

Enhancing New Multiple Sclerosis Lesion Segmentation via Self-supervised Pre-training and Synthetic Lesion Integration - Supplementary Material

Peyman Tahghighi¹✉, Yunyan Zhang^{2,3}, Roberto Souza^{3,4}, and Amin Komeili¹

- ¹ Department of Biomedical Engineering, University of Calgary, Calgary, Canada
peyman.tahghighi@ucalgary.ca
- ² Cumming School of Medicine, Department of Clinical Neurosciences, University of Calgary, Calgary, Canada
- ³ Hotchkiss Brain Institute, University of Calgary, Calgary, Canada
- ⁴ Department of Electrical and Software Engineering, University of Calgary, Calgary, Canada

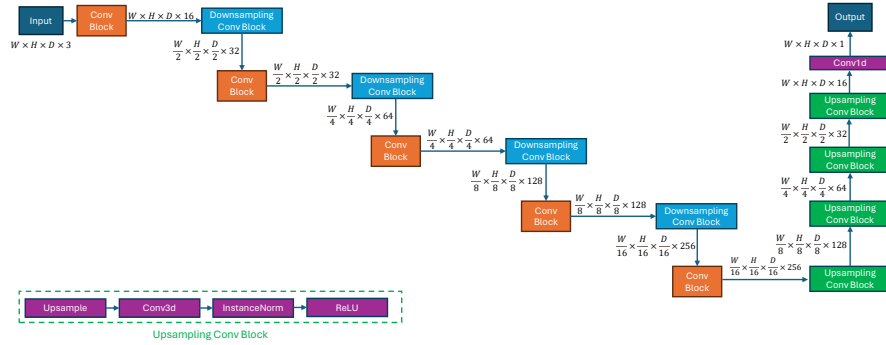


Fig. 1. Diagram of VNet model modified for self-supervised pre-training. The last encoder block was followed by four upsampling blocks before the final convolution.

Table 1. Five-fold cross-validation results for different α values. The α value represents the contribution of boundary loss for new lesion segmentation losses L_{S1} and L_{S2} .

Boundary loss coefficient	Dice(%) \uparrow	HD(mm) \downarrow	F1(%) \uparrow
$\alpha = 5$	48.35 \pm 8.29	60.32 \pm 9.63	47.76 \pm 8.98
$\alpha = 10$	56.15\pm7.06	37.13\pm13.29	56.69\pm9.12
$\alpha = 20$	47.81 \pm 9.11	58.73 \pm 15.57	46.13 \pm 7.71

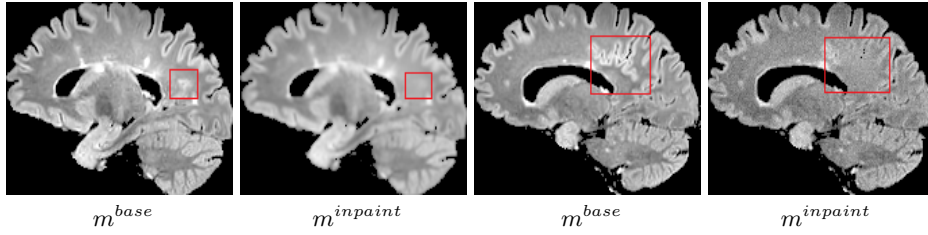


Fig. 2. Additional examples of inpainting for two different MRI scans.

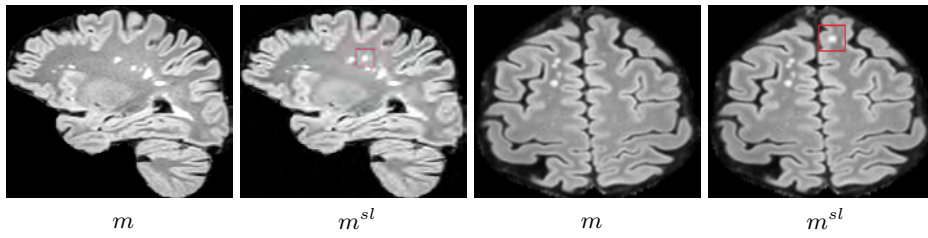


Fig. 3. Additional examples of adding synthetic lesions into two different MRI scans.

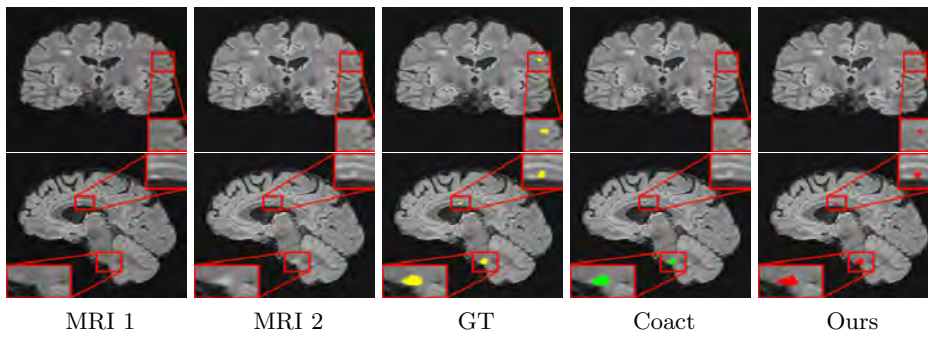


Fig. 4. Additional comparative visualization of predictions by the proposed model and Coact. GT: Ground Truth