

# Toward Automatic Segmentation for Non-human Primates



Xinhui Li<sup>1</sup>, Xindi Wang<sup>2</sup>, Kathleen Mantell<sup>3</sup>, Estefania Cruz Casillo<sup>3</sup>, Michael Milham<sup>1</sup>, Alex Opitz<sup>3</sup>, Ting Xu<sup>1</sup>

<sup>1</sup>Child Mind Institute, New York, New York, USA

<sup>2</sup>Montreal Neurological Institute, McGill University, Montreal, Québec, Canada

<sup>3</sup>Department of Biomedical Engineering, University of Minnesota, Minneapolis, Minnesota, USA

Contact: xinhui.li@childmind.org, ting.xu@childmind.org



## Introduction

Tissue segmentation of individual magnetic resonance imaging (MRI) is a fundamental step in building the nonhuman primate (NHP) model for brain stimulation. In humans, several automatic tools have been developed (e.g., FreeSurfer, CAT etc.), including the newly advanced deep-learning techniques (e.g., FastSurfer). However, due to the minimal sample size and limited training data in most NHP studies, it is challenging to extend the human segmentation tools in NHPs. Recently, our team developed a transfer-learning U-Net model which enables automatically extracting the brain mask in NHPs (Wang et al., 2020). By pre-training the model with a large human sample, the transferred model that was upgraded using a small NHP training sample outperformed the traditional brain extraction tools.

To create head models for electric field simulations and support translational efforts in neuromodulation, we leveraged the similar transfer-learning framework and extended the U-Net model to automatically segment multiple tissues including white matter (WM), gray matter (GM), cerebrospinal fluid (CSF), skull, skin, and eyes.

## Method

To create a large human training data, we first generated the segmentations in SimNIBS software (Thielscher et al., 2015) using the Human Connectome Project (HCP) MRI T1 scans (N=145).

Next, we carried out a pre-training process in 115 training samples and selected the epoch with the best performance in 15 validation samples. We tested the performance of this initial human model in the remaining 15 human datasets.

We then made use of manually segmented macaque datasets (N=3) and upgraded the pre-trained human model to fit the NHP data. Of note, to improve the data quality and intensity homogeneity of the input data, non-local means filtering and N4 bias field correction were applied on all human and NHP MRI scans.

Number of Subjects	Training	Validation	Testing	Total
Human (HCP)	115	15	15	145
NHP (PRIME-DE, NMT)	3	N/A	2	5

Table 1. Human and NHP dataset information

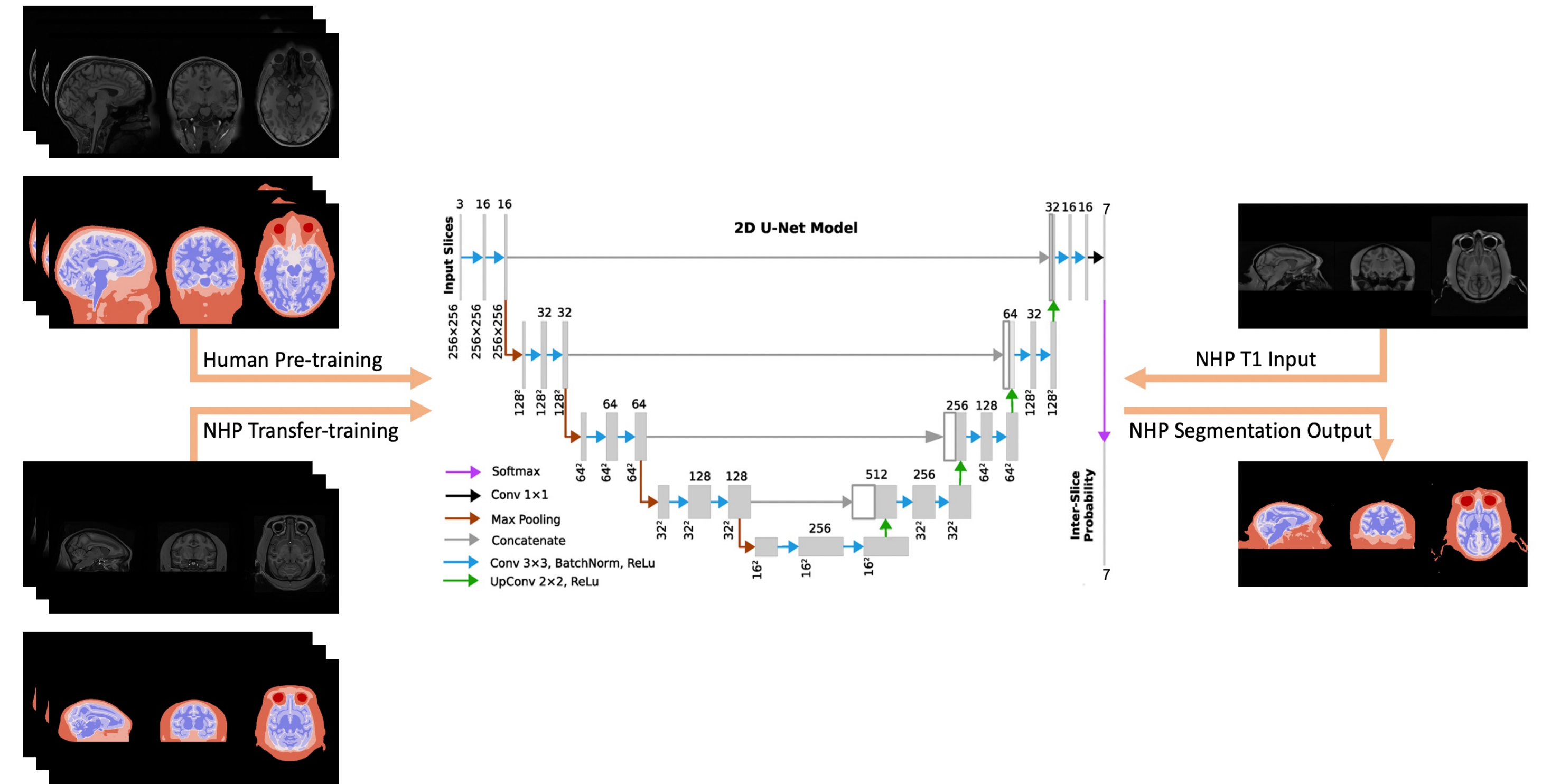


Figure 1. Transfer-learning framework

## Result

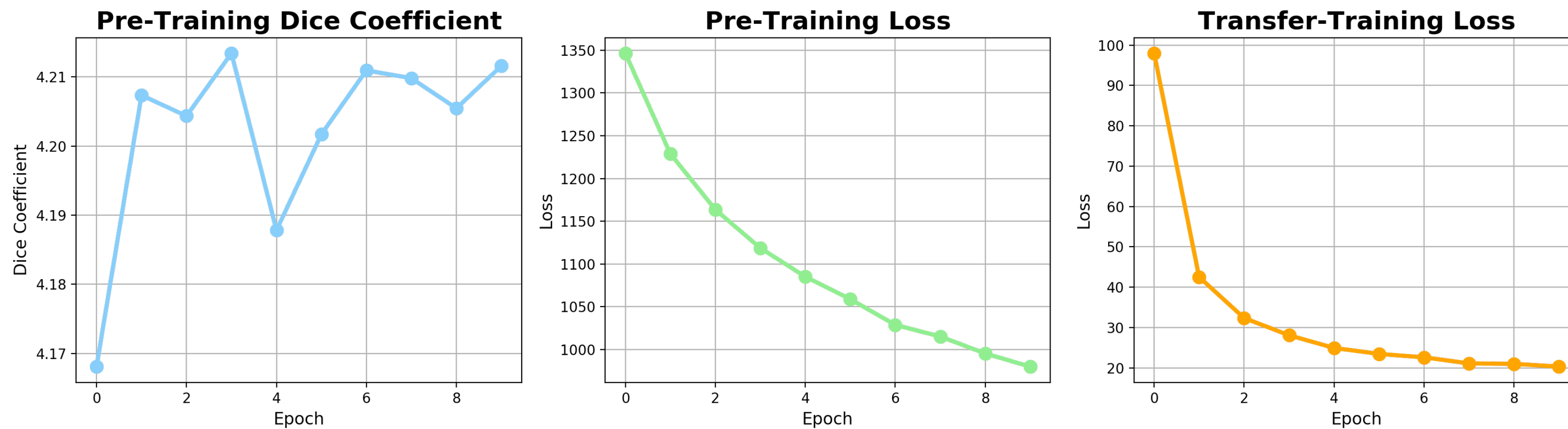


Figure 2. Learning curve

Dice Coefficient	WM	GM	CSF	Skull	Skin	Eyes
Human Test Set	0.92	0.87	0.73	0.88	0.95	0.71
NHP Within Site	0.90	0.83	0.68	0.77	0.88	0.94
NHP Across Site	0.79	0.72	0.61	0.38	0.71	0.75

Table 2. U-Net segmentation performance: Dice coefficients of human test set and NHP test set

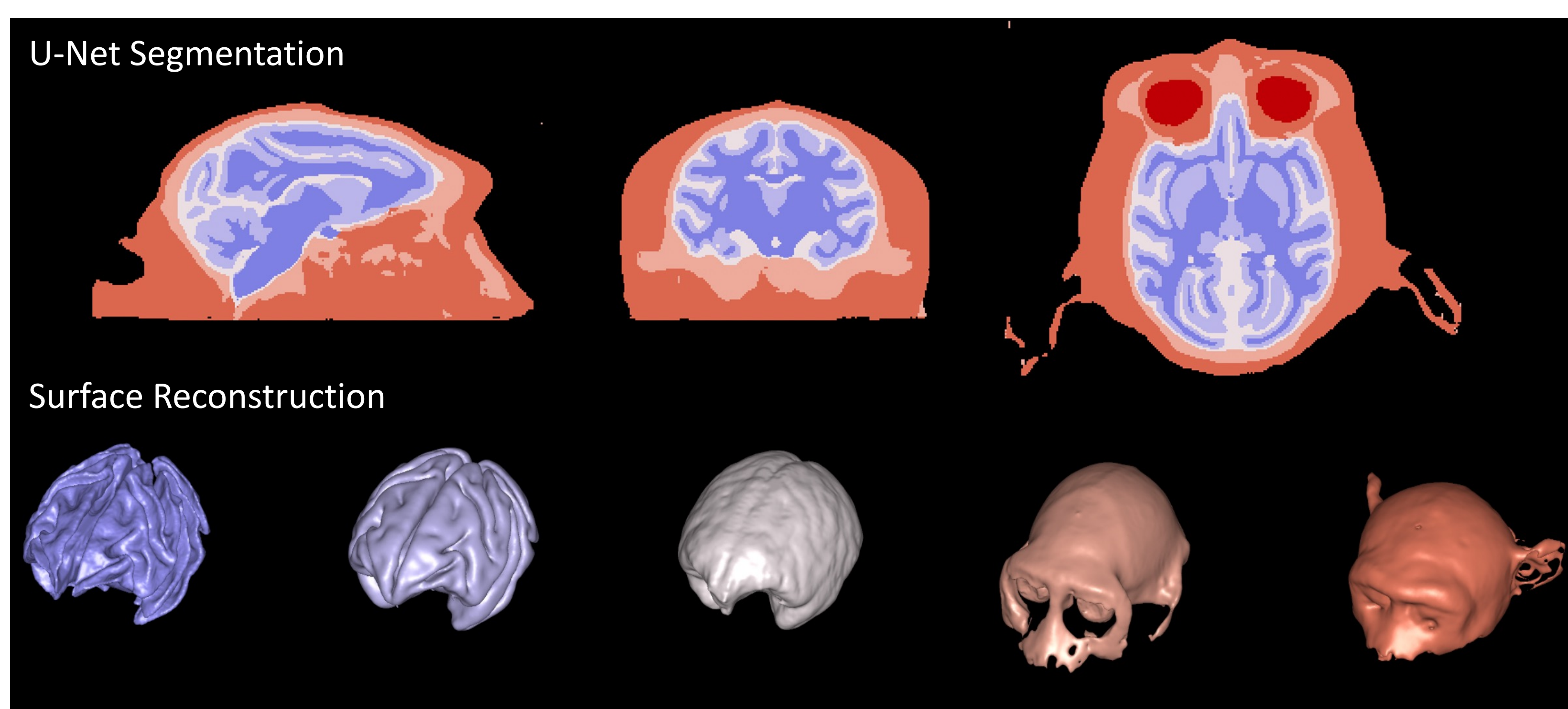


Figure 3. U-Net segmentation (top) and surface reconstruction (bottom)

- The transferred U-Net model was tested on two macaques within and across sites.
- The model exhibited fairly good segmentation for the testing macaque from the same training site (Dice=0.85±0.10, range 0.68-0.94).
- The performance across site is not satisfactory (Dice=0.70±0.16, range 0.38-0.79).

## Conclusion

We extended the transfer-learning method to automate the tissue segmentation in NHPs. Our preliminary U-Net model demonstrated a promising result in our testing set yet limited within the site. Future work may consider adding more training data from multiple sites to overcome the site effect and improve the generalizability of the model.

## Reference

- [1] Wang, X., Li, X., Cho, J. W., Russ, B., Rajamani, N., Omelchenko, A., Ai, L., Korchmaros, A., Garcia, P., Wang, Z., Kalin, N. H., Schroeder, C. E., Craddock, C., Fox, A. S., Evans, A., Messinger, A., Milham, M. P., & Xu, T. (2021). U-Net Model for Brain Extraction on Non-human Primates. *NeuroImage*.
- [2] Thielscher, A., Antunes, A., & Saturnino G. B. (2015). Field modeling for transcranial magnetic stimulation: A useful tool to understand the physiological effects of TMS? 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC).