Automatic Characterization of Cortical Nerve Fiber Distribution Patterns in 3D Polarized Light Imaging

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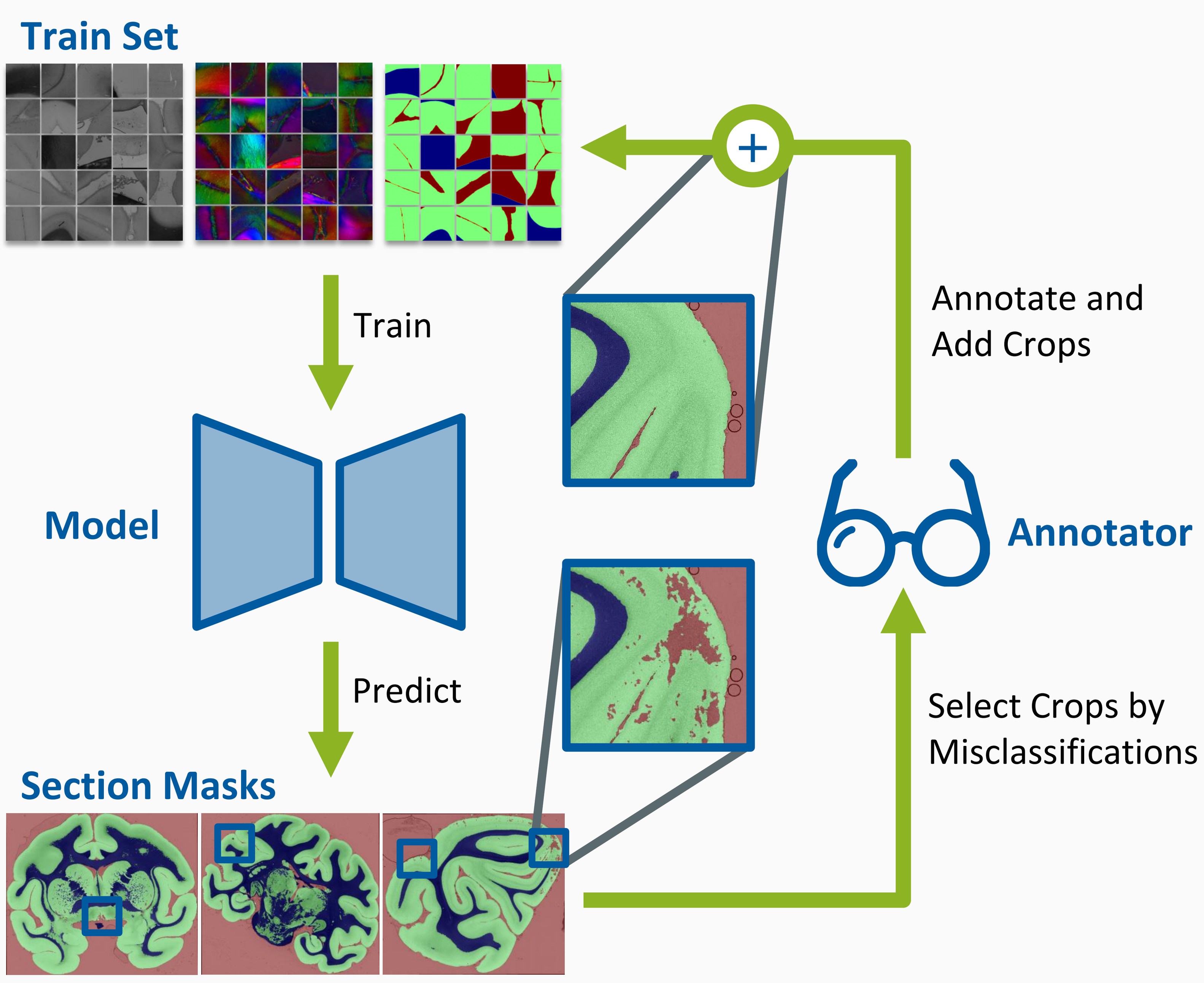
MOTIVATION

Recent advances in **3D polarized light imaging (3D-PLI)** provide a highly detailed view of the cortical fiber architecture of postmortem whole-brain sections at the micrometer scale [1]. As a prerequisite for **automated analysis of cortical architecture**, a precise extraction of the cortex is needed. Therefore, we first aim to train a robust **tissue segmentation model** for 3D-PLI images of sections from a vervet monkey brain, which separates the data into **white-matter (WM)**, **gray-matter (GM)** and **background (BG)**. Then we use the segmentations to formalize the cortical ribbon by **Laplacian streamlines**. Variations in different types of **learned feature maps** along these streamlines indicate changes in the cortical nerve fiber architecture.

TISSUE SEGMENTATION IN AN ACTIVE LEARNING LOOP

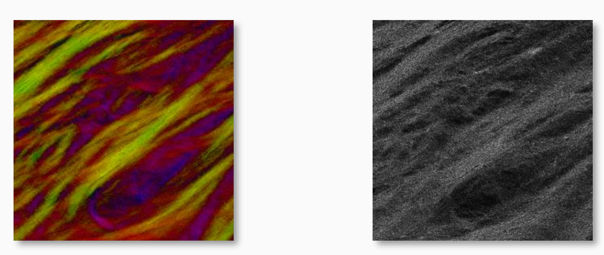


- Selection of crops that provide the **most information to the model**
- Creates a **diverse dataset** capturing many textures throughout the brain

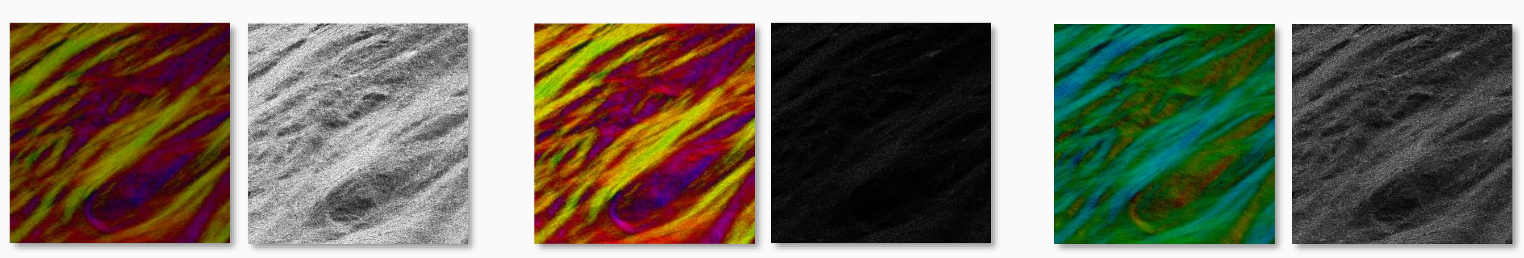
3D-PLI SPECIFIC DATA AUGMENTATIONS

3D-PLI Signal Per Pixel

$$I_\rho = \frac{I_T}{2} \cdot [1 + \sin(2\rho - 2\varphi) \cdot \sin\delta]$$



Augment Signal Parameters



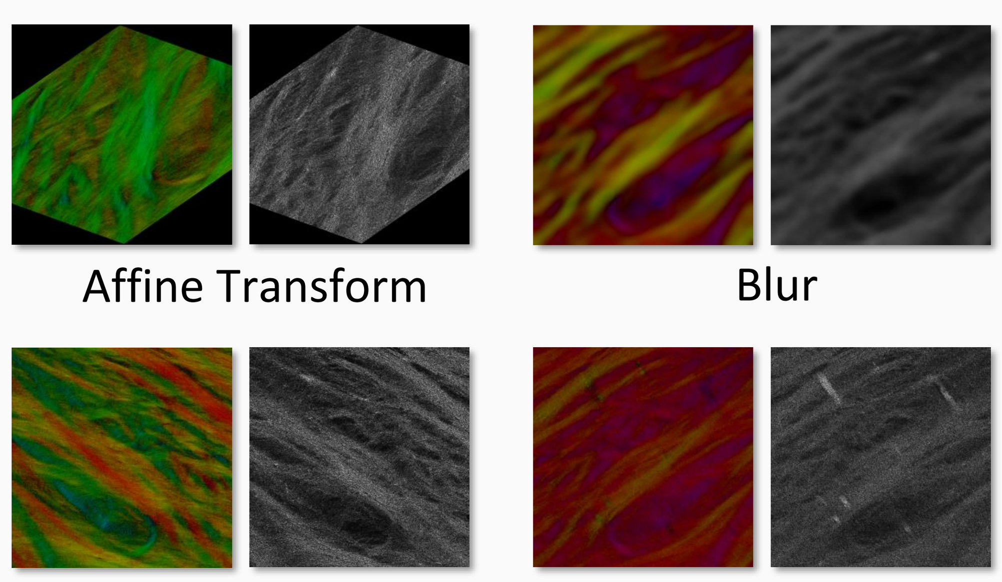
Transform, Filter and Add Signals in Fourier Space

Fourier Coefficients:

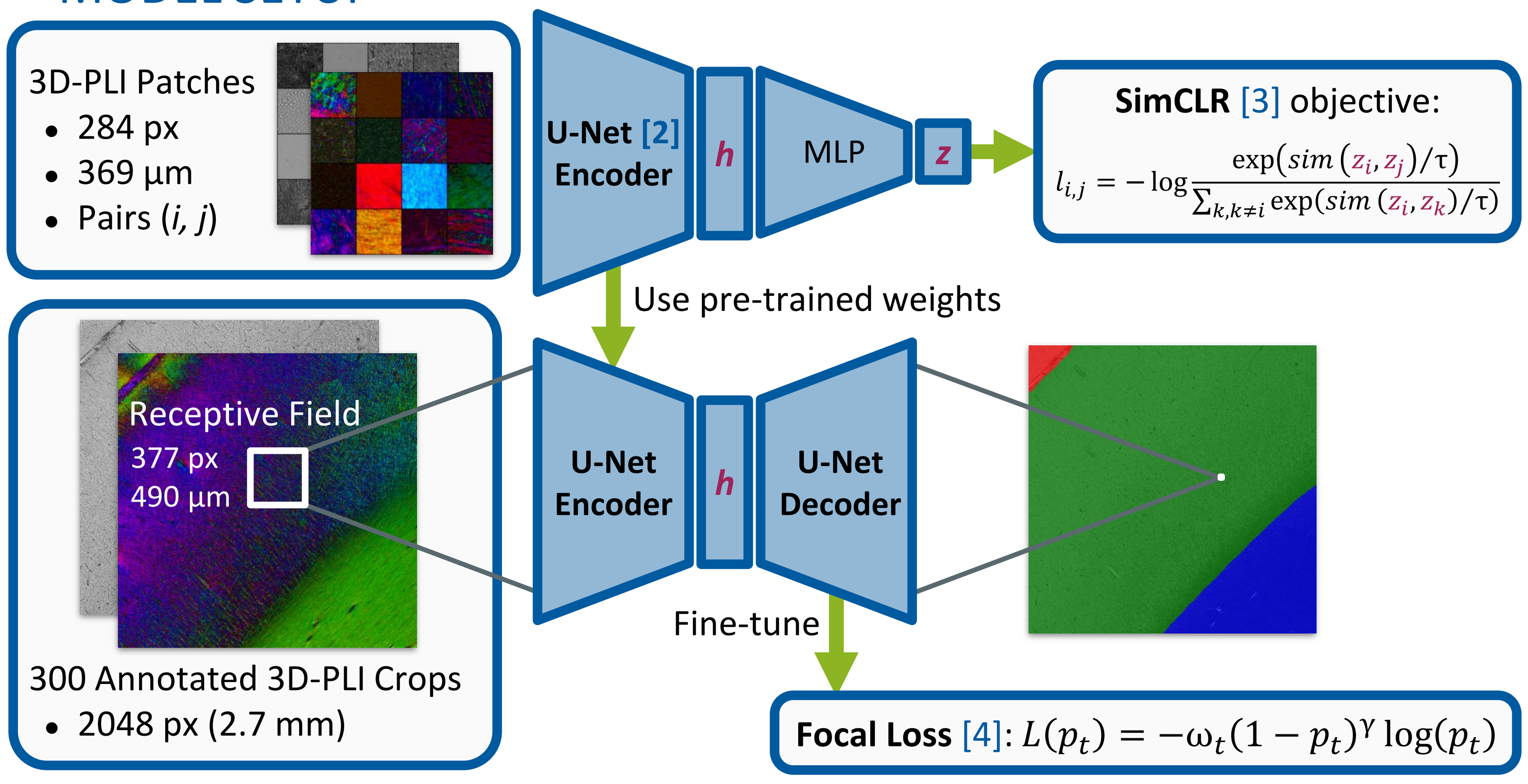
$$a_0 = \frac{I_T}{2}$$

$$a_1 = \frac{I_T}{2} \sin\delta \cos(2\varphi)$$

$$b_1 = -\frac{I_T}{2} \sin\delta \sin(2\varphi)$$



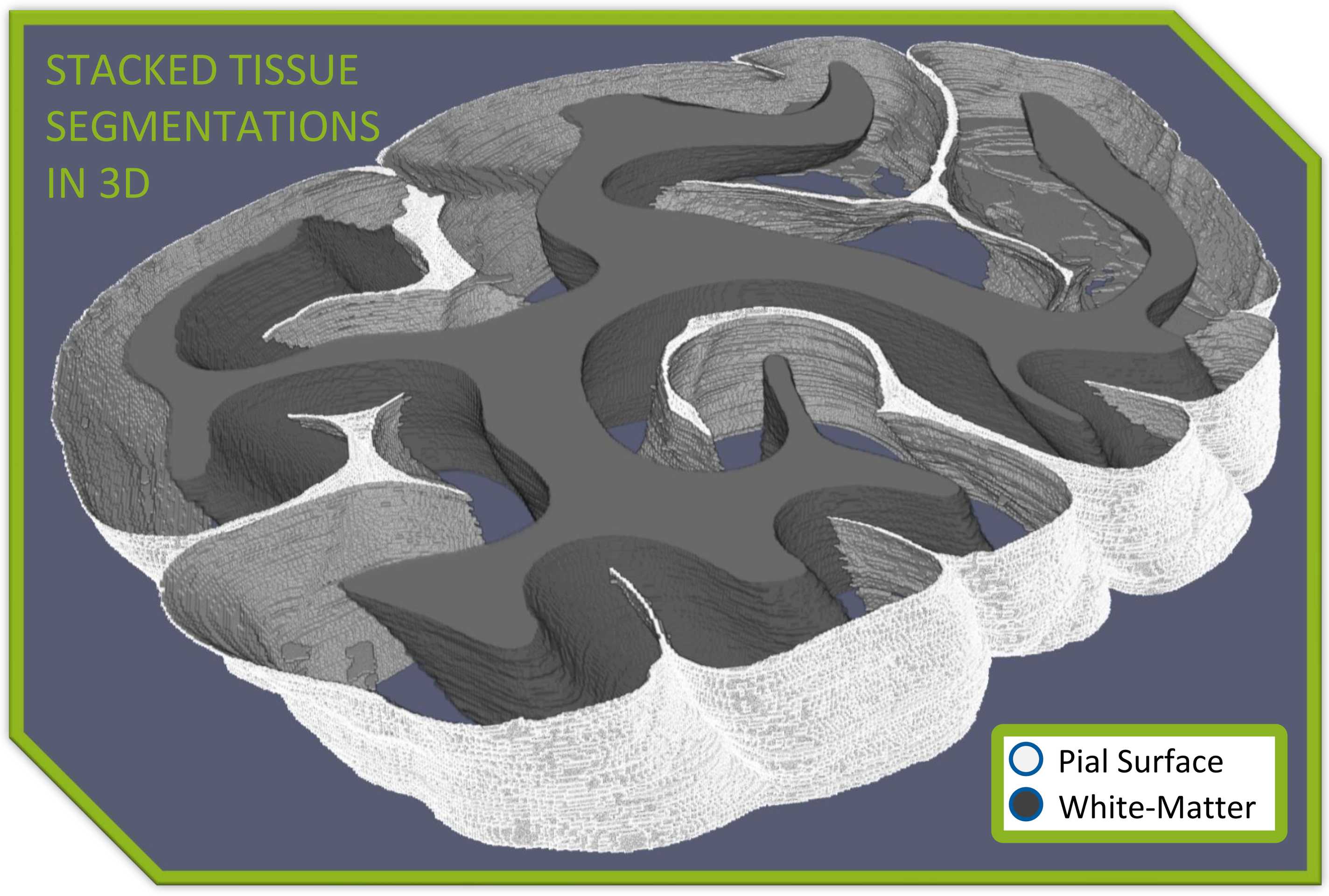
MODEL SETUP



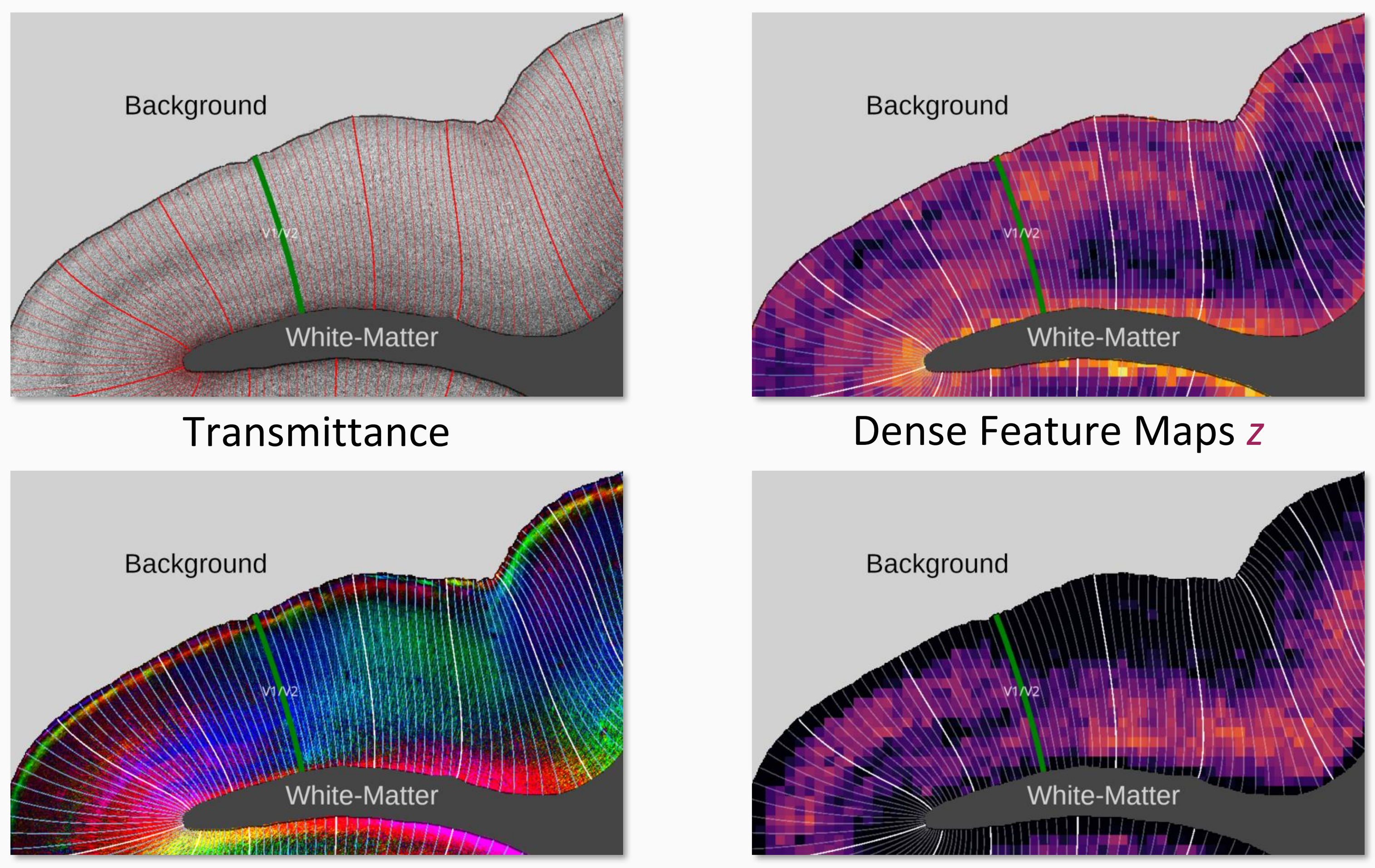
$$l_{i,j} = -\log \frac{\exp(sim(z_i, z_j)/\tau)}{\sum_{k,k\neq i} \exp(sim(z_i, z_k)/\tau)}$$

Focal Loss [4]: $L(p_t) = -\omega_t (1 - p_t)^\gamma \log(p_t)$

- **Contrastive pre-training** of a **U-Net encoder** produces **feature maps** ***h*** and ***z***
- Finetuning of the **U-Net decoder** on the segmentation task using **Focal Loss**



AUTOMATED ANALYSIS OF CORTICAL ARCHITECTURE



- Analyze the cortex along **Laplacian streamlines** between **WM** and **BG**
- Variations in the **feature maps** ***z***, ***h*** indicate changes in the architecture
- The green line highlights the border between visual areas **V1** and **V2**

CONCLUSIONS

- Could achieve a **frequency weighted IOU of 99.2 %** on the segmentation task
- **Consistent boundaries** in 3D (masks were not used for 3D reconstruction)
- Segmentations **enable automated analysis** of large scale data

References
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[4] T.-Y. Lin et al., Proceedings of the IEEE international conference on computer vision, pp. 2980–2988 (2017)

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