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




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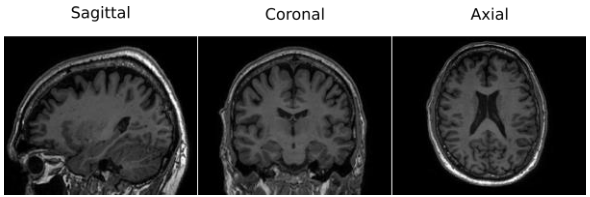
Cortical Surface Reconstruction

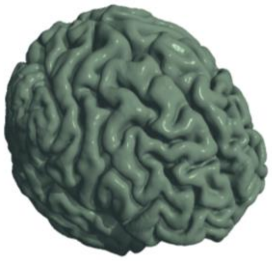
Extract inner and outer boundary surfaces of the cortex from the MRI scan



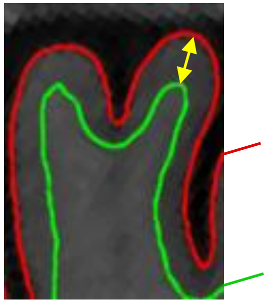
3D MRI scan

Inner surface of cortex

Outer surface of cortex



Morphological measurements



Outer surface

Inner surface

Cortical Surface Reconstruction

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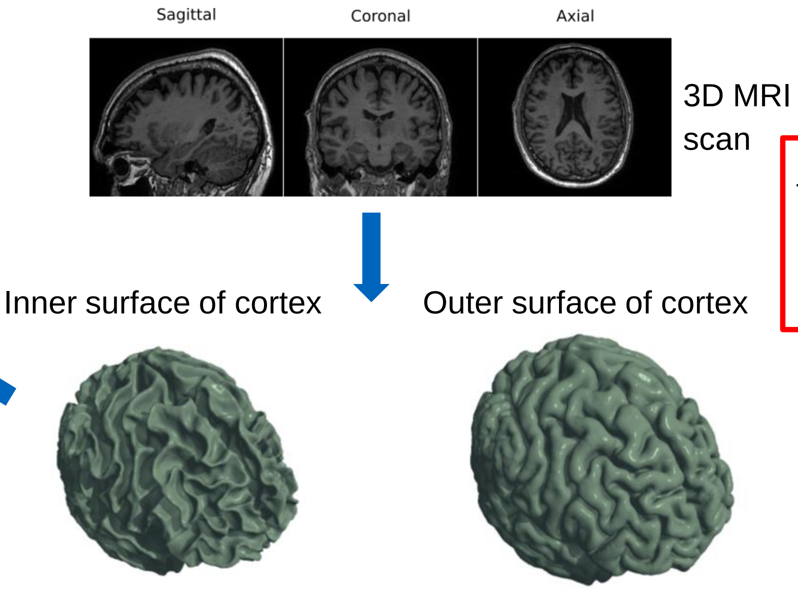
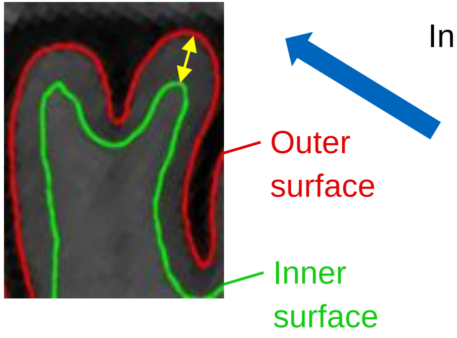


Difficulties:

- Partial volume effect
- Tightly folded geometry
- Guaranteed spherical topology

Morphological measurements



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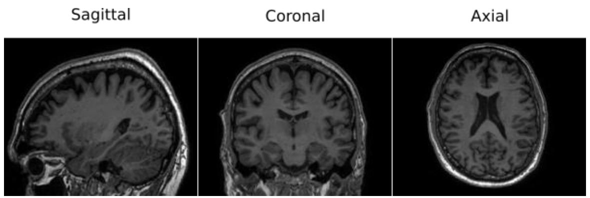


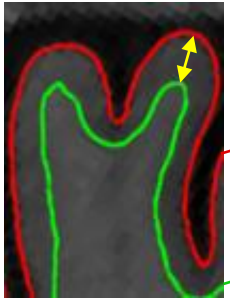
3D MRI scan

Vox2Cortex

Inner surface of cortex

Outer surface of cortex

Morphological measurements

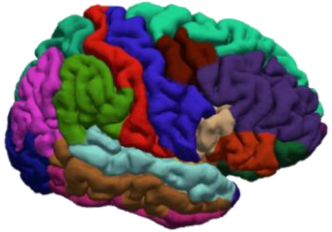


Outer surface

Inner surface

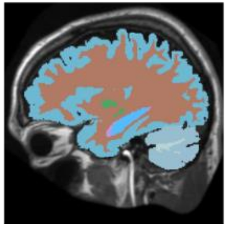
Existing Approaches for Cortical Surface Reconstruction

Traditional frameworks



FreeSurfer [1]

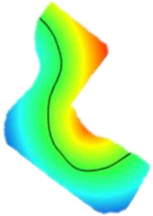
Voxel-based segmentation



+ Topology correction
+ Surface extraction

Any segmentation method,
e.g., nnUNet [2]

Implicit surfaces



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DeepCSR [3]

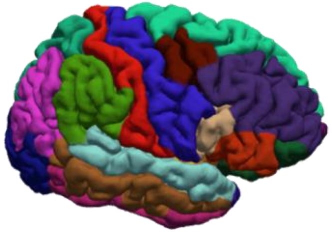
[1] B. Fischl. “FreeSurfer”. In: Neuroimage 62.2 (2012), pp. 774–781

[2] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. Maier-Hein. “nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation.” In: Nature methods (2020)

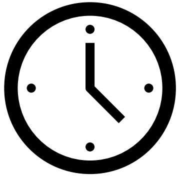
[3] R. S. Cruz, L. Lebrat, P. Bourgeat, C. Fookes, J. Fripp, and O. Salvado. “DeepCSR: A 3D Deep Learning Approach for Cortical Surface Reconstruction”. In: 2021 IEEE Winter Conference on Applications of Computer Vision (WACV) (2021)

Existing Approaches for Cortical Surface Reconstruction

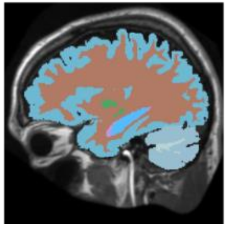
Traditional frameworks



>4h per scan



Voxel-based segmentation



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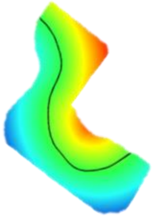

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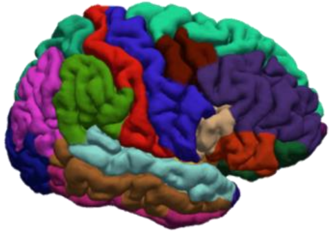

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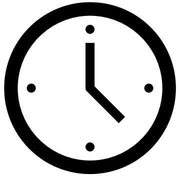

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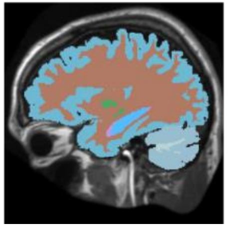

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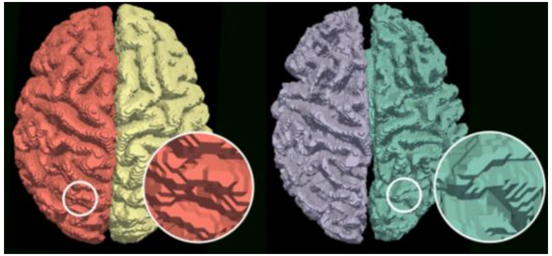
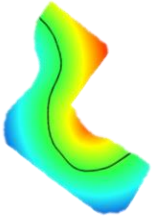
Staircase artifacts



Implicit surfaces



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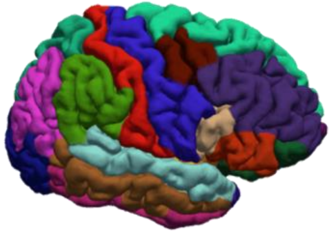

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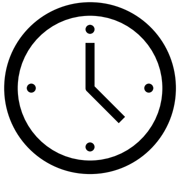

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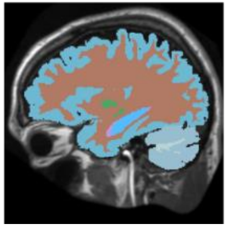

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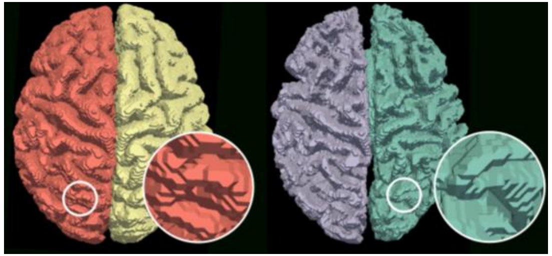
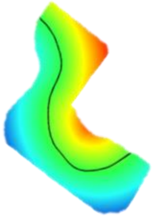


Implicit surfaces



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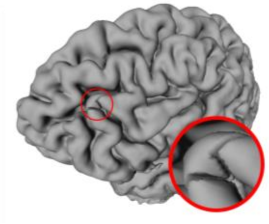
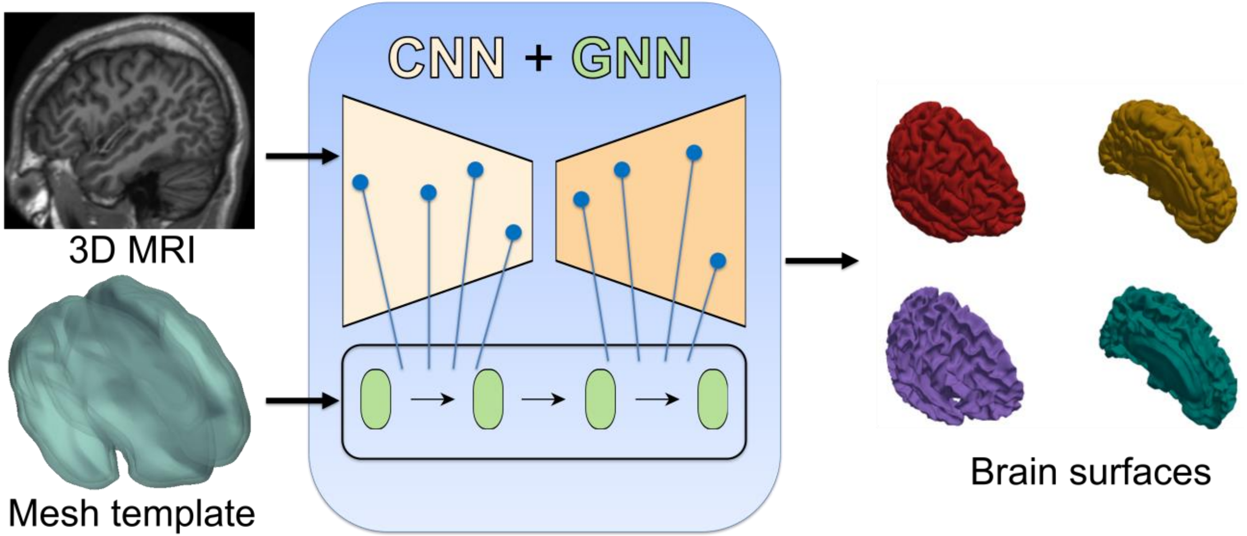
Geometric errors

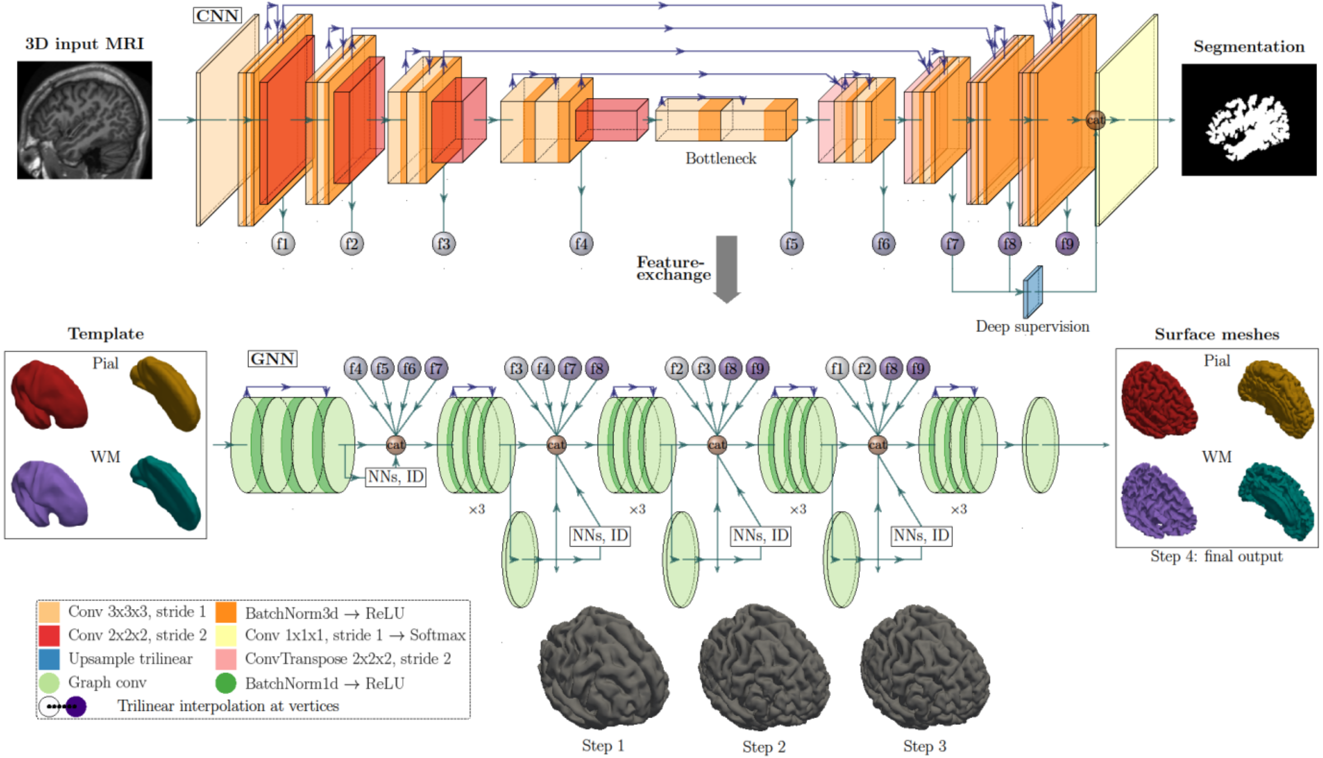


Vox2Cortex Architecture

Deform a brain template based on features extracted from the input image



Vox2Cortex Architecture



Loss Function

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

y^{p}: Predicted mesh & binary segmentation

y^{gt}: Ground-truth mesh & binary segmentation

Loss Function

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

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

y^{p}: Predicted mesh & binary segmentation

y^{gt}: Ground-truth mesh & binary segmentation

Loss Function

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

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

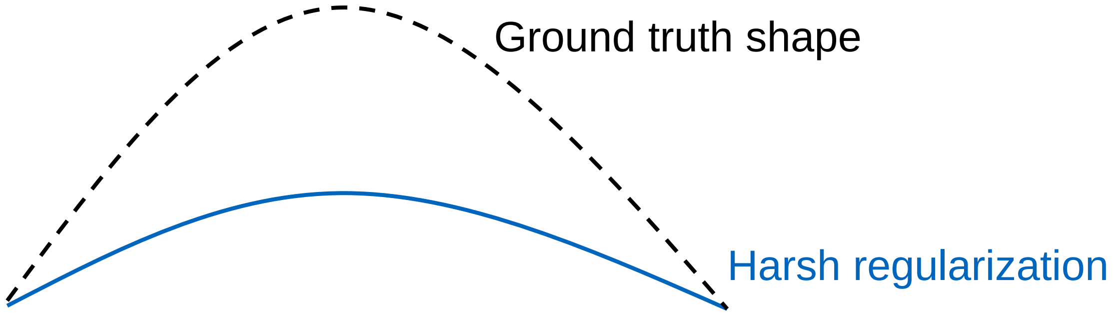
$$\mathcal{L}_{\mathrm{mesh}}(y^{\mathrm{p}}, y^{\mathrm{gt}}) = \underbrace{\mathcal{L}_{\mathrm{mesh},\, cons}(y^{\mathrm{p}}, y^{\mathrm{gt}})}_{\text{Chamfer (point) + normal loss}} + \overbrace{\mathcal{L}_{\mathrm{mesh},\, reg}(y^{\mathrm{p}})}^{\text{Surface regularity}}$$

y^{p}: Predicted mesh & binary segmentation

y^{gt}: Ground-truth mesh & binary segmentation

Curvature-Weighted Chamfer Loss

Weight point loss locally to thwart regularizers in densely folded regions



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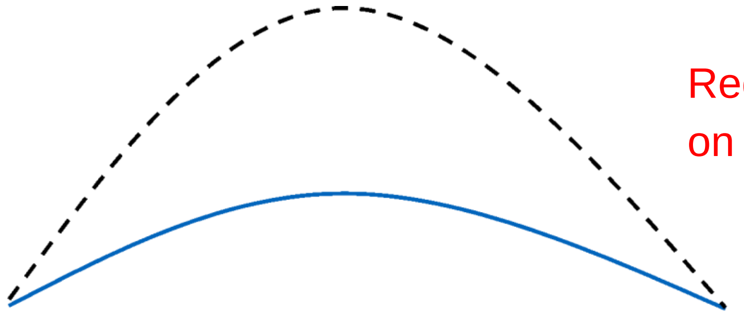
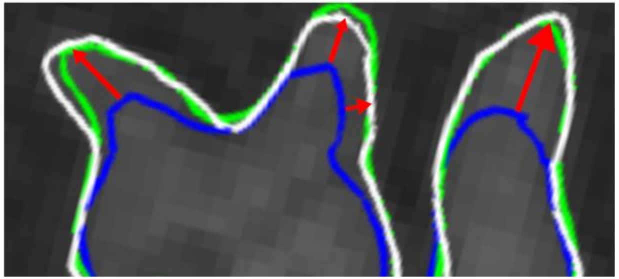


Regularization reweighted based on ground-truth curvature

Curvature-Weighted Chamfer Loss

Weight point loss locally to thwart regularizers where necessary



Blue: standard Chamfer

Green: curvature-weighted Chamfer

White: FreeSurfer [1]

[1] B. Fischl. “FreeSurfer”. In: Neuroimage 62.2 (2012), pp. 774–781

Quantitative Results: Surface Accuracy

ASSD: average symmetric surface distance
HD: 90-percentile Hausdorff distance
WM: white matter

		Left WM Surface		Right WM Surface		Left Pial Surface		Right Pial Surface	
Data	Method	ASSD (mm)	HD (mm)	ASSD (mm)	HD (mm)	ASSD (mm)	HD (mm)	ASSD (mm)	HD (mm)
ADNI	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 [1]	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 [2]	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 [1]	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

[1] R. S. Cruz, L. Lebrat, P. Bourgeat, C. Fookes, J. Fripp, and O. Salvado. “DeepCSR: A 3D Deep Learning Approach for Cortical Surface Reconstruction”. In: 2021 IEEE Winter Conference on Applications of Computer Vision (WACV) (2021)

[2] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. Maier-Hein. “nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation.” In: Nature methods (2020)

Quantitative Results: Inference Time

Method	Inference time
Vox2Cortex (ours)	18.0s
Vox2Cortex* (ours)	2.1s
DeepCSR [2]	445.7s
FreeSurfer [1]	>4h

*~42,000 instead of 168,000 vertices per surface

[1] B. Fischl. “FreeSurfer”. In: Neuroimage 62.2 (2012), pp. 774–781

[2] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. Maier-Hein. “nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation.” In: Nature methods (2020)

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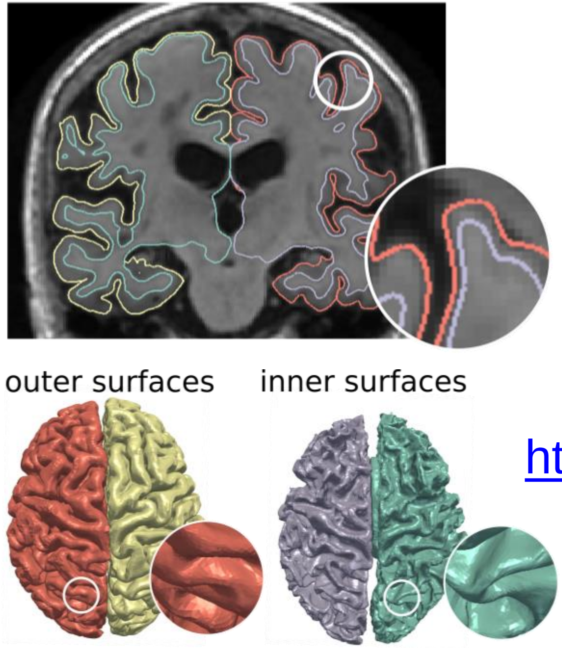
Vox2Cortex



https://ai-med.github.io/Vox2Cortex/

Contact

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www.ai-med.de