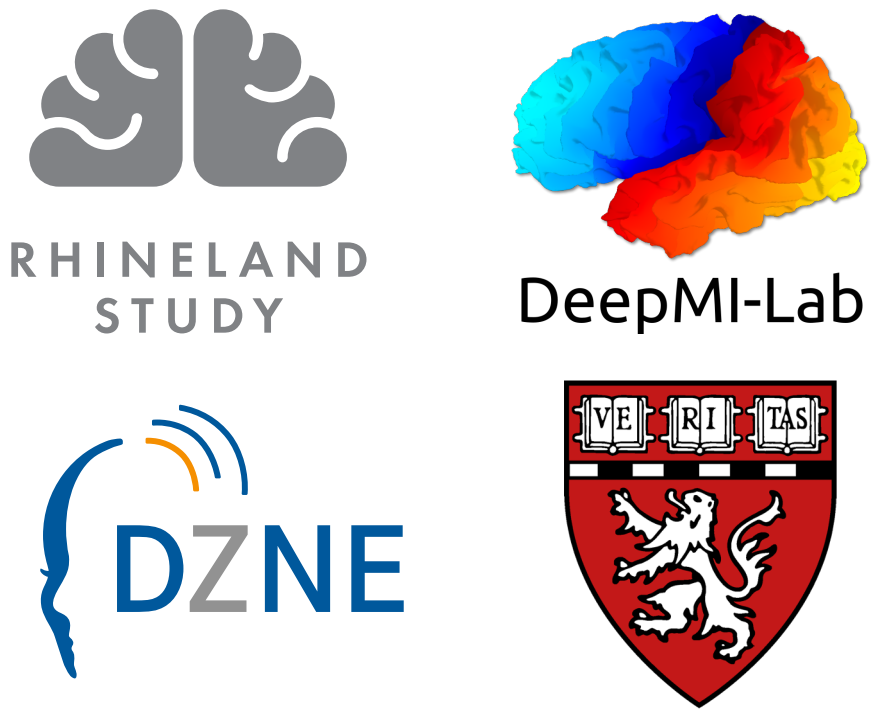


# Automated Olfactory Bulb Segmentation on High-Resolutional T2-Weighted MRI

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## Introduction

- The olfactory bulb (OB) plays a crucial role in olfactory function.
- To date, there is a lack of an automatic processing method for OB segmentation in the neuroimage analysis community.
- Automatic OB segmentation is a challenging task due to its small size, location and poor visibility on traditional MRI scans.
- Here, we introduce the first publicly available deep learning pipeline to segment the OBs in sub-millimeter T2-weighted whole-brain MRI.
- The proposed pipeline is tested and validated in the Rhineland Study – a large prospective cohort study based in Bonn, Germany.

## Our Proposal

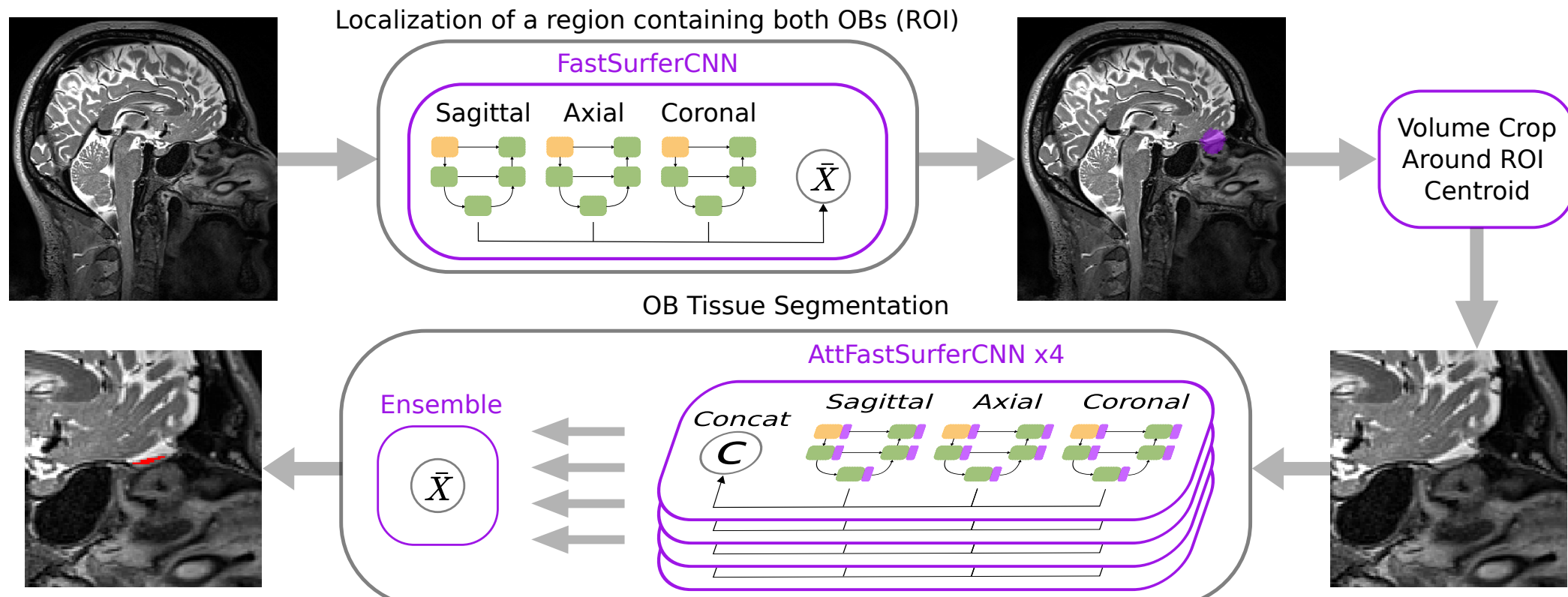


Fig 1. Proposed pipeline for OB segmentation. The pipeline is divided in three stages: First, localization of a ROI containing both OBs. Then, OB tissue segmentation within the localized volume, and finally, an ensemble of the predicted label maps.

- We modify our *FastSurferCNN*<sup>1</sup> to focus on the OB.
- To improve performance for small structures, we suitably included the self-attention mechanism proposed by Zhang et al.<sup>2</sup> into *FastSurferCNN*.
- The new architecture termed *AttFastSurferCNN* promotes attention to spatial information by improving the modeling of local and global-range dependencies, which in turn increases semantic consistency.
- The pipeline combines the prediction of four *AttFastSurferCNN*s, ensuring that only OB voxels with a high inter-model agreement are segmented.

## Ground Truth Dataset Characteristics

Usage	Cohort	N	Age Range	Women, n (%)
Training set	The Rhineland Study	357	30-85	204 (57.1%)
Testing set		203	30-87	114 (56.2%)
Generalizability set	Human Connectome Project (HCP) <sup>3</sup>	30	22-35	14 (46.6%)

## Validation in the Rhineland Study (N=203)

### - OB Segmentation Accuracy

Network	Dice Mean (SD)	AVD Mean (SD)
<i>AttFastSurferCNN</i>	<b>0.8525 (0.0561)*</b>	0.2692 (0.1913)
<i>FastSurferCNN</i>	0.8506 (0.0577)	<b>0.2667 (0.1860)</b>
Inter-rater variability	0.8211 (0.0590)	0.3057 (0.2685)

Significance : \* p < 0.05, paired Wilcoxon signed-rank test

### - Replication of known age and sex effect on OB volumes

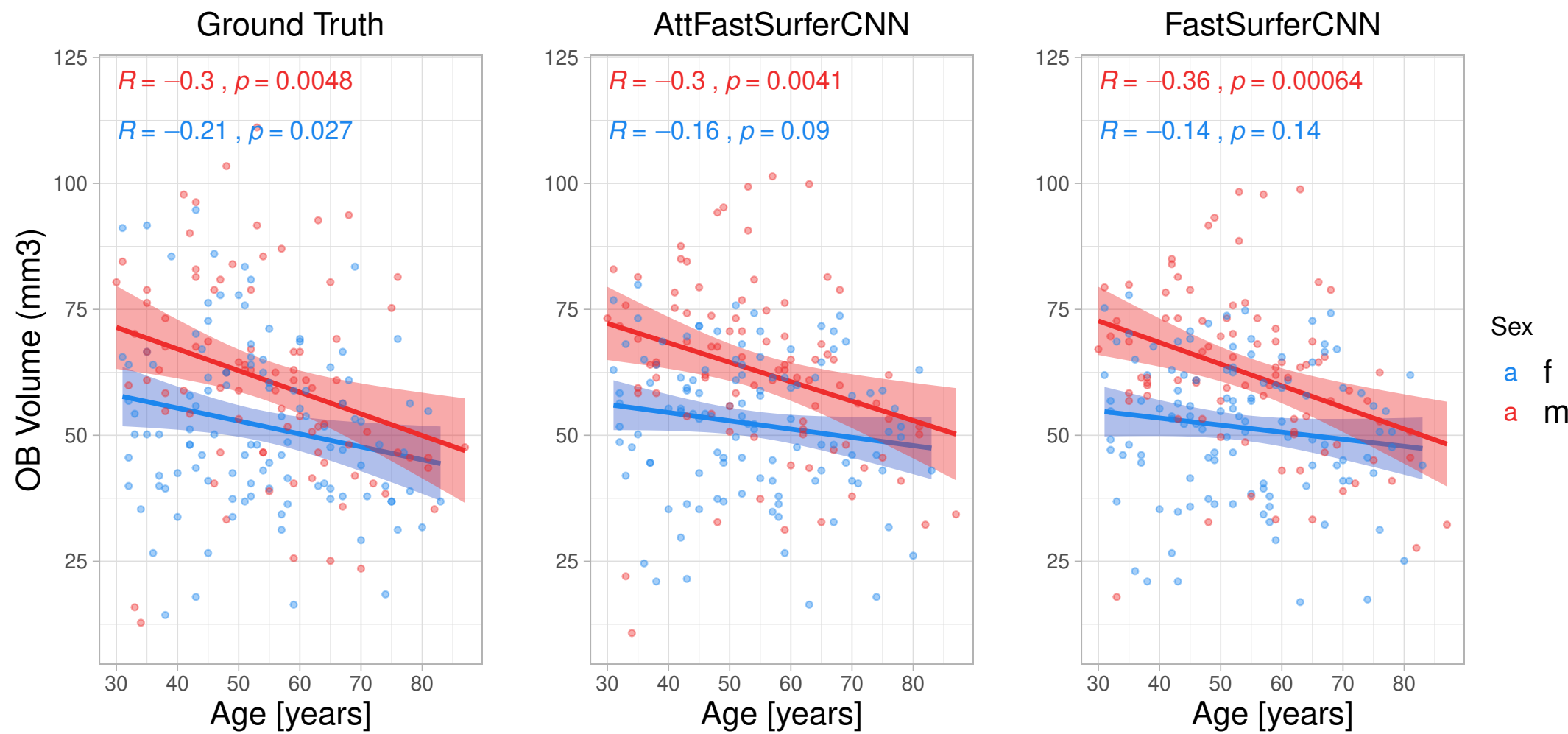
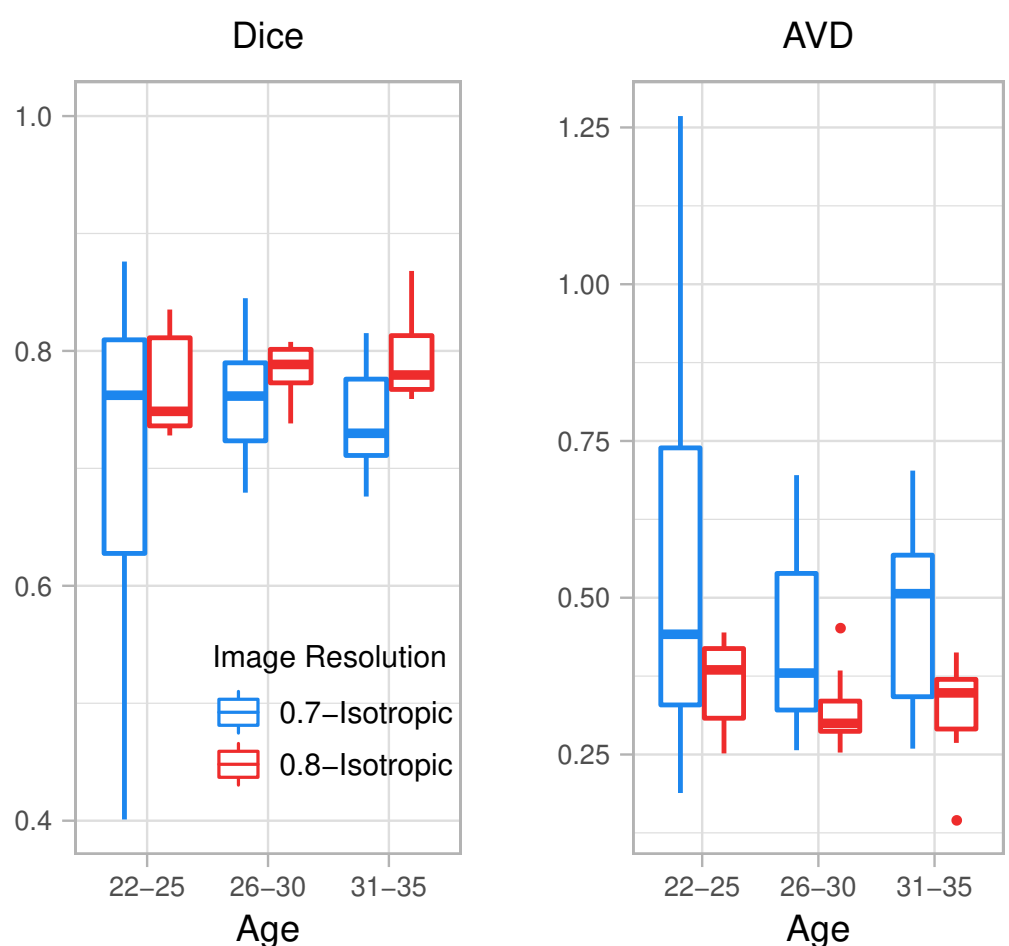


Fig 2. Association between age and olfactory bulb volumes in men and women for the ground truth (manual labels) and automated methods.

- The predicted OB volumes are significantly decreased with age (*AttFastSurferCNN*: ( $\beta = -0.230$ ,  $p < 0.01$ ), and *FastSurferCNN*: ( $\beta = -0.203$ ,  $p < 0.01$ )), following the behaviour of the manual data ( $\beta = -0.319$ ,  $p < 0.01$ ) and other studies<sup>4,5</sup>.
- AttFastSurferCNN* presents an improvement in the modeling of the age effects compared to the standard *FastSurferCNN* ( $R^2$  : **0.205** vs 0.193).

## Generalizability in the HCP dataset (N=30)



- Segmentation results are more stable at original training resolution (0.8 mm isotropic).
- Accuracy decreases at native HCP resolution, specifically for ages outside the training range (22 to 25).
- HCP consist of de-faced scans, never encounter during training.

Fig 3. Segmentation similarity scores from the HCP dataset stratified by age category, as well as comparison of the pipeline's performance at native HCP resolution (0.7 mm isotropic) and at the networks original training resolution (0.8 mm isotropic).

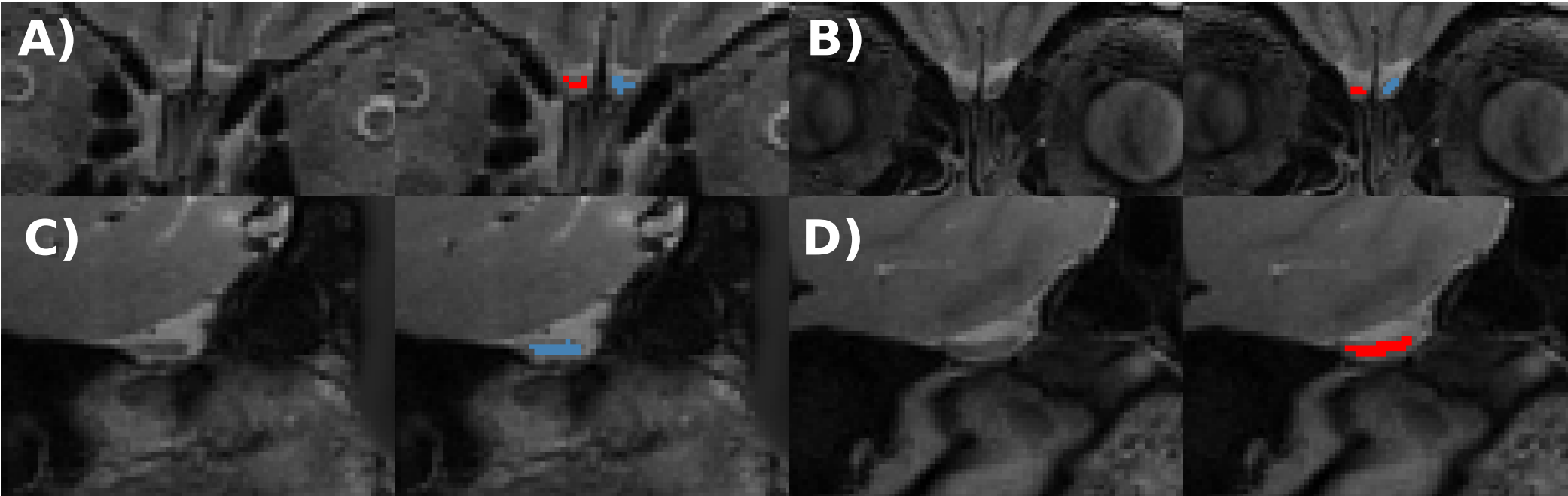


Fig 4. Examples of the pipeline results in the Rhineland Study (A-B) and HCP dataset (C-D). Accurate automatic segmentation of total OB on a heterogenous population (blue : left OB and red : right OB).

## Conclusion

- The proposed pipeline provides a robust and reliable solution for assessing OB volumes in a large cohort study.
- AttFastSurferCNN* recovers OB significantly better than the standard *FastSurferCNN* and outperforms manual inter-rater scores.
- AttFastSurferCNN* shows an improvement when evaluating volume associations despite the slight changes at the image metric level.
- The pipeline shows good generalizability to an independent dataset (HCP) with different acquisition parameters and demographics.
- The pipeline is rigorous validated in terms of segmentation accuracy, as well as sensitivity to replicate known OB volume associations.

## Contact and tool

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Tool : [github.com/Deep-MI/olf\\_bulb\\_segmentation](https://github.com/Deep-MI/olf_bulb_segmentation)

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## References

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