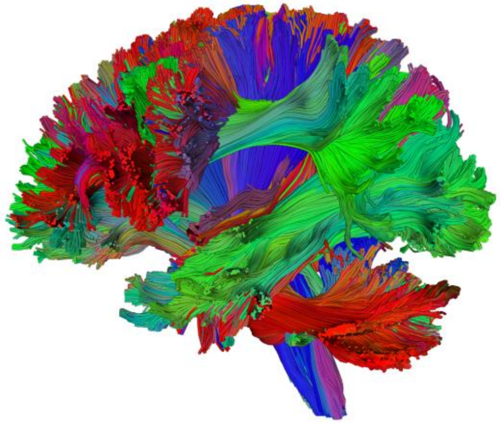
Kaveh Moradkhani

Ph.D. student in Software and IT Engineering at ÉTS University



In the world of medical image processing, our goal is to provide life-saving solutions and help those in need. It's a noble cause that we're proud to be a part of

Paper Presentation

October 18rd 2023

Under the supervision of

Pro. Sylvain Bouix

ÉTS
Le génie pour l'industrie

Neuro-iX

Vox2Cortex: Fast Explicit Reconstruction of Cortical Surfaces from 3D MRI Scans with Geometric Deep Neural Networks

01 MAIN AIM UNDERSTANDING TOPIC MAIN CHALLENGE

02 RELATED WORK METHODOLOGY

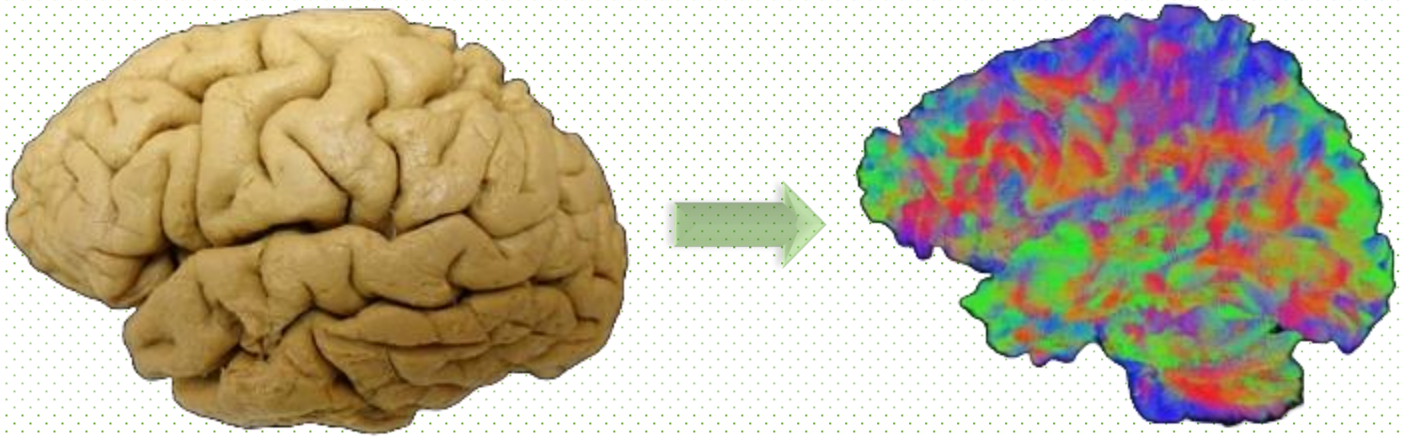
03 DATASETS PRE-PROCESSING COMPARISON

04 LIMITATION FEATURE CONCLUSION

MAIN AIM

Main Aim

The main objective of this work is to develop a fast and highly accurate reconstruction of the cortex, which has high clinical value

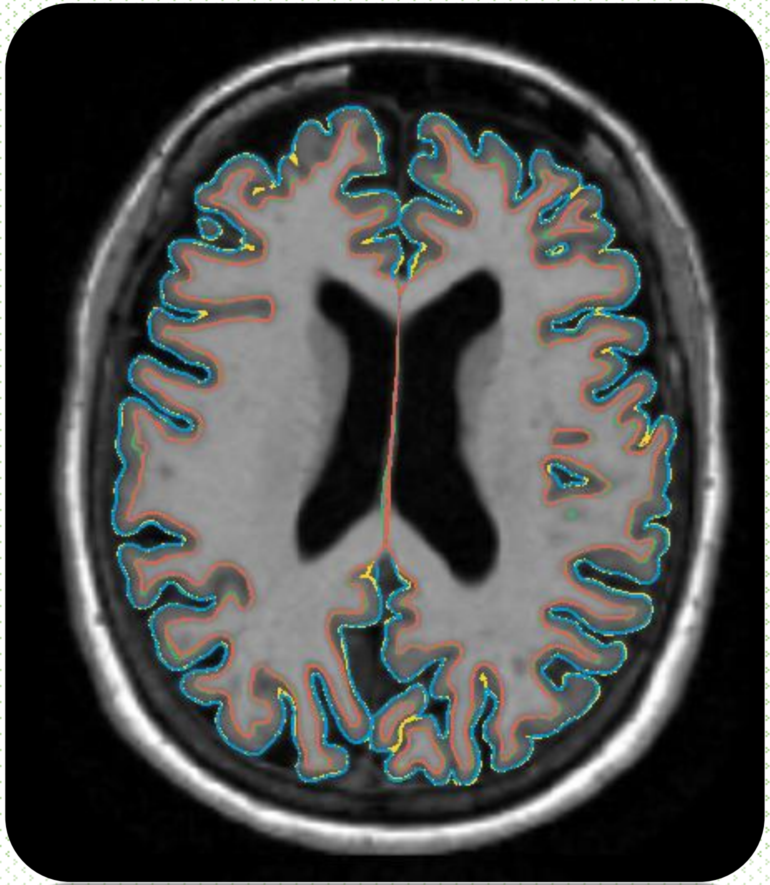


UNDERSTANDING TOPIC

Unlocking the Power of Cortical Surface Reconstruction

❖ Precise analysis of cortical thickness

❖ Sulcal morphology

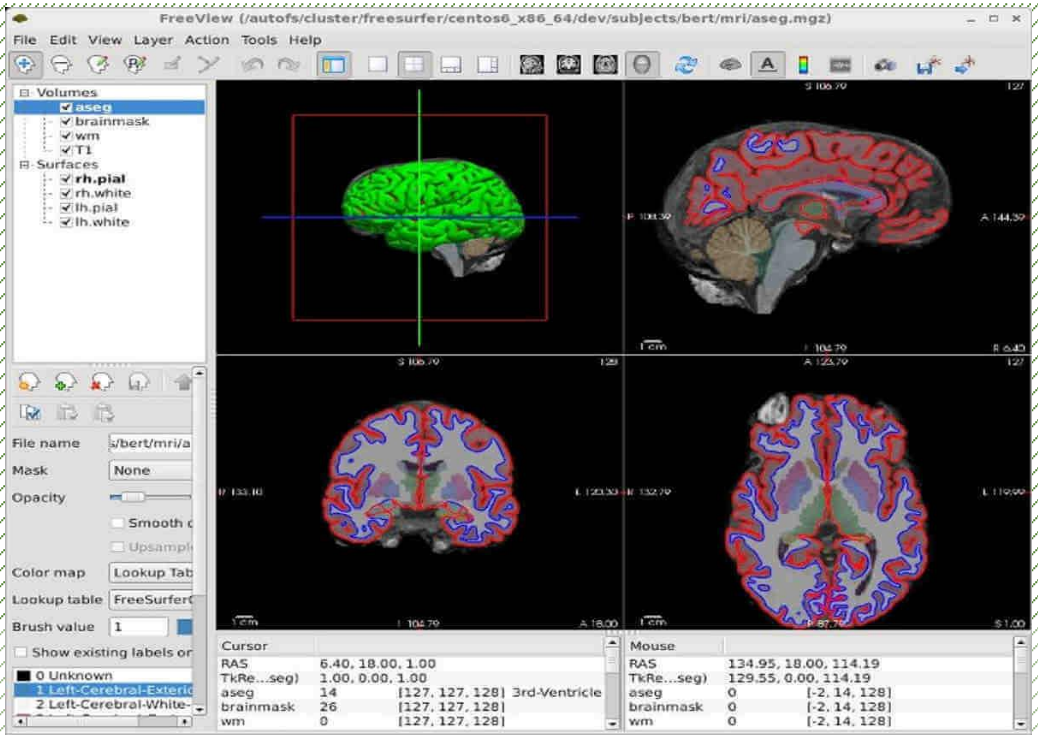


MAIN CHALLENGE

MAIN CHALLENGE

❖Lengthy runtimes of multiple hours

❖Intricate post-processing



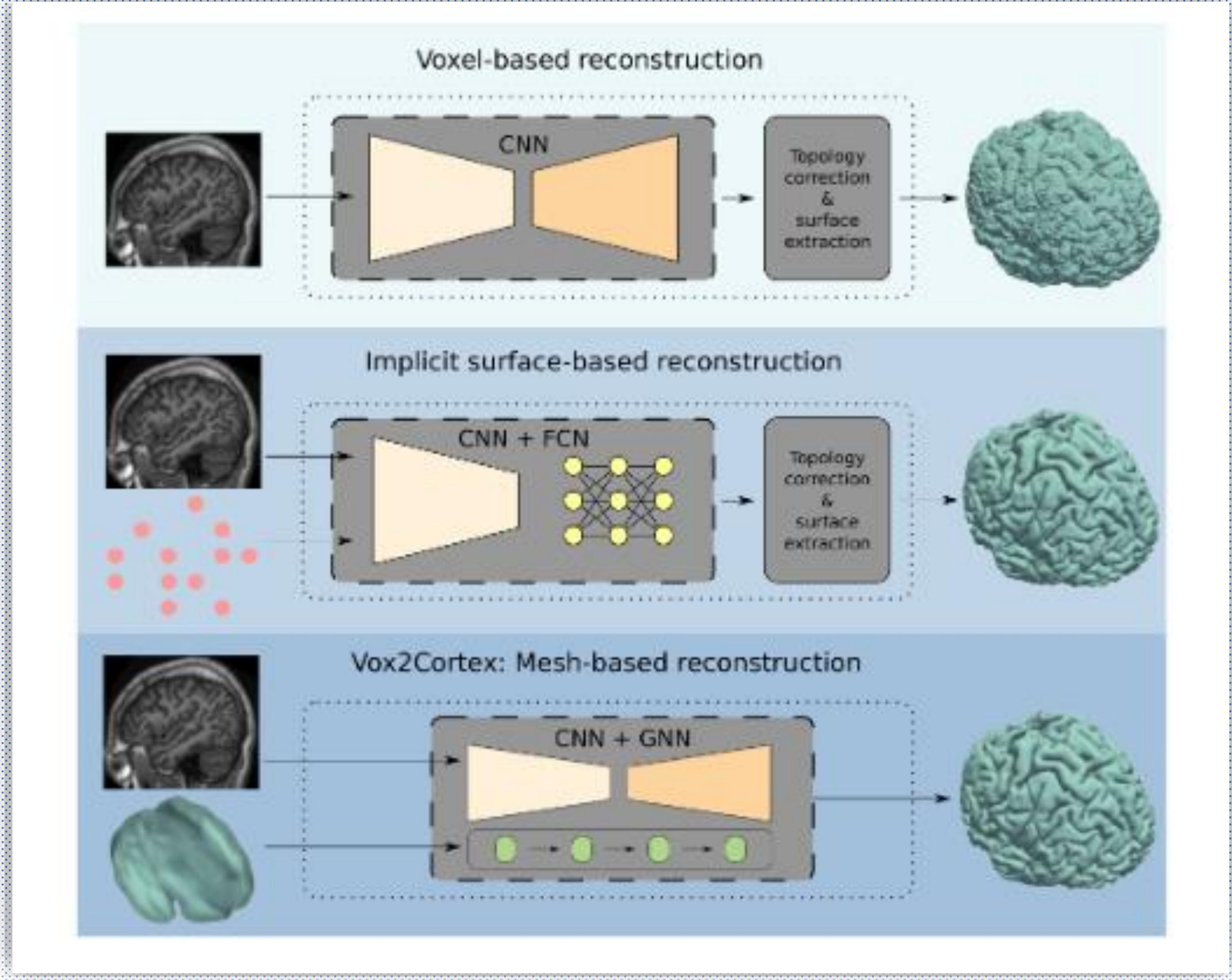
FreeSurfer

RELATED WORK

Related Work

- **Voxel-based surface reconstruction:**
  - ❖ FastSurfer
  - ❖ Deep implicit representations
  - ❖ SegRecon
- **Mesh-based surface reconstruction:**
  - ❖ Voxel2Mesh
  - ❖ MeshDeformNet
  - ❖ PialNN

Related Work

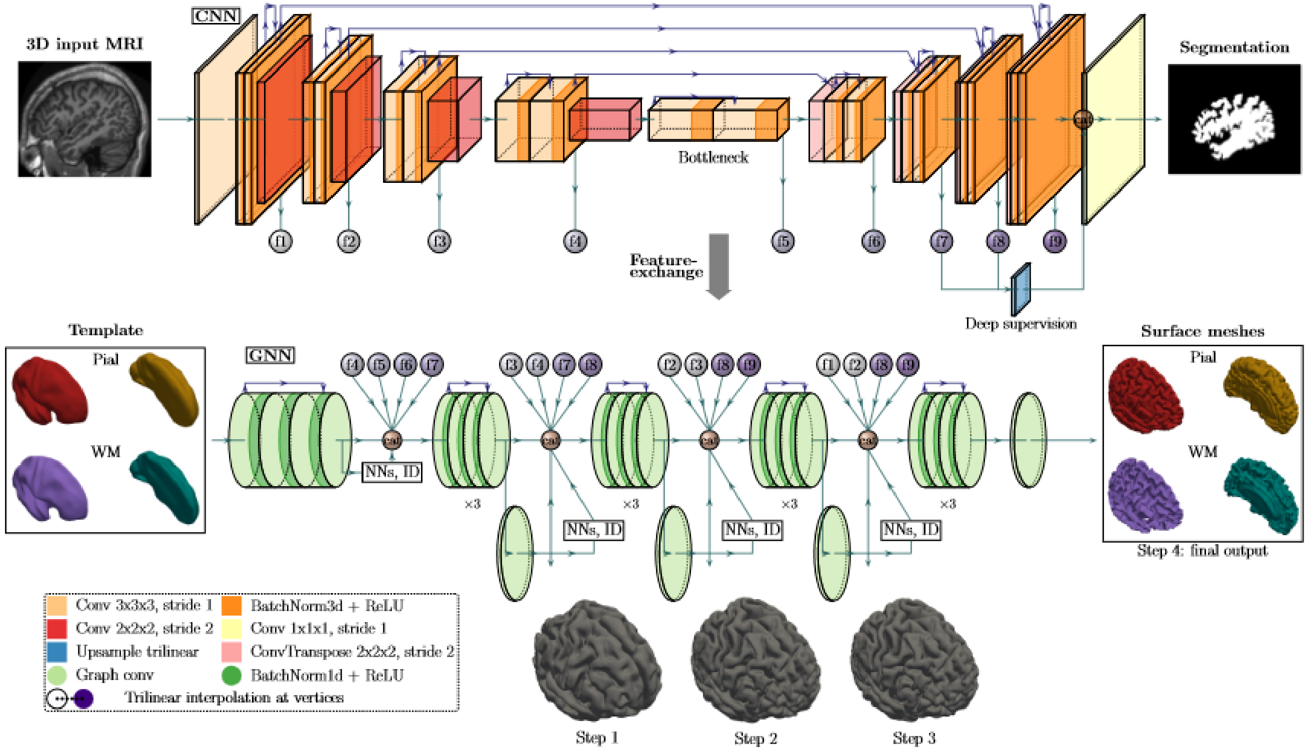


METHODOLOGY

METHODOLOGY

Detail of the individual building blocks:

- ❖ **Image encoding and decoding (CNN)**
- ❖ **Mesh deformation (GNN)**



Loss Functions

❖ The loss function of Vox2Cortex:

$$\mathcal{L}(y^{\mathrm{P}}, y^{\mathrm{gt}}) = \mathcal{L}_{\mathrm{vox}}(y^{\mathrm{P}}, y^{\mathrm{gt}}) + \mathcal{L}_{\mathrm{mesh}}(y^{\mathrm{P}}, y^{\mathrm{gt}})$$

❖ Voxel loss:

$$\mathcal{L}_{\mathrm{vox}}(y^{\mathrm{P}}, y^{\mathrm{gt}}) = \sum_{l=1} \mathcal{L}_{\mathrm{BCE}}(B_l^{\mathrm{P}}, B^{\mathrm{gt}})$$

Loss Functions

Mesh loss:

$$\mathcal{L}_{\mathrm{mesh}}(y^{\mathrm{P}}, y^{\mathrm{gt}}) = \mathcal{L}_{\mathrm{mesh},\,cons}(y^{\mathrm{P}}, y^{\mathrm{gt}}) + \mathcal{L}_{\mathrm{mesh},\,reg}(y^{\mathrm{P}})$$

$$\begin{aligned}\mathcal{L}_{\mathrm{mesh},\,cons}(y^{\mathrm{P}}, y^{\mathrm{gt}}) = \sum_{s=1}^{S}\sum_{c=1}^{C}\Big[&\lambda_{1,c}\,\mathcal{L}_{\mathrm{C}}(\mathcal{M}^{\mathrm{P}}_{s,c}, \mathcal{M}^{\mathrm{gt}}_{c}) \\ &+ \lambda_{2,c}\,\mathcal{L}_{\mathrm{n},\,inter}(\mathcal{M}^{\mathrm{P}}_{s,c}, \mathcal{M}^{\mathrm{gt}}_{c})\Big].\end{aligned}$$

$$\begin{aligned}\mathcal{L}_{\mathrm{mesh},\,reg}(y^{\mathrm{P}}) = \sum_{s=1}^{S}\sum_{c=1}^{C}\Big[&\lambda_{3,c}\,\mathcal{L}_{\mathrm{Lap},\,rel}(\mathcal{M}^{\mathrm{P}}_{s,c}, \boldsymbol{\Delta}^{\mathrm{P}}_{s,c}) \\ &+ \lambda_{4,c}\,\mathcal{L}_{\mathrm{n},\,intra}(\mathcal{M}^{\mathrm{P}}_{s,c}) \\ &+ \lambda_{5,c}\,\mathcal{L}_{\mathrm{edge}}(\mathcal{M}^{\mathrm{P}}_{s,c})\Big].\end{aligned}$$

DATASETS AND PRE-PROCESSING

Datasets and Pre-processing

❖ Pre-processing

- Registering MRI scans to the MNI152 space
- Resize to 128×144×128 voxels

❖ Dataset

ADNI

- Provides MRI T1 scans for subjects with Alzheimer’s Disease, Mild Cognitive Impairment, and healthy subjects
- Balanced according to diagnosis, age, and sex
- ADNIlarge contains 1,155 subjects
- ADNIsmall contains 299 subjects

OASIS

- Contains MRI T1 scans of 416 subjects
- 100 subjects have been diagnosed with very mild to moderate Alzheimer’s disease
- Balanced on diagnosis, age, and sex

COMPARISON

COMPARISON

- Average Symmetric Surface Distance (ASSD)
- 90-Percentile Hausdorff Distance (HD)

		Left WM Surface		Right WM Surface		Left Pial Surface		Right Pial Surface	
Data	Method	ASSD	HD	ASSD	HD	ASSD	HD	ASSD	HD
ADNI large	Vox2Cortex	**0.345** ±0.056	**0.720** ±0.125	**0.347** ±0.046	**0.720** ±0.087	**0.327** ±0.031	**0.755** ±0.102	**0.318** ±0.029	**0.781** ±0.102
	DeepCSR [4]	0.422 ±0.058	0.852 ±0.134	0.420 ±0.058	0.880 ±0.156	0.454 ±0.059	0.927 ±0.243	0.422 ±0.053	0.890 ±0.197
	nnUNet [23]	1.176 ±0.345	1.801 ±2.835	1.159 ±0.242	1.739 ±1.880	1.310 ±0.292	3.152 ±2.374	1.317 ±0.312	3.295 ±2.387
OASIS	Vox2Cortex	**0.315** ±0.039	**0.680** ±0.137	**0.318** ±0.048	0.682 ±0.151	**0.362** ±0.036	**0.894** ±0.141	**0.373** ±0.041	**0.916** ±0.137
	DeepCSR [4]	0.360 ±0.042	0.731 ±0.104	0.335 ±0.050	**0.670** ±0.195	0.458 ±0.056	1.044 ±0.290	0.442 ±0.058	1.037 ±0.294

LIMITATION

Limitations

- No Ground Truth: they used FreeSurfer surfaces as pseudo ground-truth due to the absence of manually generated ground-truth surfaces for their data

- Limited Data Scope: their analysis only includes healthy subjects and those with dementia, so the model may not perform accurately in the presence of other brain morphological changes like tumors

- Data Specificity: their model's performance is based on the discussed data and may not generalize well to unseen data from different domains

- Fairness: they balanced data splits with respect to age and sex, their model might still have biases and potentially discriminate against underrepresented groups

FEATURE

Feature

- Vox2Cortex simultaneously predicts white matter (WM) and pial surfaces of both hemispheres, resulting in an output of four meshes

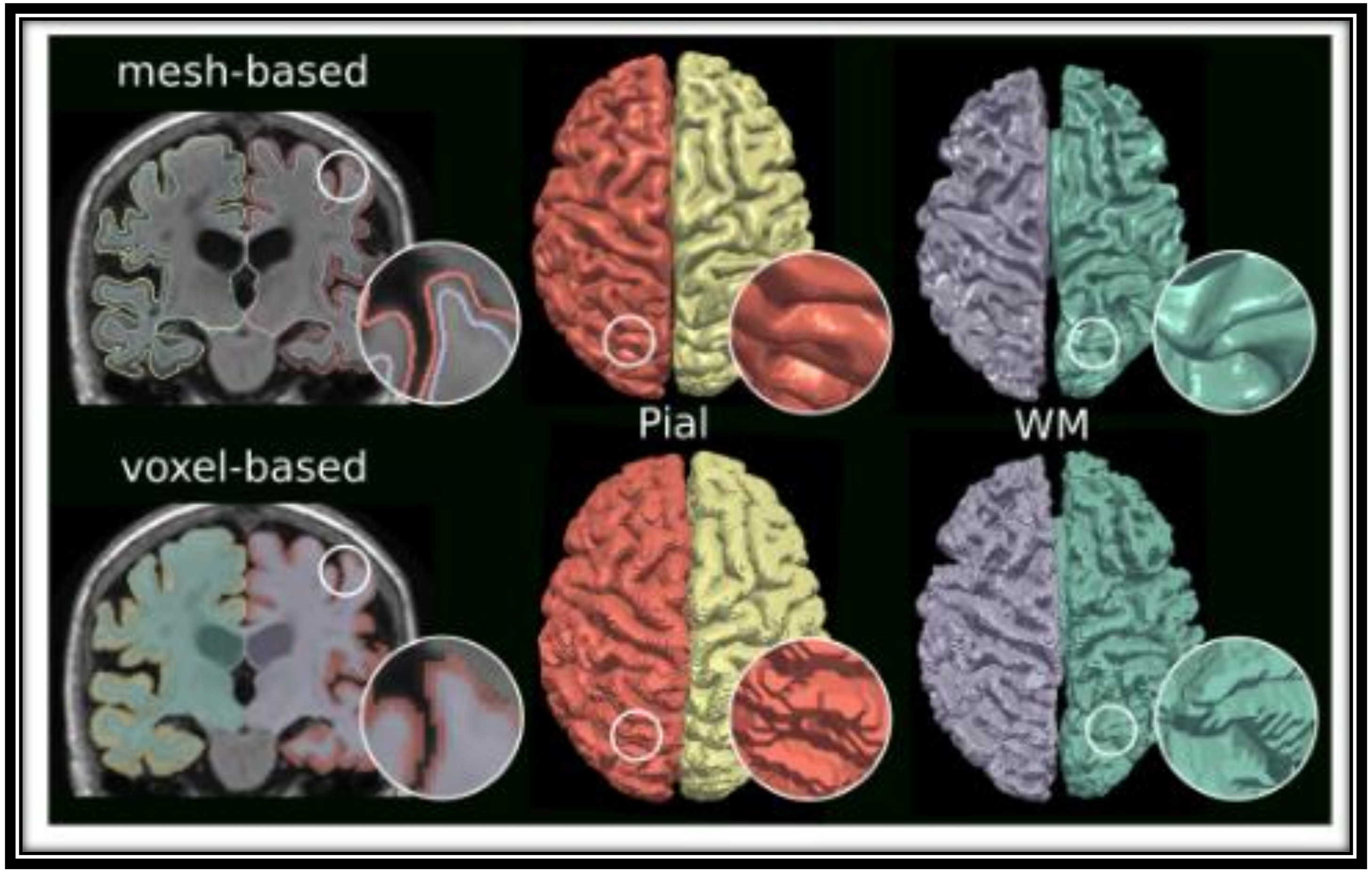
- Vox2Cortex models the interdependency between WM and pial surfaces by exchanging information between them

- In contrast to time-consuming traditional methods for brain analysis, such a network performs the segmentation in seconds

- The current standard for cortical surface reconstruction is FreeSufer, which produces smooth, accurate, and topologically correct surface meshes but runs for several hours per scan

- Current deep-learning approaches for cortical surface reconstruction focus on voxel-based or implicit surface reconstruction methods

Example



CONCLUSION

Conclusion

In summary, Vox2Cortex is a groundbreaking approach for explicit cortical surface reconstruction, offering speed, accuracy, and many promising applications

Thank you!