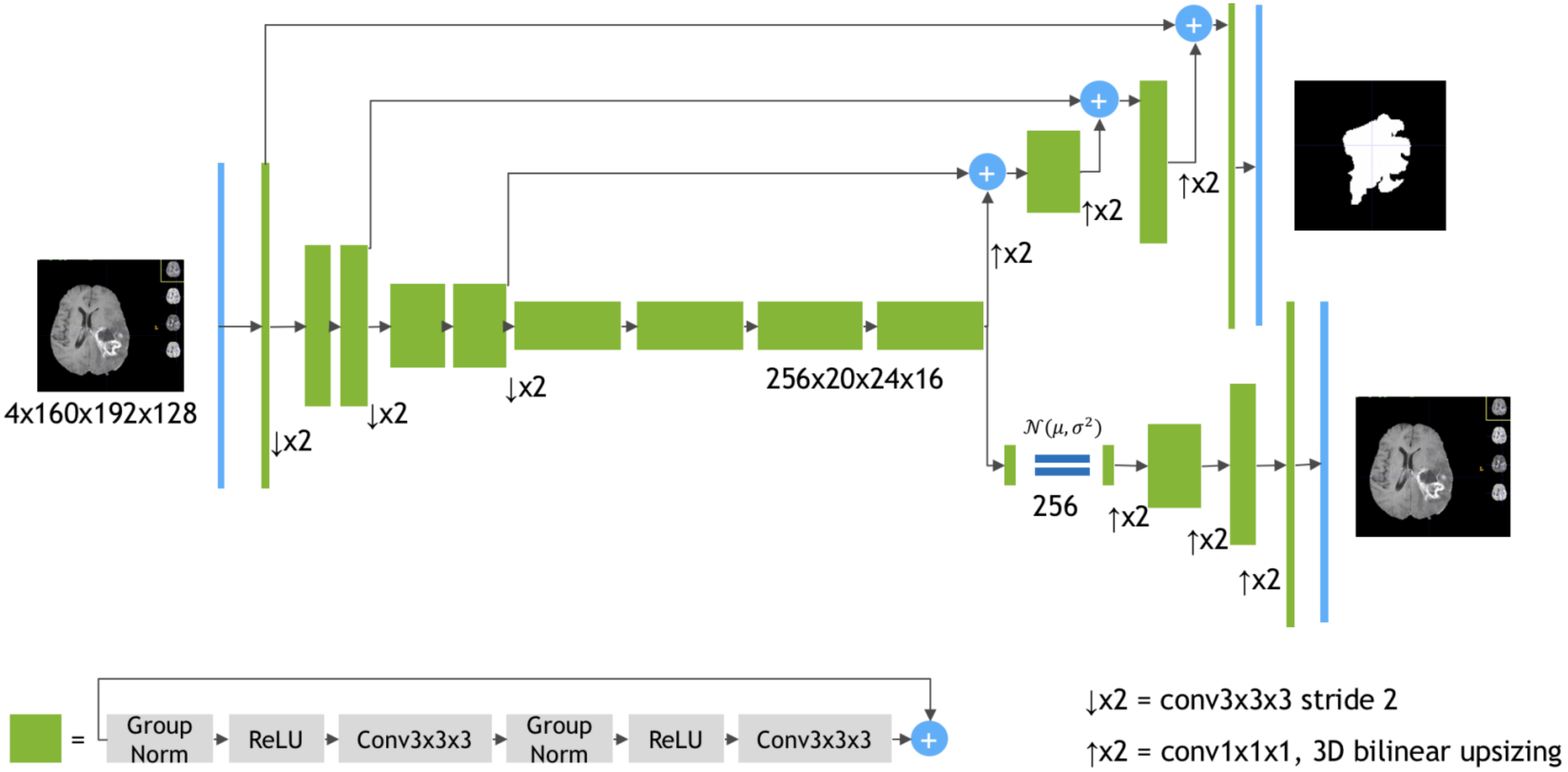
Lesion mask

1 mm:
Dimensions: 197 × 233 × 189
Voxel size: 1.0 mm × 1.0 mm × 1.0 mm

2 mm:
Dimensions: 98 × 116 × 94
Voxel size: 2.0 mm × 2.0 mm × 2.0 mm

T1-weighted sMRI scan and its associated lesion mask

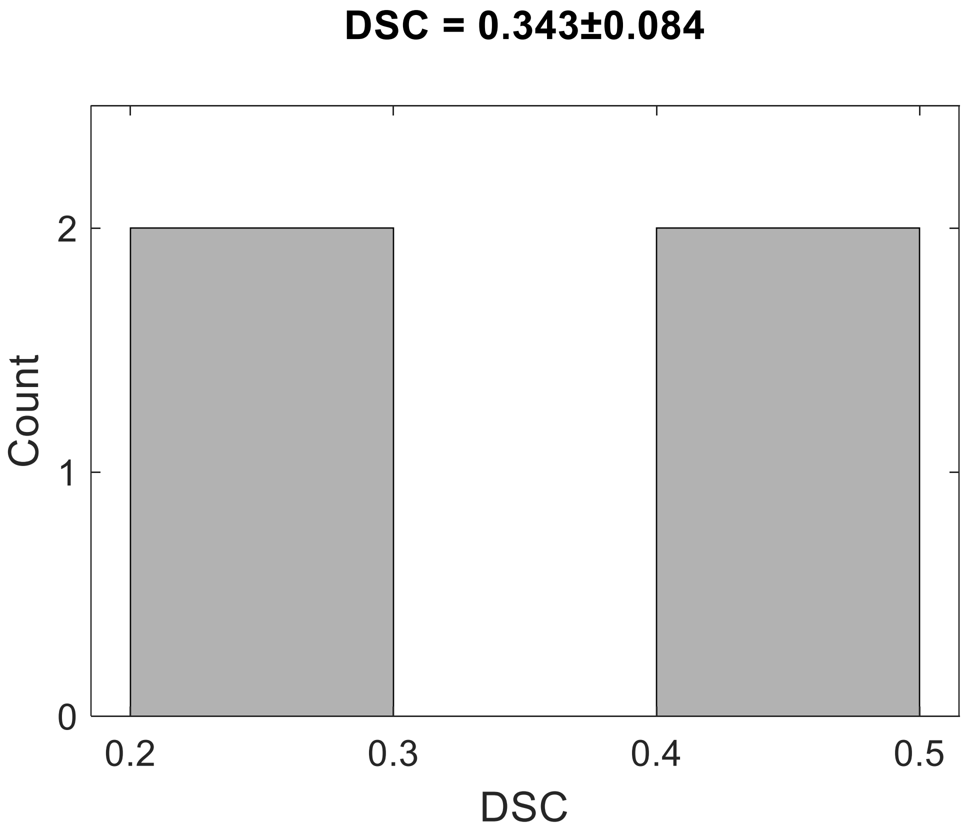
- Model architectures
  - CNN-based (2015-)
    - U-Net-style (encoder-decoder with skip connections): U-Net, U-Net++, Attention U-Net
    - ResNet-backbone: DeepLab series, PSPNet
  - Transformer-based (2020-)
    - SETR
    - SegFormer
    - SwinUNet

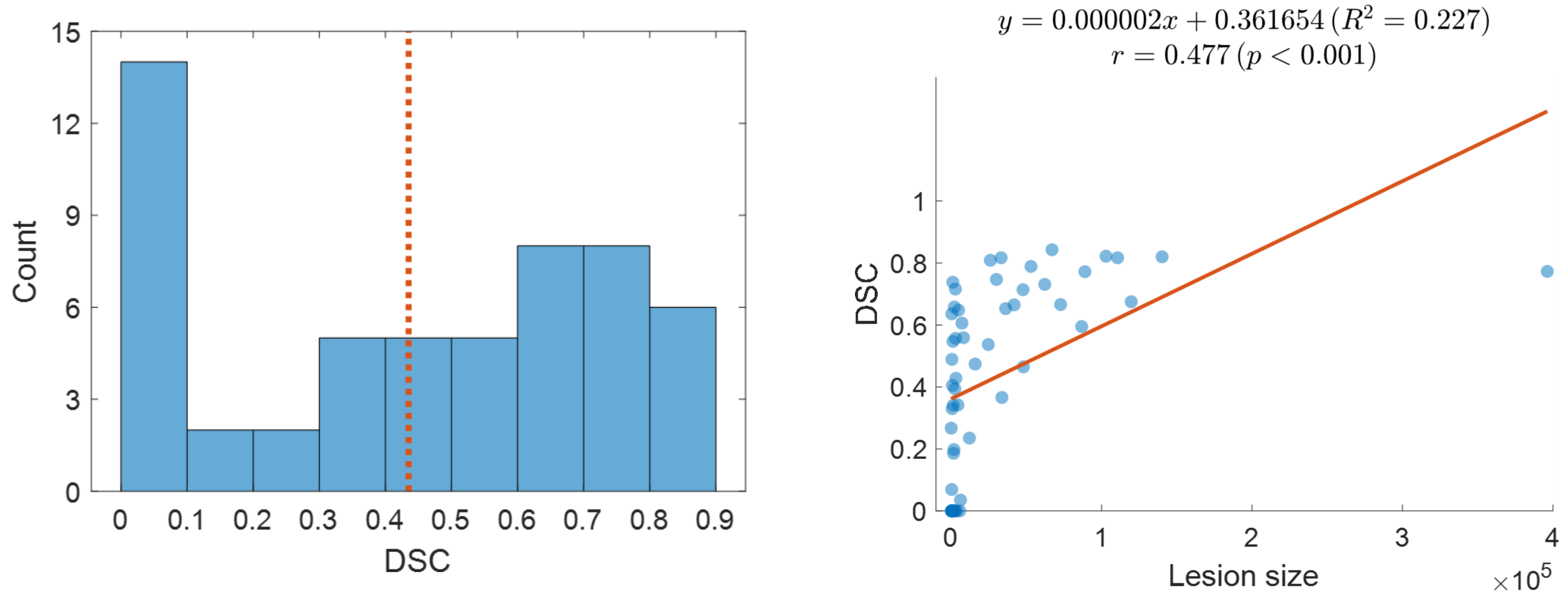


[Myronenko, 2018]

SegResNet architecture

- Performance on test set

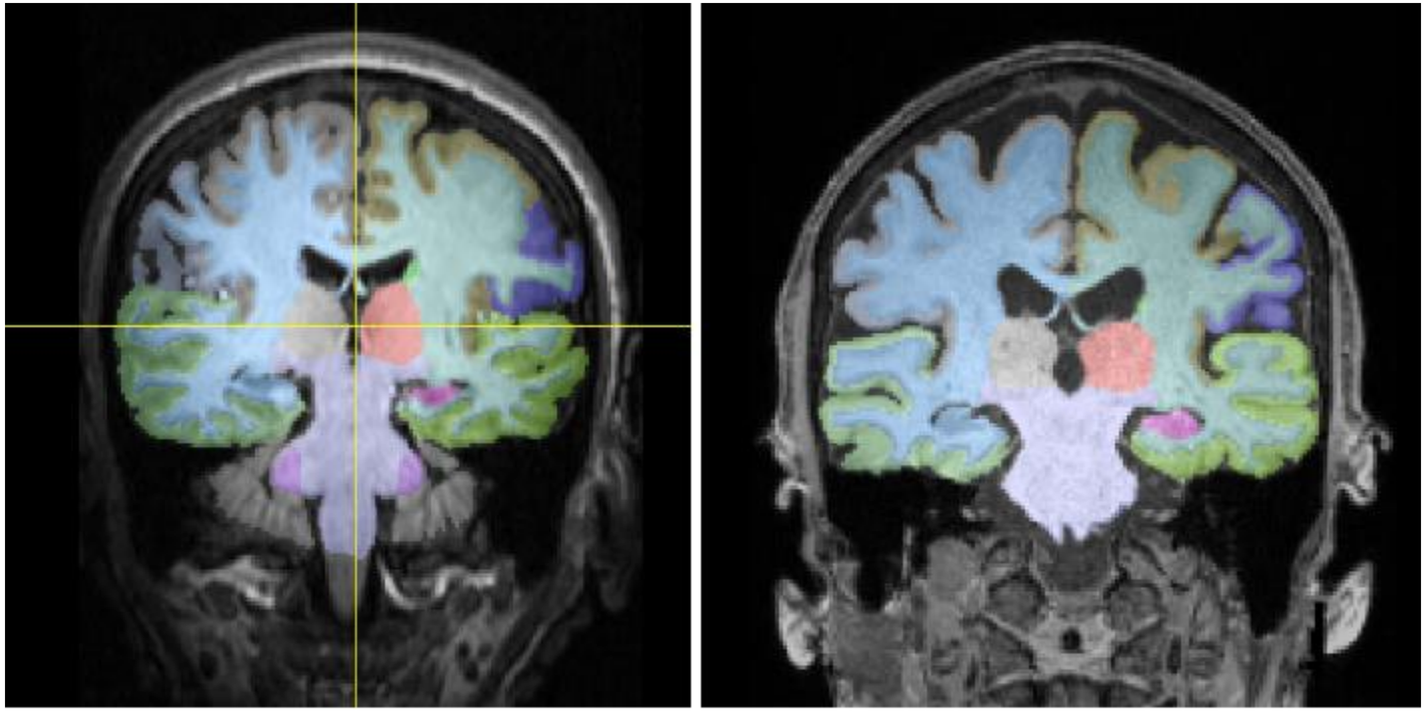




15
12
9
6
3
0
Count
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
DSC
$y = 0.000002x + 0.361654\,(R^2 = 0.227)$
$r = 0.477\,(p < 0.001)$
1
0.8
0.6
0.4
0.2
0
DSC
0
1
2
3
4
Lesion size
$\times 10^5$

Practical Implementation of AI Models (2): Brain Age Estimation

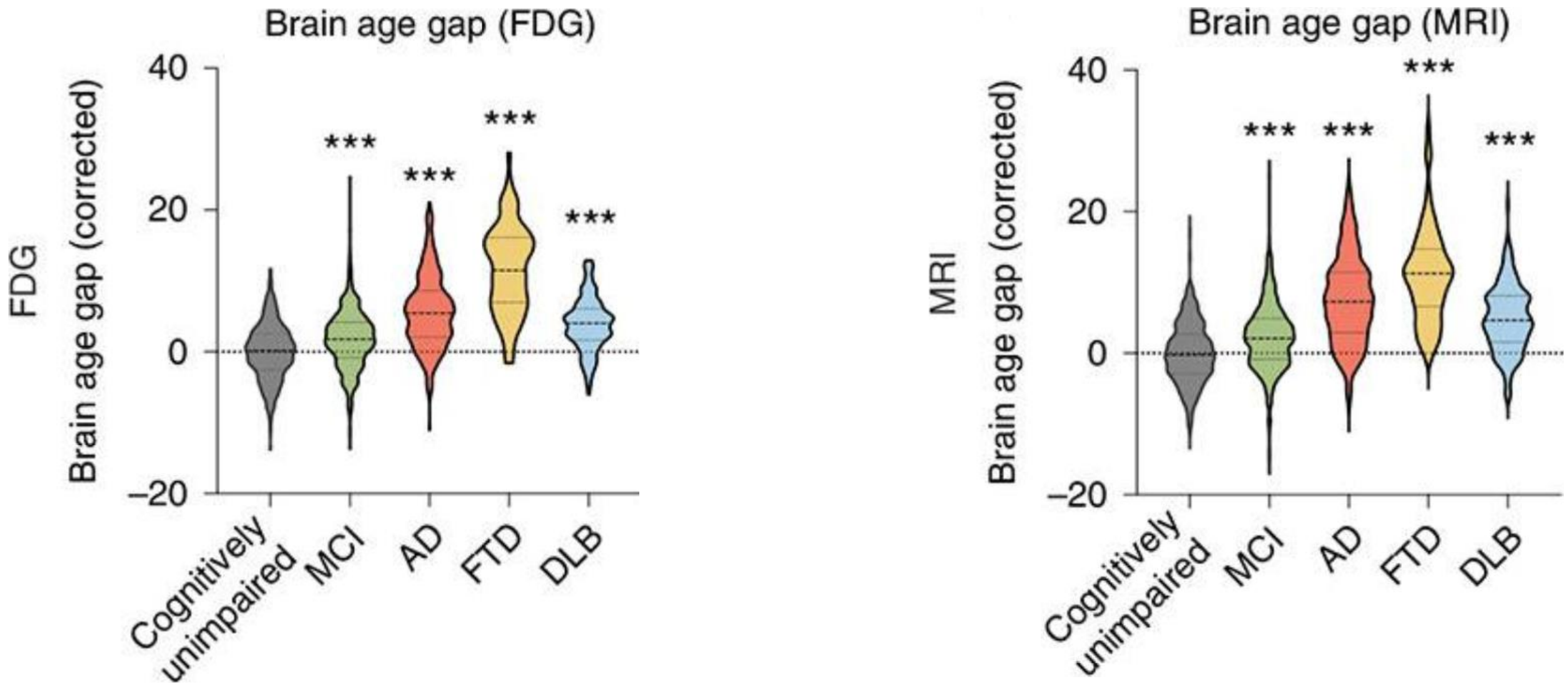
- Brain age
  - Biological age estimated from information usually derived from brain MRI data
  - Sums up the progression of ageing processes in the brain
    - Reflects relatively advanced or delayed brain maturation, while all individuals’ brains undergo the general progression such as grey matter atrophy



[https://www.brainkey.ai/blog/brain-age-how-we-calculate-it-and-what-it-means]

Typical brain images for young (22 years) and old (83 years) individuals

- Brain age gap (BAG, also called brain-predicted age difference, delta, etc.)
  - Difference between brain age and chronological age: BAG = estimated brain age − chronological age
  - Indicates whether an individual’s brain appears to have aged more or less than the population average for their actual chronological age
    - BAG > 0: advanced or premature brain ageing
    - BAG < 0: delayed or resilient brain ageing



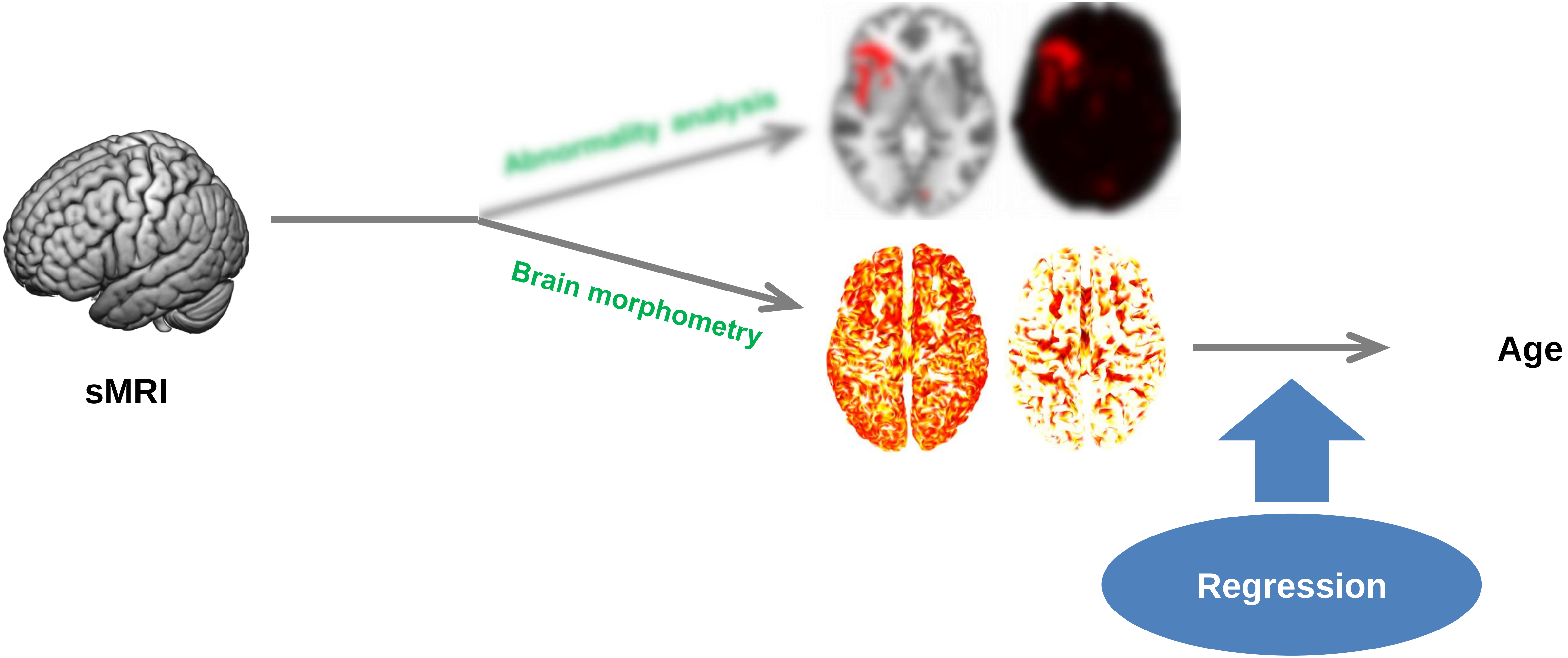
MCI, mild cognitive impairment
AD, Alzheimer's disease
FTD, frontotemporal dementia
DLB, dementia with Lewy bodies

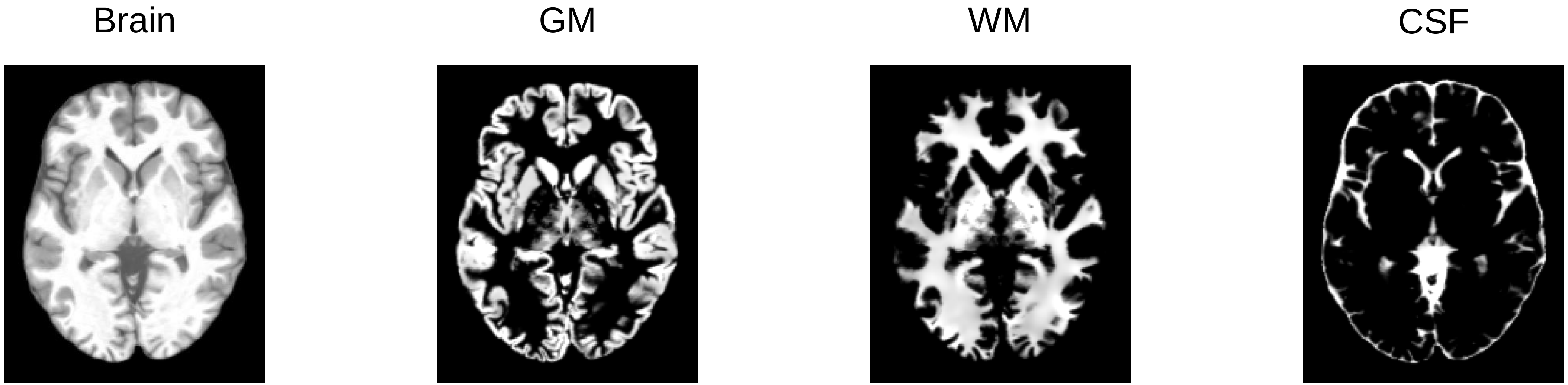
[Lee et al., 2022]

Advanced brain ageing (BAG > 0) in brain diseases

- Brain age estimation
  - Process of predicting an individual's brain age based on brain features usually extracted from brain MRI data
  - Key purpose: estimating an individual's brain age relative to their chronological age
  - Models brain age using neuroimaging features through supervised learning algorithms to predict chronological age

- Human Connectome Project (HCP)
  - Launched in 2009 as a Blueprint Grand Challenge by the National Institutes of Health in the US
  - HCP Lifespan 2.0
    - Released in 2021
    - Includes imaging and behavioural data
    - HCP Aging (HCP-A, *n* = 725 aged 36-100 years)
- Practice dataset
  - HCP-A dataset (*n* = 722)
    - Maps from sMRI and diffusion-weighted MRI (dMRI) data
    - Training set: *n* = 660
    - Test set: *n* = 62

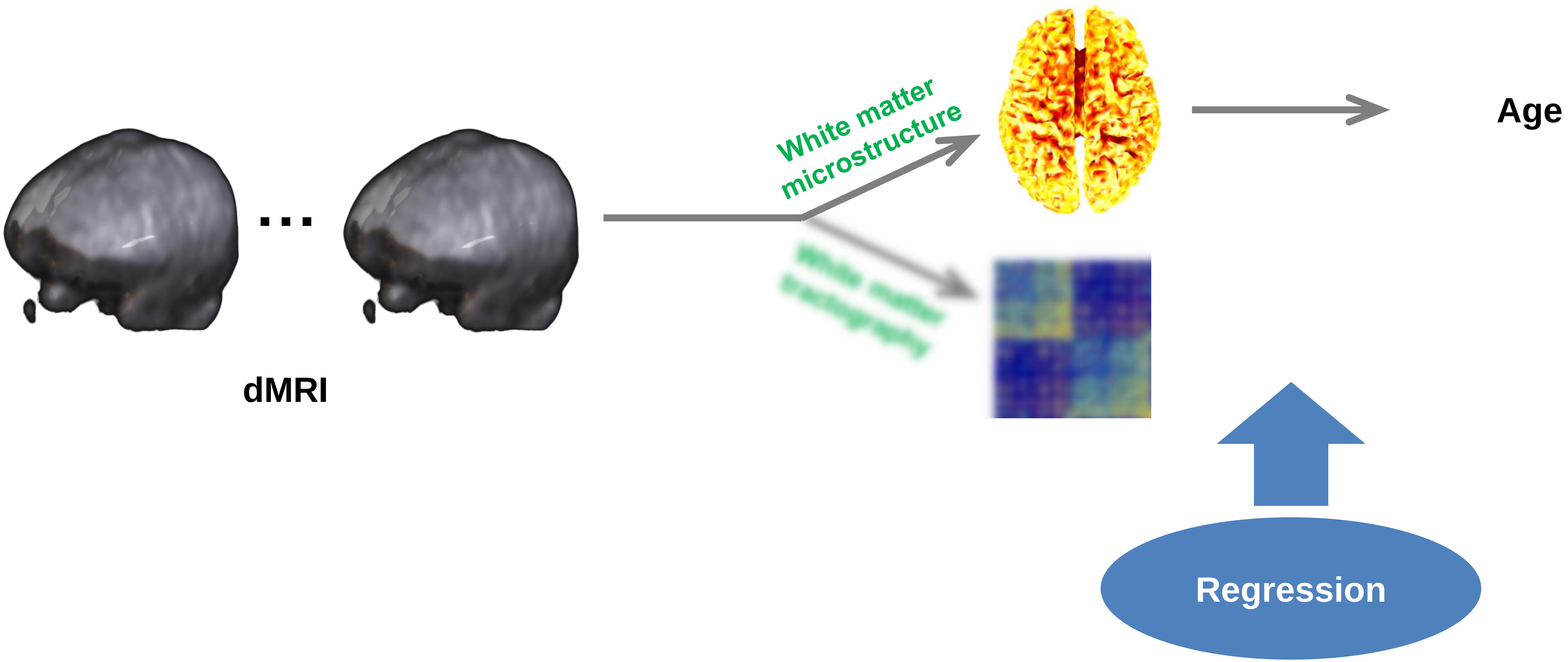

Abnormality analysis
Brain morphometry
sMRI
Age
Regression



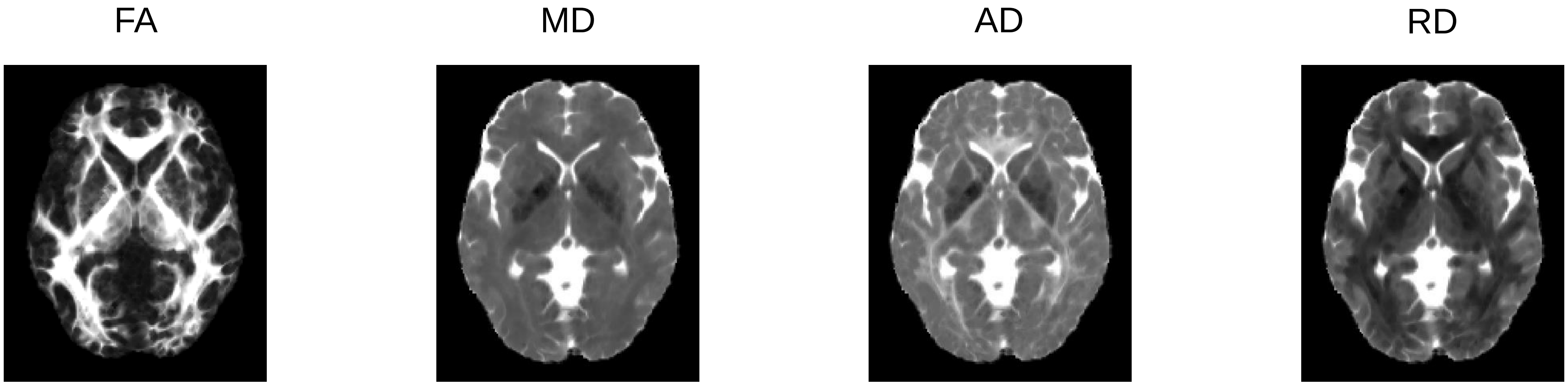
1 mm:
Dimensions: 157 × 189 × 156
Voxel size: 1.0 mm × 1.0 mm × 1.0 mm

2 mm:
Dimensions: 79 × 95 × 79
Voxel size: 2.0 mm × 2.0 mm × 2.0 mm

Maps from sMRI data



dMRI
White matter microstructure
Age
Regression

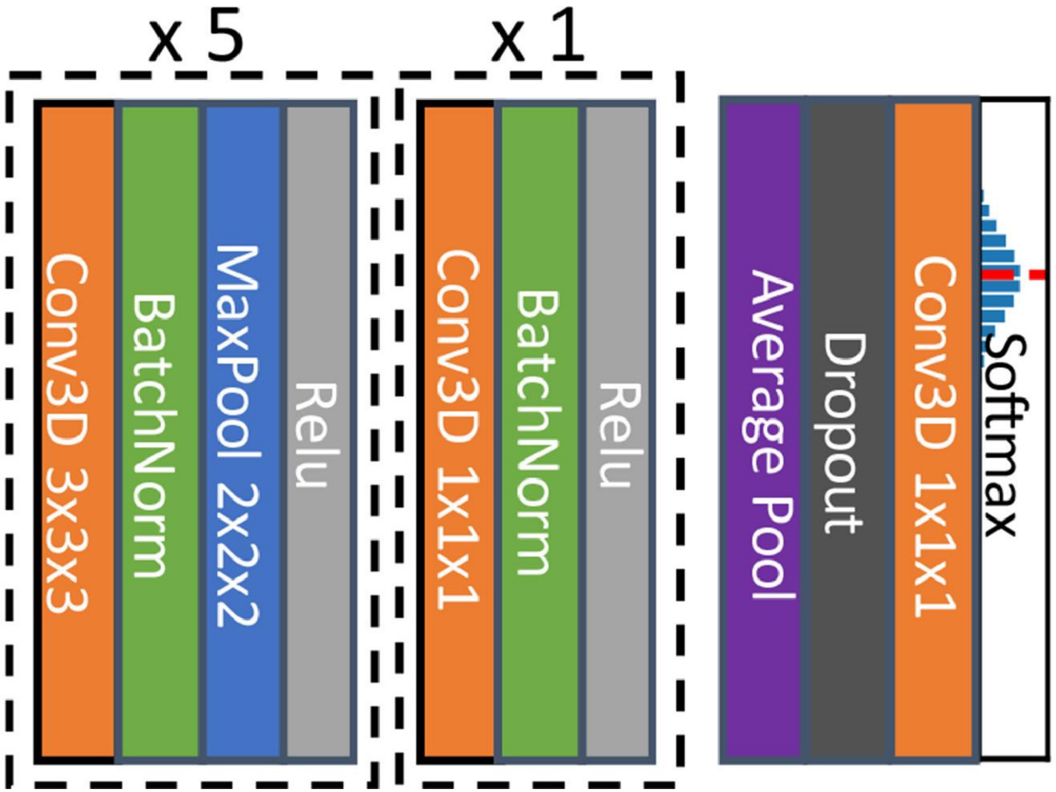


1 mm:
Dimensions: 157 × 189 × 156
Voxel size: 1.0 mm × 1.0 mm × 1.0 mm

2 mm:
Dimensions: 79 × 95 × 79
Voxel size: 2.0 mm × 2.0 mm × 2.0 mm

Maps from dMRI data

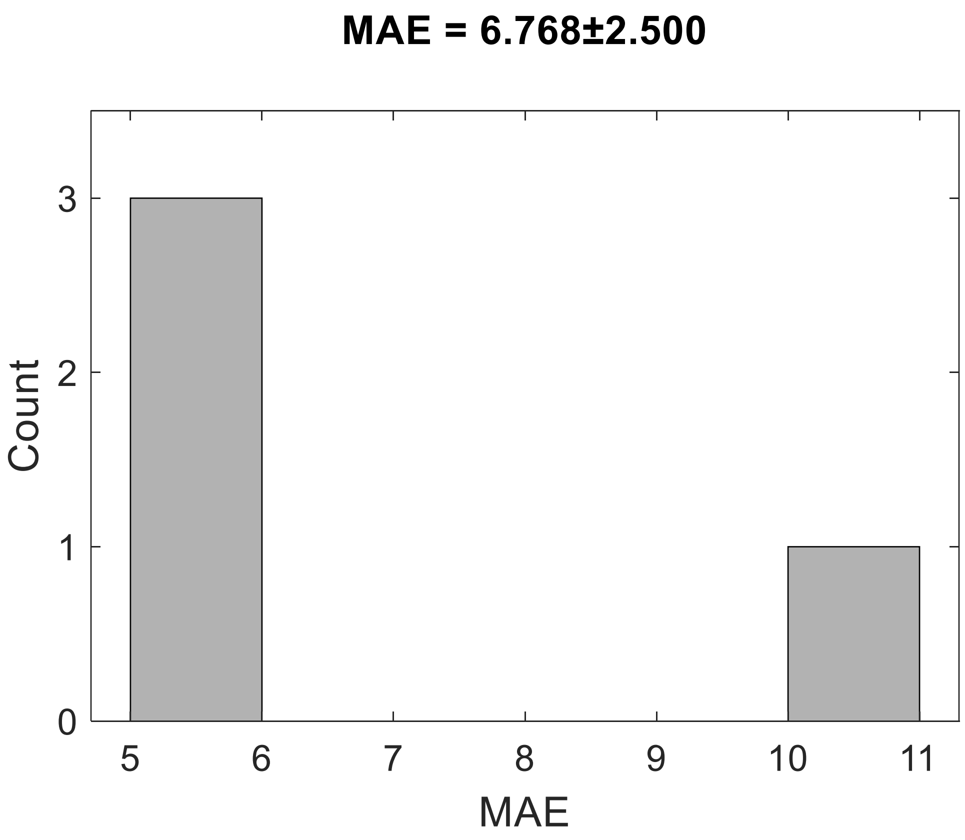
- Model architectures
  - CNN-based (2012-)
    - ResNet (skip connection)
    - DenseNet (dense connection)
    - SENet (channel attention)
    - EfficientNet (compound scaling)
  - Transformer-based (2017-)
    - ViT
    - Swin Transformer

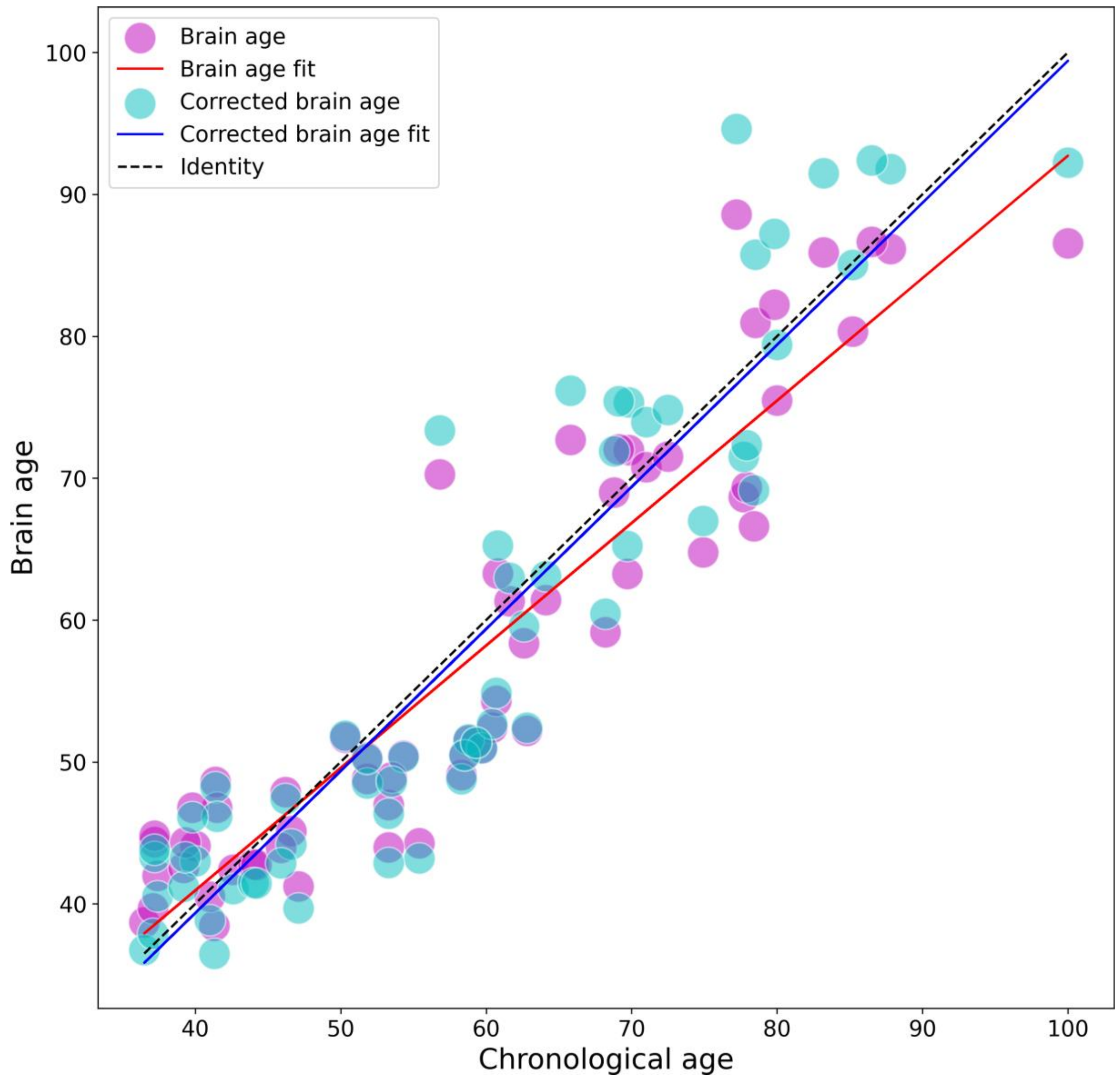


[Peng et al., 2021]

Simple Fully Convolution Network (SFCN) architecture

- Performance on test set





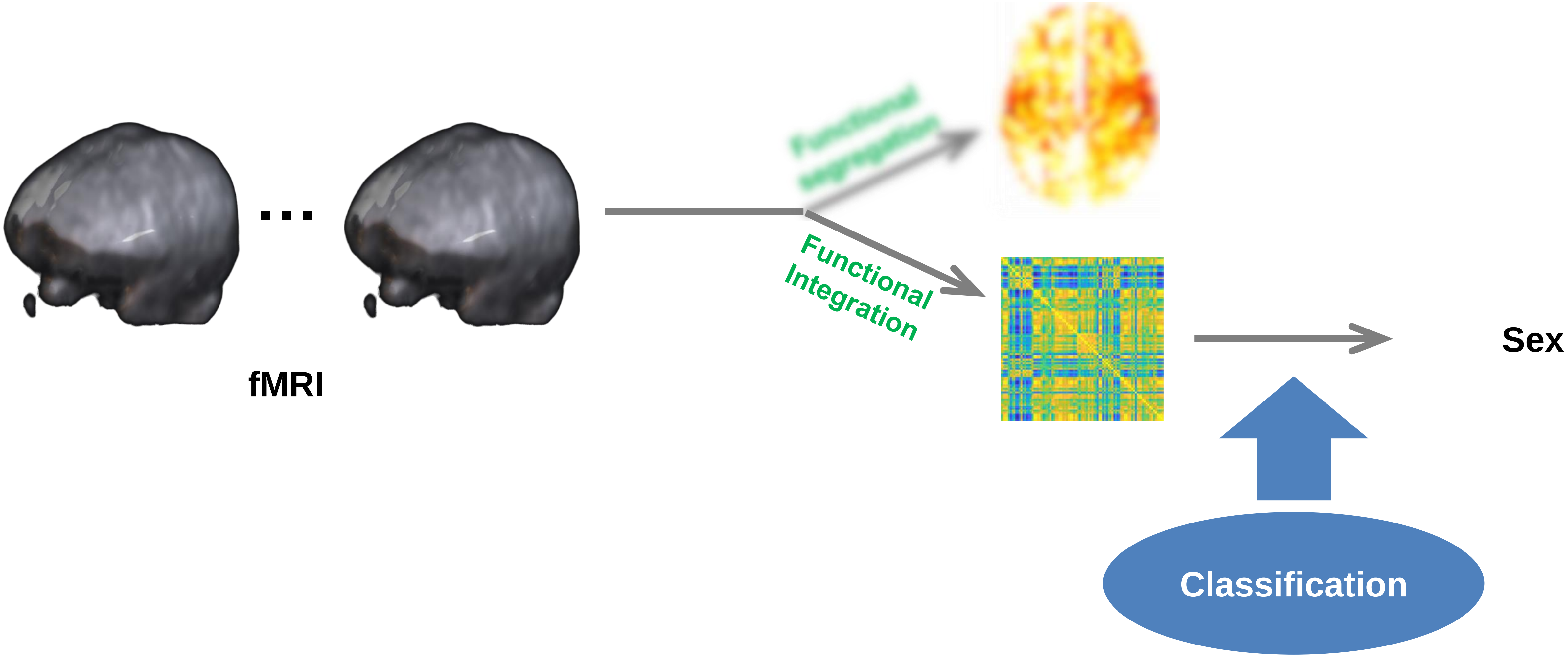
Brain age
Brain age fit
Corrected brain age
Corrected brain age fit
Identity
Brain age
Chronological age
100
90
80
70
60
50
40
40
50
60
70
80
90
100

Practical Implementation of AI Models (3): Sex Classification

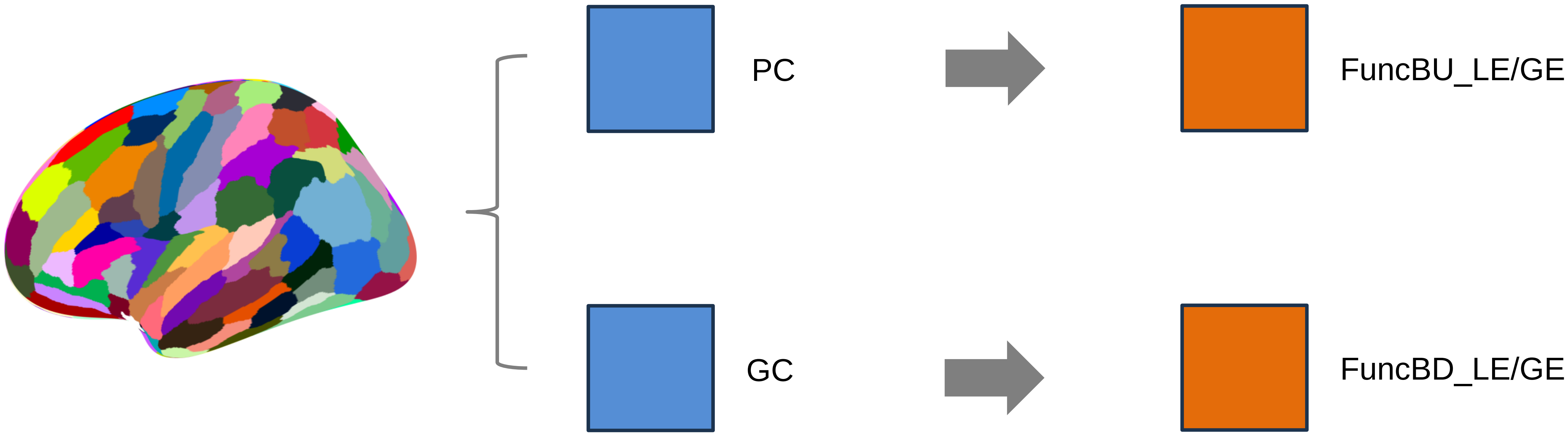
- Sex
  - Refers to biological traits, unlike gender's social/cultural aspects
  - Based on biological and physical characteristics
    - Typically categorized as females and males
  - Not changeable without medical intervention
    - Independent of personal identity or expression

- Sex classification
  - Process of categorising an individual's brain sex based on brain features usually extracted from brain MRI data
  - Key purpose: predicting an individual's brain sex score along the male-female spectrum as well as their binary sex category
  - Models brain sex using neuroimaging features through supervised learning algorithms to predict sex assigned at birth

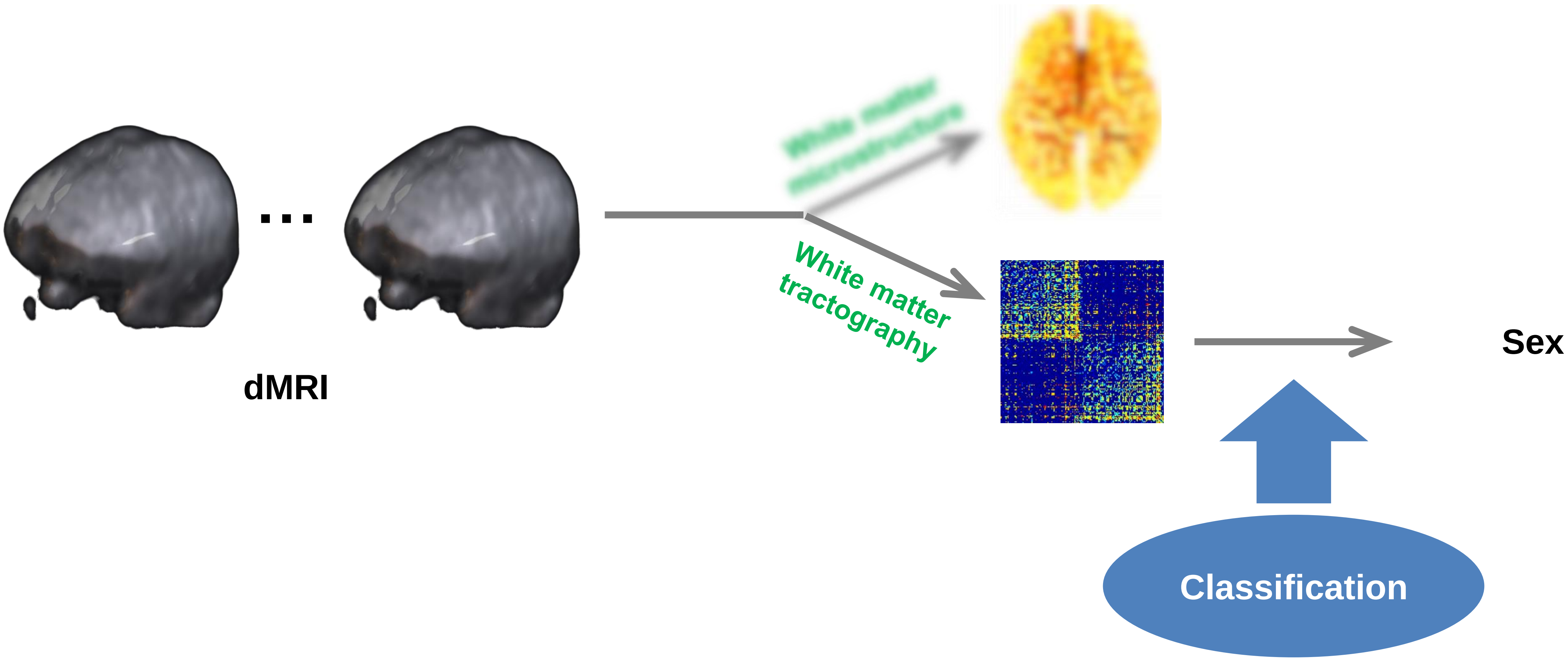
- UK Biobank
  - Launched in 2006 as a large-scale prospective cohort study by the Medical Research Council and Wellcome Trust in the UK
  - Recruited around half a million participants aged 40-69 years across the UK
  - Includes imaging data for a subset of participants
- Practice dataset
  - Part of UK Biobank (n = 498)
    - Brain networks and network metrics from resting state functional MRI (fMRI) data and dMRI data
    - Training set: n = 450
    - Test set: n = 48

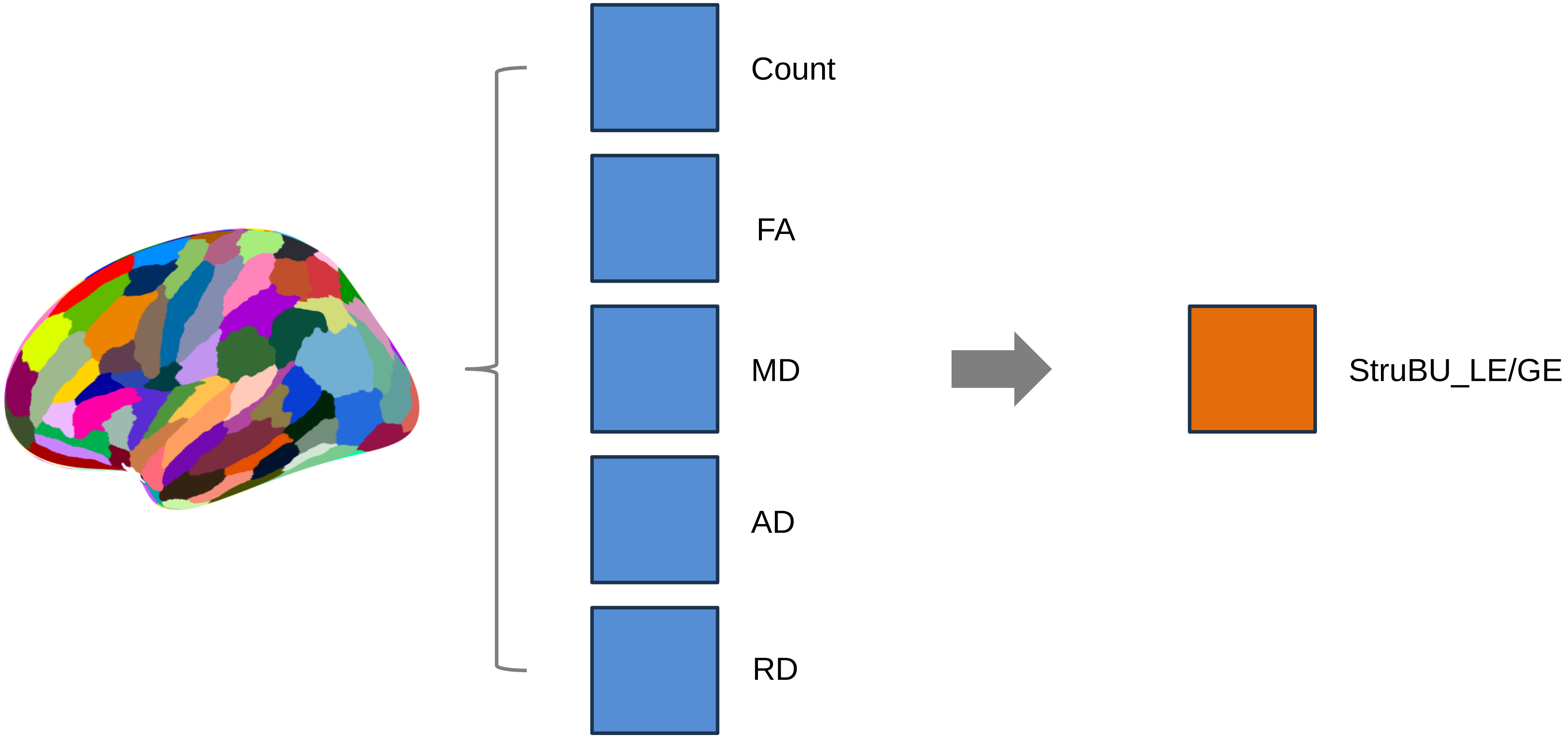


fMRI
Functional segregation
Functional Integration
Sex
Classification



Functional brain network and network metrics from resting state fMRI data

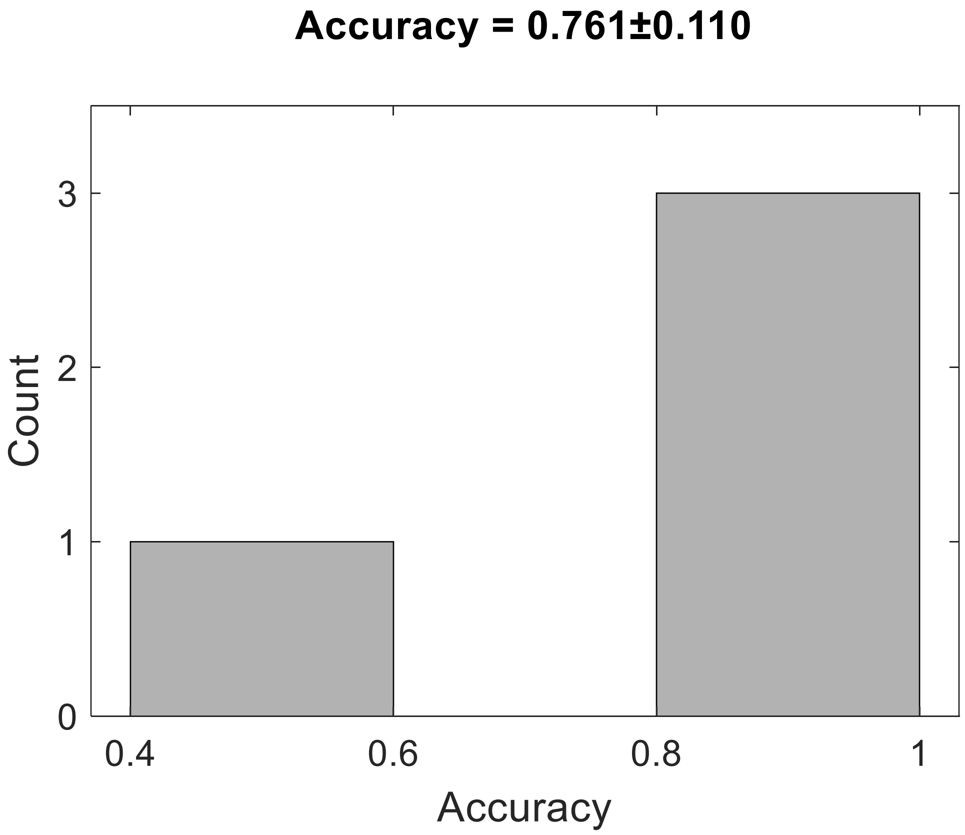

dMRI
White matter tractography
Sex
Classification

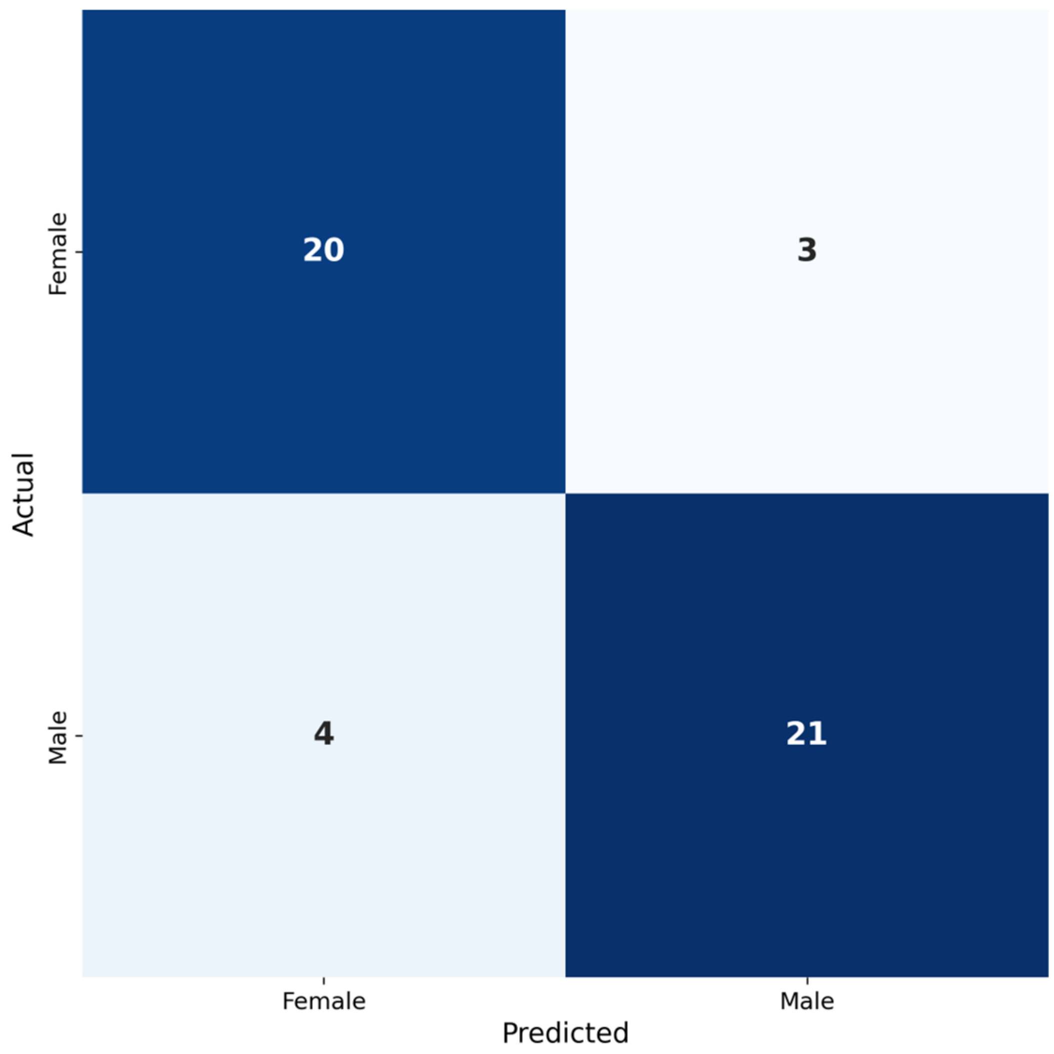


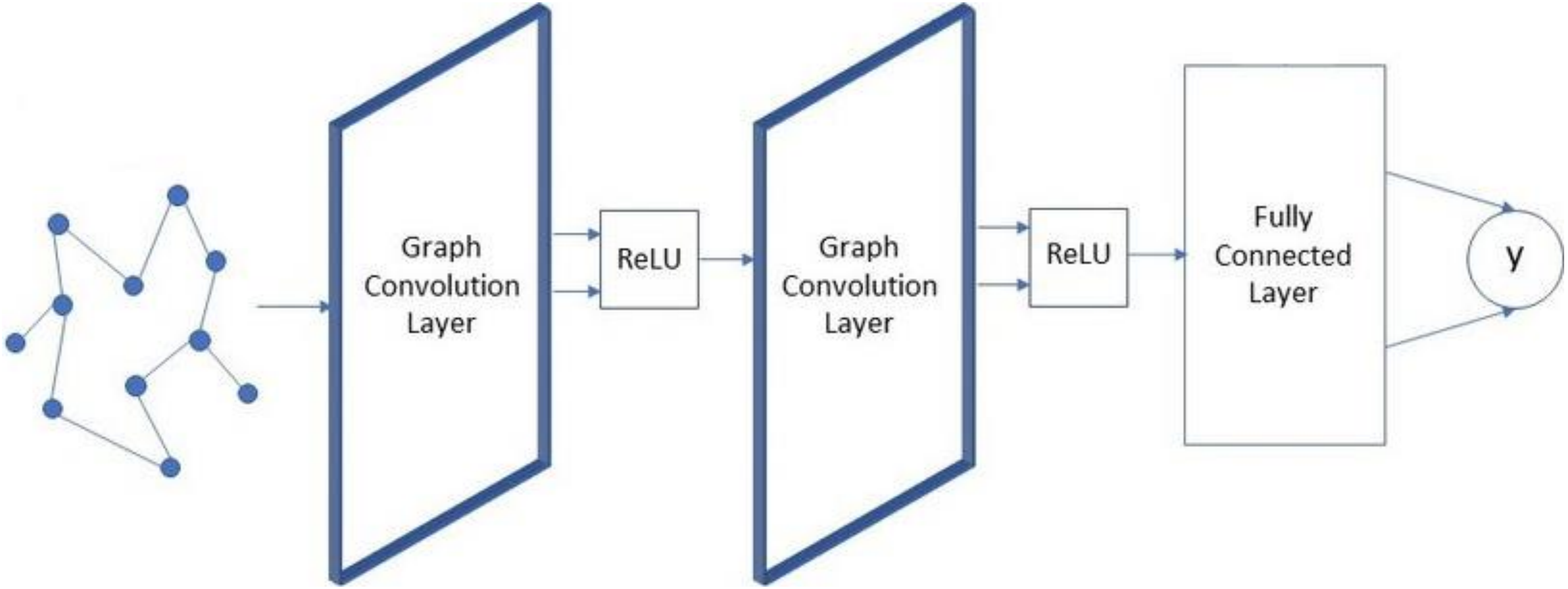
Structural brain network and network metrics from dMRI data

- Model architectures
  - Early spatial-based (2009-)
  - Spectral-based (2013-)
    - ChebNet
    - GCN
  - Modern spatial-based (2017-)
    - MPNN
    - GraphSAGE
    - GAT
  - Transformer-based (2020-)
    - Graph Transformer
    - Graphormer

- Performance on test set




20
3
4
21
Female
Male
Actual
Female
Male
Predicted



[Vijayan and Mohler, 2018]

GCN architecture