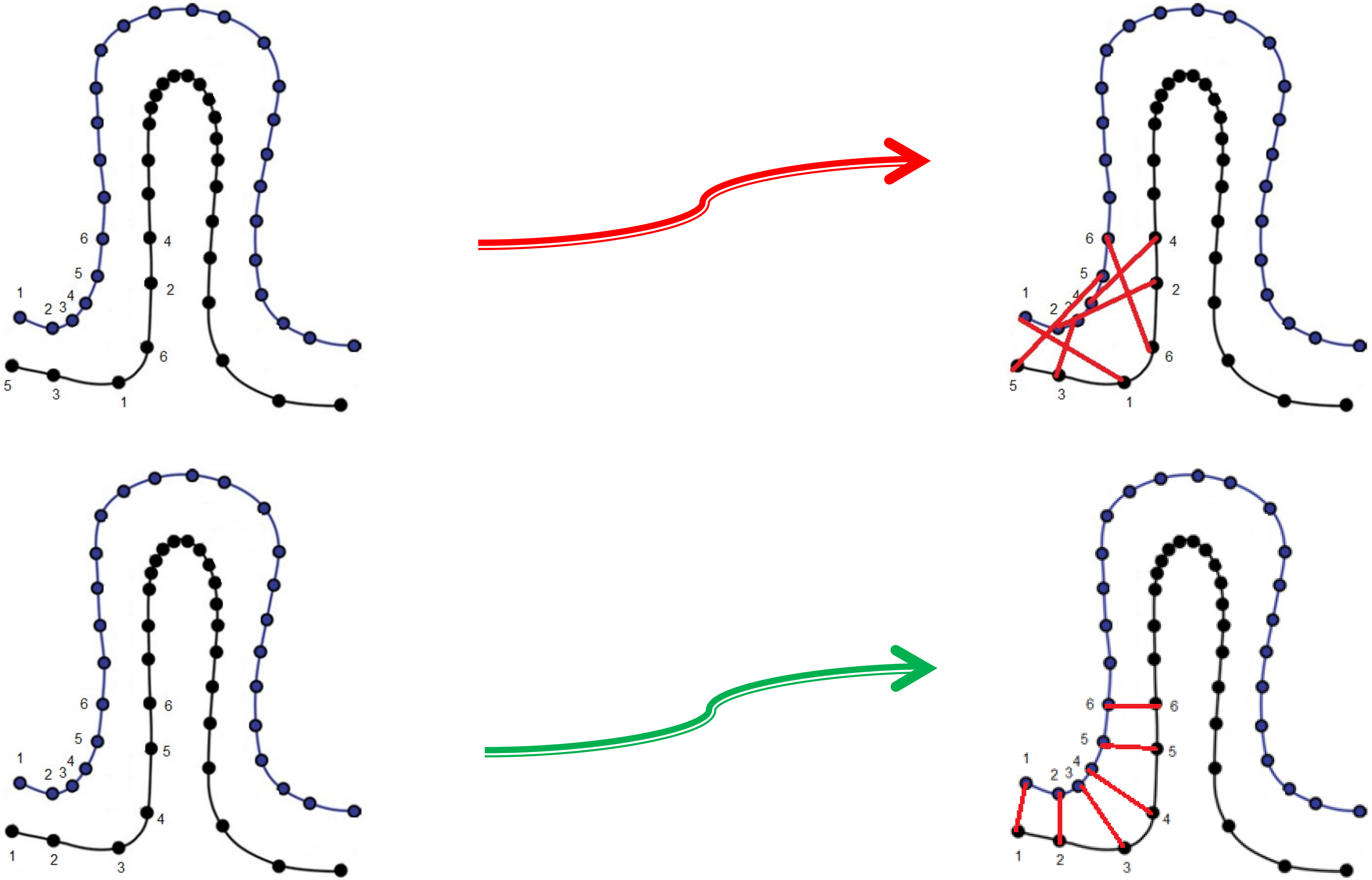
Neural deformation fields for template-based reconstruction of cortical surfaces from MRI

Fabian Bongratz, Anne-Marie Rickmann, Christian Wachinger

Medical Image Analysis, 22 January 2024

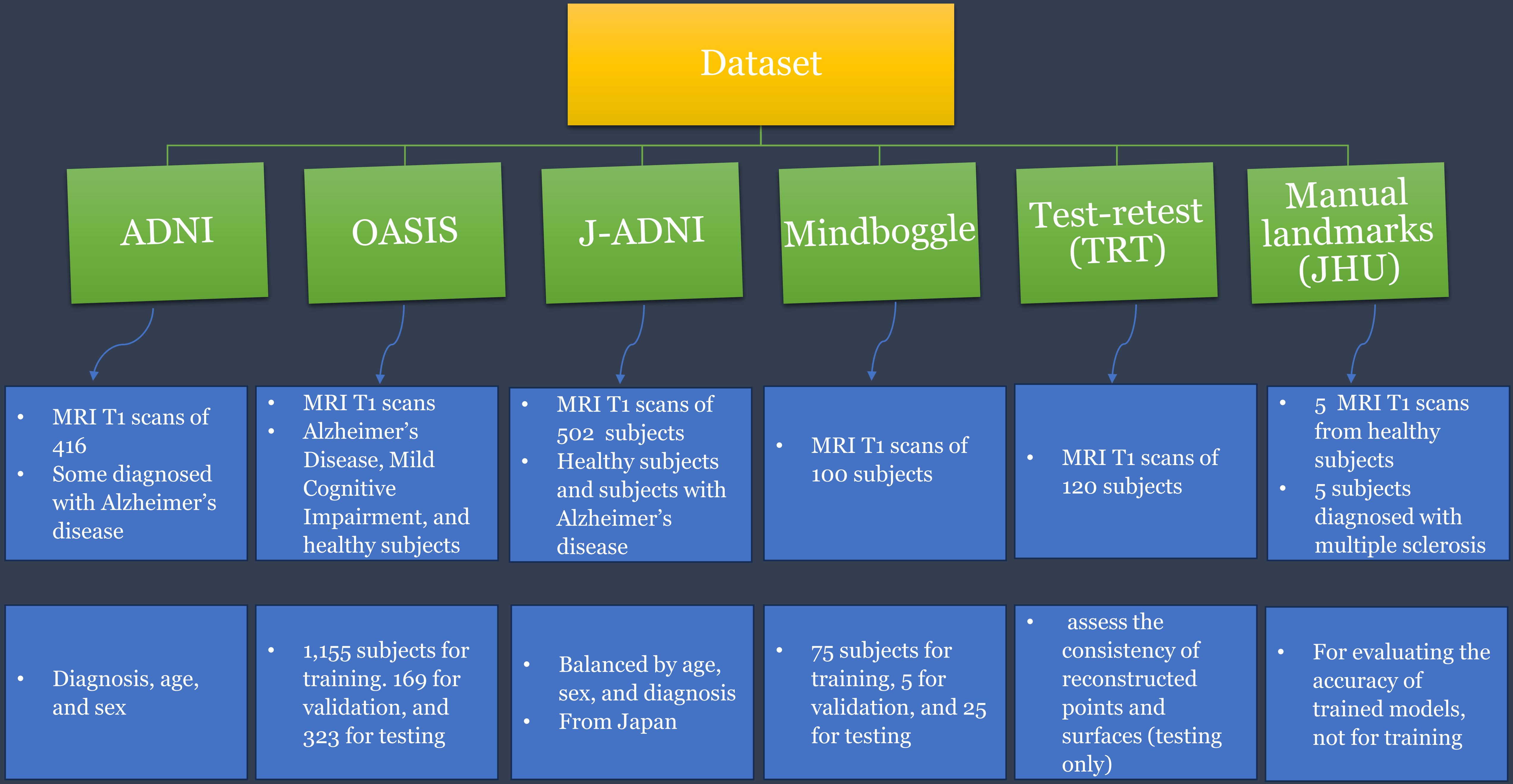
Neuro-iX

Main Challenge

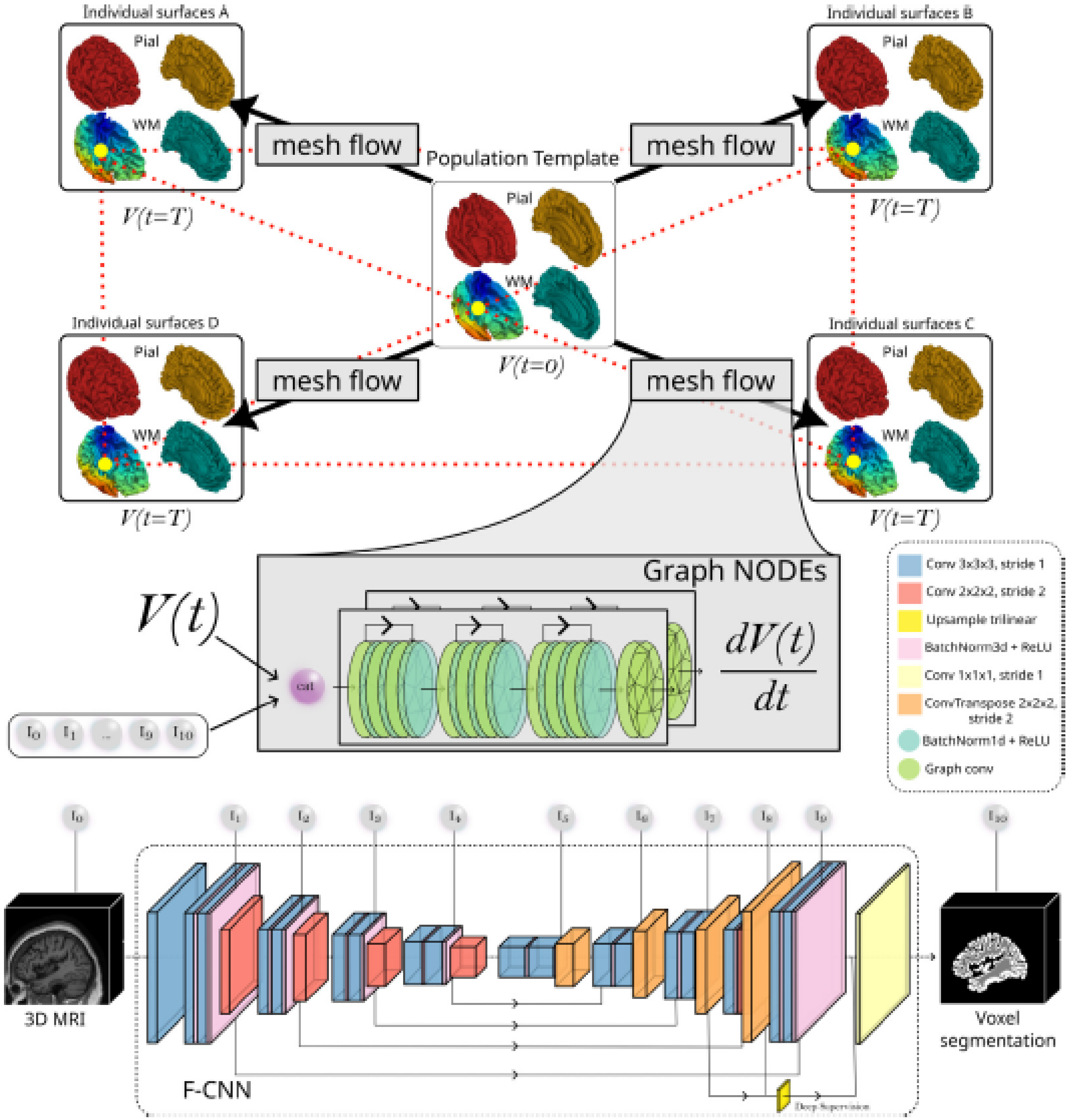


Main Object

The main objective is to devise a method leveraging Graph Neural Networks (GNN), Convolutional Neural Networks (CNN), and flow fields to maintain vertex correspondences with an input template, while exceeding the efficiency, accuracy, and consistency limitations of current approaches


Dataset
ADNI
OASIS
J-ADNI
Mindboggle
Test-retest (TRT)
Manual landmarks (JHU)
• MRI T1 scans of 416
• Some diagnosed with Alzheimer’s disease
• MRI T1 scans
• Alzheimer’s Disease, Mild Cognitive Impairment, and healthy subjects
• MRI T1 scans of 502 subjects
• Healthy subjects and subjects with Alzheimer’s disease
• MRI T1 scans of 100 subjects
• MRI T1 scans of 120 subjects
• 5 MRI T1 scans from healthy subjects
• 5 subjects diagnosed with multiple sclerosis
• Diagnosis, age, and sex
• 1,155 subjects for training. 169 for validation, and 323 for testing
• Balanced by age, sex, and diagnosis
• From Japan
• 75 subjects for training, 5 for validation, and 25 for testing
• assess the consistency of reconstructed points and surfaces (testing only)
• For evaluating the accuracy of trained models, not for training

METHODOLOGY



Graph NODEs:

$$\mathcal{M} = \{\mathcal{V}, \mathcal{F}\}$$

$$\frac{dV(t)}{dt} = f^{(s)}(\mathcal{I}, V(t)), \qquad s \in \{0, \dots, S-1\}$$

$$\frac{dV(t)}{dt} = f(t, \mathcal{I}. V(t)) = f^{(\lfloor t \rfloor)}(\mathcal{I}, V(t))$$

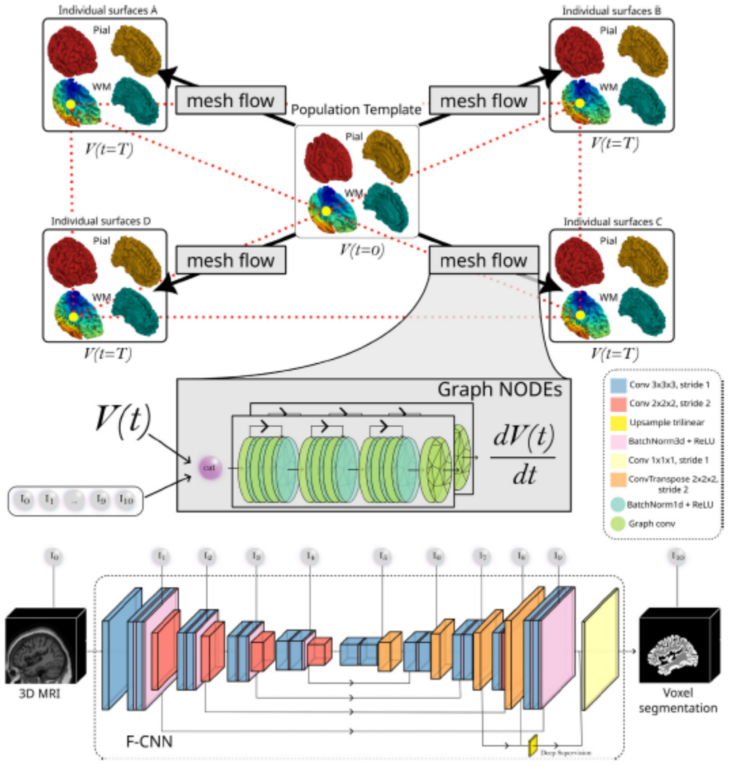
$$V^{(k+1)} = V^{(k)} + h f^{(\lfloor t_k \rfloor)}(\mathcal{I}, V^{(k)})$$

$\mathcal{V}$: vertices

$\mathcal{F}$: faces

$\mathcal{I} = \{\mathcal{I}_0, \dots, \mathcal{I}_{10}\}$: A set of latent features extracted from the input scan

$\mathcal{V}(t)$: are the coordinates of the vertices of the mesh at time t



Graph NODEs:

- Each deformation field $f^{(s)}$ is represented by a graph neural network (GNN) block

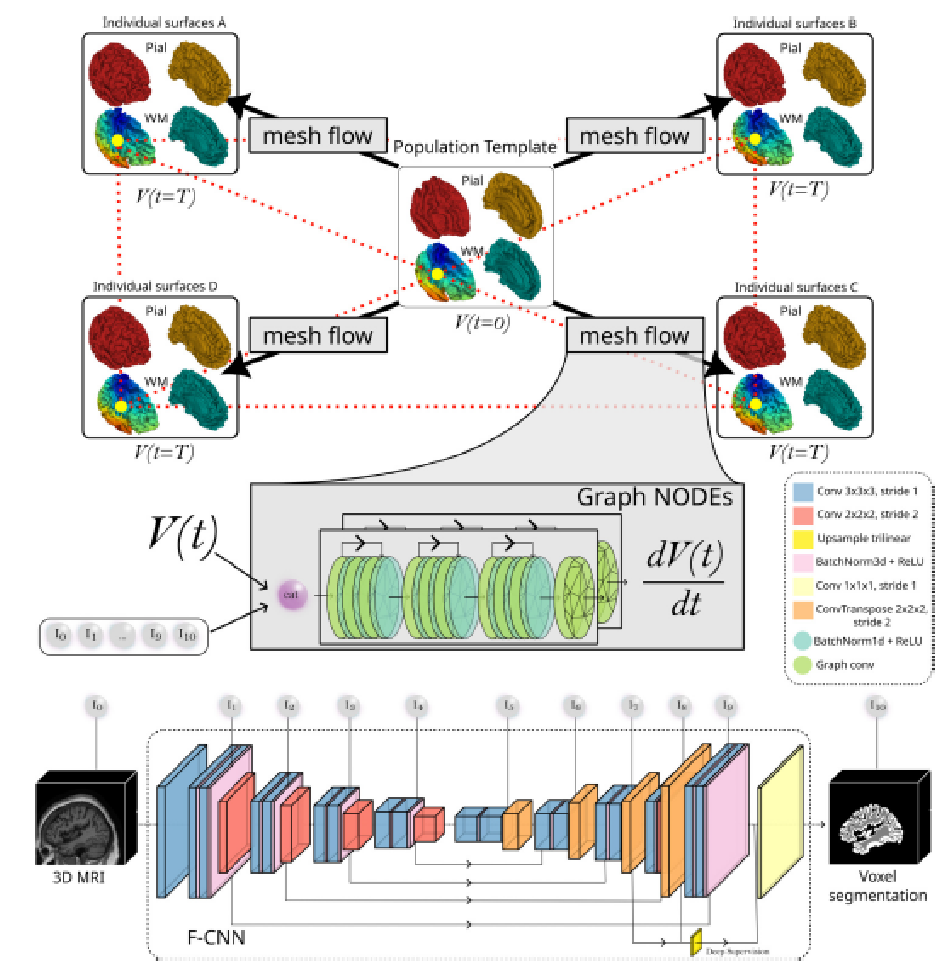
$$f_i' = \frac{1}{1 + |\mathcal{N}(i)|}\left[W_0 f_i + W_1 \sum_{j \in \mathcal{N}(i)} f_j + b\right]$$

$f_i' \in \mathbb{R}^{d_{out}}$

$f_i \in \mathbb{R}^{d_{in}}$

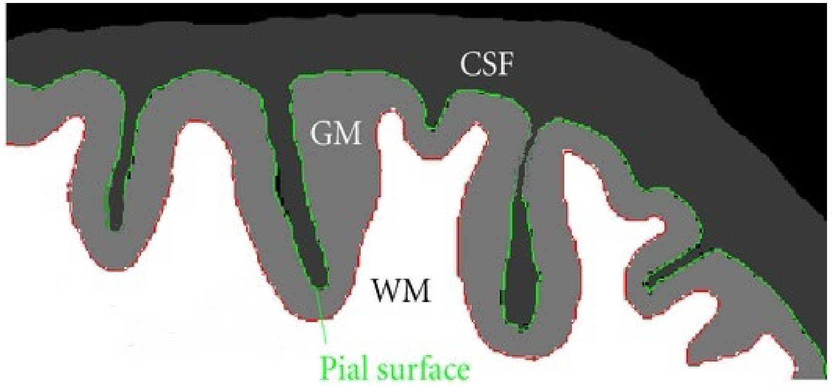
$v_i \in \mathcal{V}$

$\mathcal{N}$ (i) is the set of neighbors of v_i in the template mesh



Interdependence between inner and outer brain surfaces

- Interdependence between white matter and pial surfaces is crucial in cortical surface reconstruction
- Virtual edges enhance interdependence modeling, facilitating information exchange between inner and outer surfaces for accurate reconstruction in V2C-Flow
- These virtual edges exist only within the mesh processed by the GNN and are not present in the final output meshes
- V2C-Flow's method prevents implausible intersections between white and gray matter surfaces by jointly deforming and aligning inner and outer surfaces, resulting in more accurate and realistic cortical surface reconstructions



Loss Function

$$\theta = arg_{\theta} \min \left[\mathbb{E}_{(x, y^{gt}) \sim D} \left[\mathcal{L}_{vox}\left(y^{p}, y^{gt}\right) + \mathcal{L}_{mesh}\left(y^{p}, y^{gt}\right) \right] \right]$$

Voxel loss:

$$\mathcal{L}_{vox}\left(y^{p}, y^{gt}\right) = \sum_{l=1}^{L} \mathcal{L}_{CE}\left(B_{l}^{p}, B^{gt}\right)$$

θ: Network weights
x: Input MRI scan
y^{gt}: Ground-truth surfaces and segmentations
y^{p}: Predicted cortical surfaces and segmentations

L: Number of classes in voxel segmentation
B_{l}^{p}: Predicted voxel segmentation map
B^{gt}: Ground-truth voxel segmentation map

Mesh Loss:

$$\mathcal{L}_{mesh}\left(y^{p}, y^{gt}\right) = \sum_{s,c}\left[\mathcal{L}_{CWC}\left(M_{s,c}^{p}, M_{c}^{gt}\right) + \lambda_1 \mathcal{L}_{edge}\left(M_{s,c}^{p}\right) + \lambda_2 \mathcal{L}_{NC}\left(M_{s,c}^{p}\right)\right]$$

Edge loss:

$$\mathcal{L}_{edge}(M) = \frac{1}{|\mathcal{E}|}\sum_{(i,j)\in\mathcal{E}} \left\|v_i - v_j\right\|^2$$

Normal consistency loss:

$$\mathcal{L}_{NC}(M) = \frac{1}{|\mathcal{E}|}\sum_{\substack{f_0 \cap \in \mathcal{E} \\ f_0, f_1 \in \mathcal{F}}} 1 - \cos(n(f_0), n(f_1))$$

where $\mathcal{E}$ is the set of edges of the mesh.

where n(f) assigns a normal to each face f of the mesh

f_0: Face 0 in the mesh

f_1: Face 1 in the mesh

$f_0 \cap f_1$: Intersection of faces 0 and 1

$n(f)$: Normal vector assigned to face f

Cos (n (f_0), n (f_1)): Cosine of the angle between normals of adjacent faces

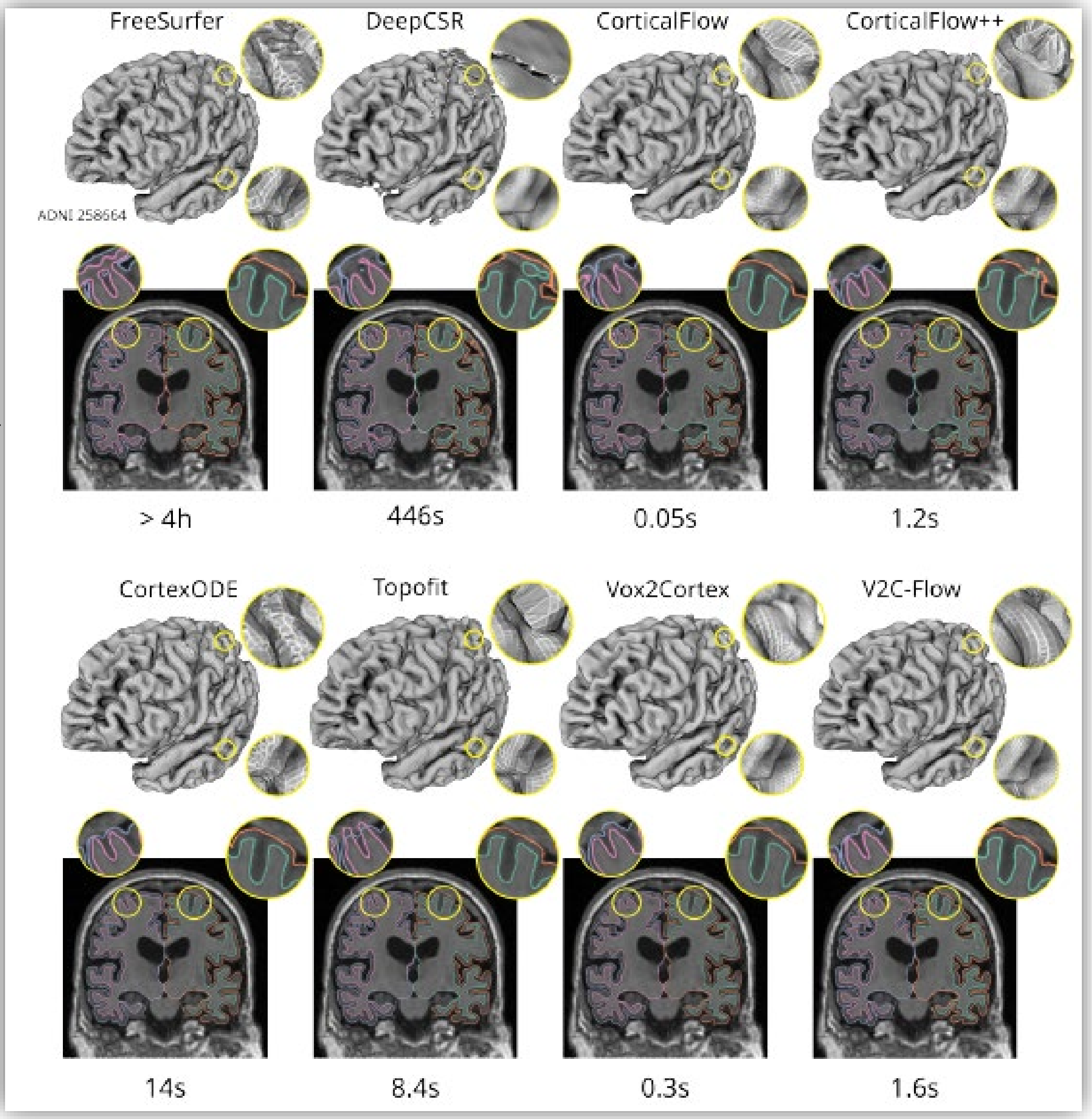
Surface accuracy

- Standard folded fsaverage template (F)
- Smoothed fsaverage template (S)
- Population template generated from ADNI (P)

Method	Left WM surface		Right WM surface		Left pial surface		Right pial surface	
	ASSD	HD_{90}	ASSD	HD_{90}	ASSD	HD_{90}	ASSD	HD_{90}
V2C-Flow (S)	.179 ±.041	**.393 ±.095**	.177 ±.031	**.389 ±.076**	**.176 ±.030**	.400 ±.066	**.174 ±.022**	**.389 ±.055**
V2C-Flow (P)	**.176 ±.041**	.398 ±.098	**.174 ±.030**	.393 ±.077	.177 ±.029	.405 ±.065	.176 ±.022	.402 ±.053
V2C-Flow (F)	.183 ±.040	.407 ±.097	.182 ±.032	.405 ±.081	.181 ±.030	.415 ±.067	.179 ±.024	.406 ±.057
V2C (Bongratz et al., 2022)	.197 ±.041	.435 ±.100	.198 ±.031	.431 ±.076	.210 ±.033	.500 ±.094	.216 ±.028	.515 ±.084
CF (Lebrat et al., 2021)	.209 ±.040	.479 ±.101	.208 ±.031	.478 ±.085	.216 ±.033	.519 ±.072	.215 ±.024	.516 ±.062
CF^{++} (Santa Cruz et al., 2022)	.181 ±.038	.401 ±.089	.181 ±.032	.401 ±.080	**.169 ±.034**	**.375 ±.069**	**.169 ±.028**	**.375 ±.059**
DeepCSR (Santa Cruz et al., 2021)	.422 ±.058	.852 ±.134	.420 ±.058	.880 ±.156	.454 ±.059	.927 ±.243	.422 ±.053	.890 ±.197
CODE (Ma et al., 2022)	**.172 ±.044**	**.367 ±.096**	**.172 ±.034**	**.363 ±.077**	.183 ±.035	**.381 ±.070**	.191 ±.034	.393 ±.066
TopoFit (Hoopes et al., 2022)	.211 ±.039	.469 ±.096	.210 ±.032	.477 ±.083	.217 ±.036*	.490 ±.084*	.247 ±.034*	.557 ±.081*

Inference time

- V2C-Flow is highly efficient, completing the inference of all four cortical surfaces in less than two seconds
- Outperforms several previous methods in terms of speed
- Training V2C-Flow requires three days, making it approximately 10 times faster than CorticalFlow++ which takes four weeks for training

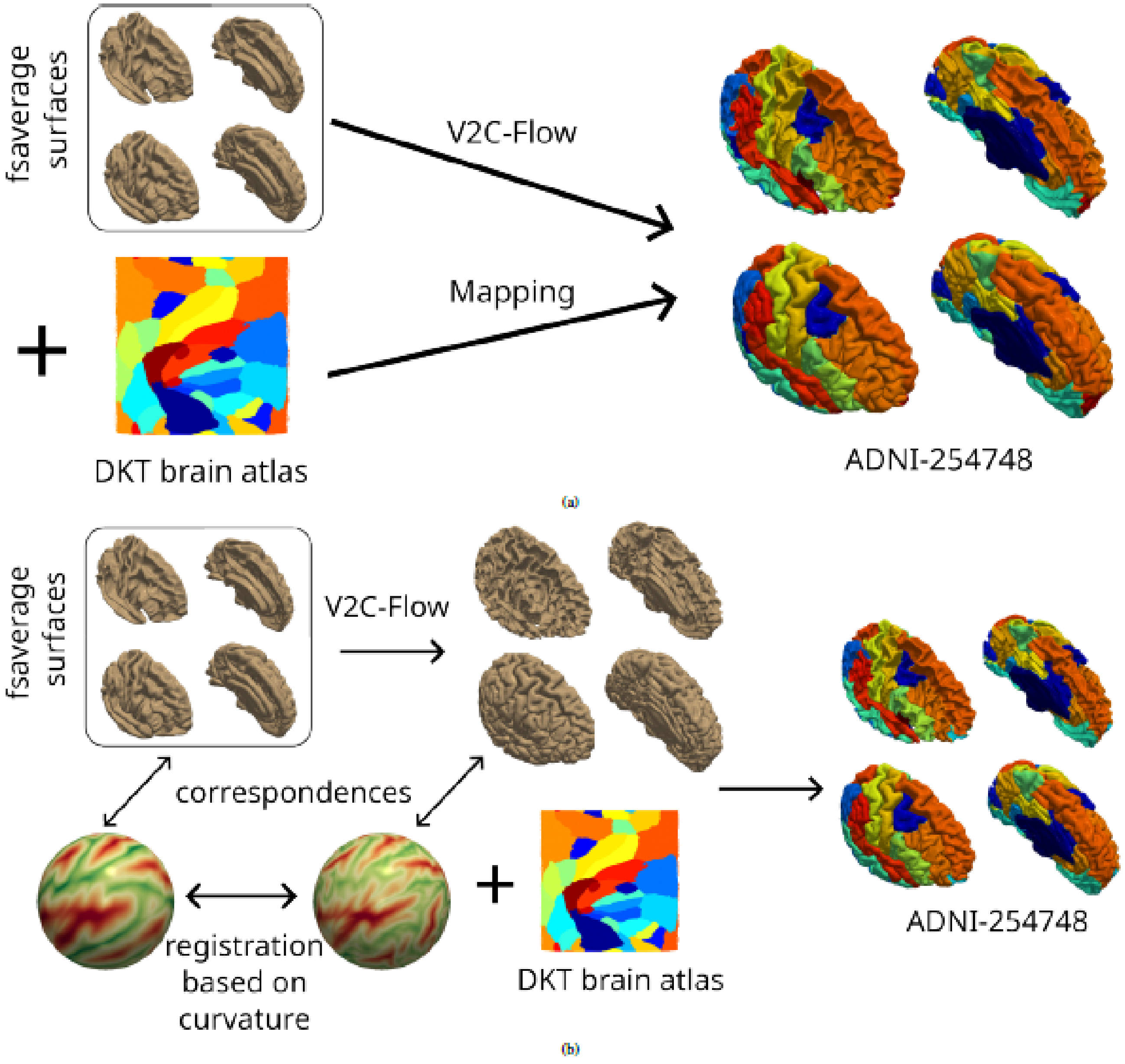


Generalization to new data

Training set	Test set	ASSD	HD_{90}
ADNI (1154)	J-ADNI (101)	0.236 ±0.071	0.496 ±0.155
J-ADNI (350)	J-ADNI (101)	0.269 ±0.092	0.580 ±0.190
ADNI (1154)	Mindb. (100)	0.230 ±0.052	0.494 ±0.123
Mindb. (75)	Mindb. (20)*	0.258 ±0.045	0.596 ±0.120
ADNI (1154)	OASIS (80)	0.255 ±0.075	0.554 ±0.190
OASIS (292)	OASIS (80)	0.215 ±0.038	0.485 ±0.097

surface parcellation

- Direct Mapping Method: This approach is the fastest for parcellation because it doesn't involve additional processing steps
- Registration-Based Method: While slower, this method has the potential to achieve higher accuracy by leveraging curvature-based registration



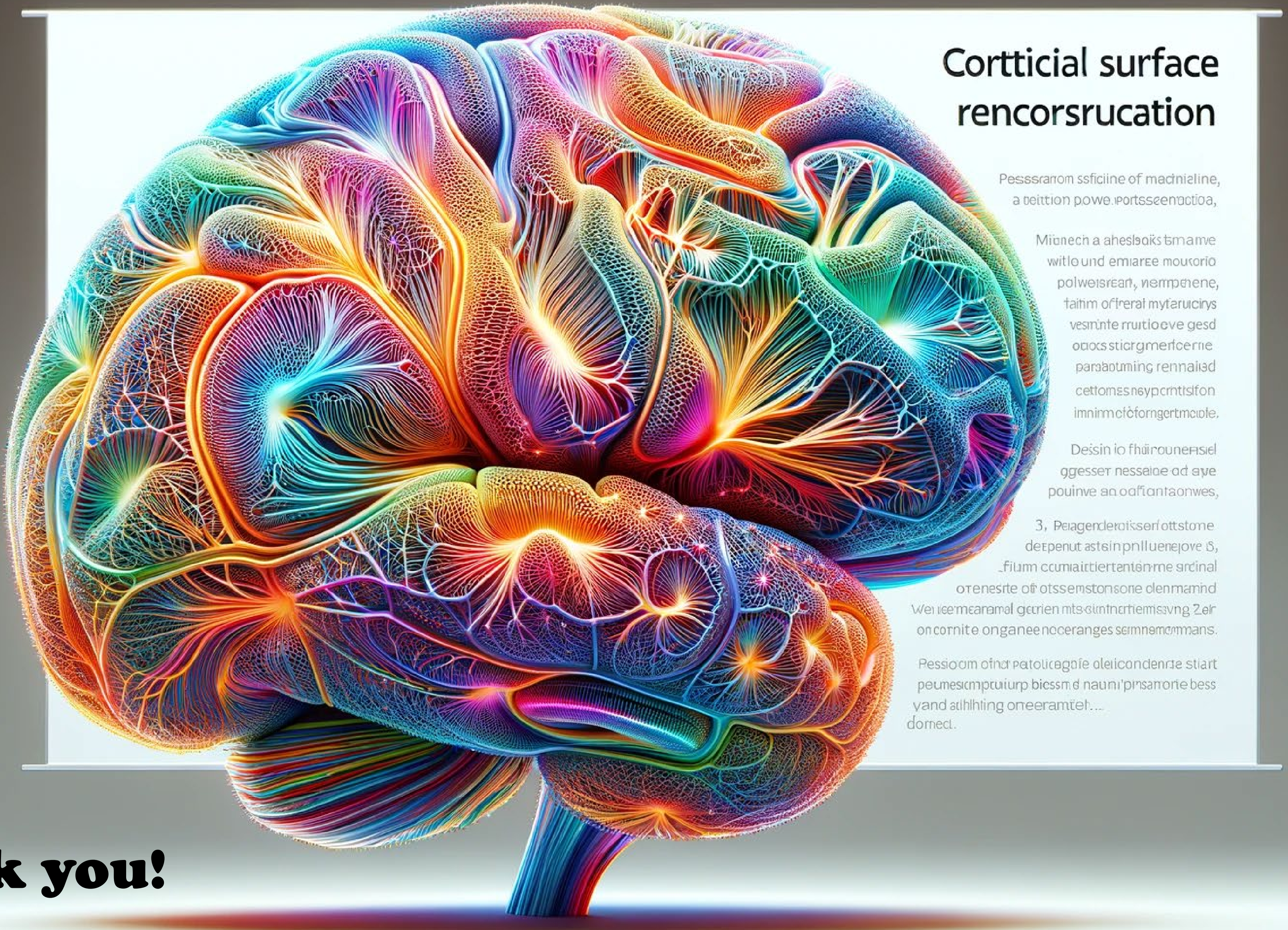
Limitation

- Potential Errors in Surface Extraction:
  - FreeSurfer, while valuable, may generate inaccurate surfaces for specific MRI scans
  - Noisy labels in datasets can lead to inaccuracies in results from deep learning models

- Limited Availability of Gold Standard Data:
  - Creating a comprehensive gold standard dataset for human-annotated target meshes in cortical surface extraction from MRI scans is challenging due to the complexity and variability of cortical structures

- Generalizability to Different Pathologies:
  - V2C-Flow's performance has been evaluated on individuals with conditions like cognitive impairment, Alzheimer's disease, and multiple sclerosis

  - Evaluation on surfaces in the presence of other brain pathologies such as tumors has not been conducted, indicating a limitation in the method's scope of assessment



Thank you!