BRAIN SEGMENTATION USING DEEP LEARNING

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BACKGROUND & PROBLEM DEFINITION

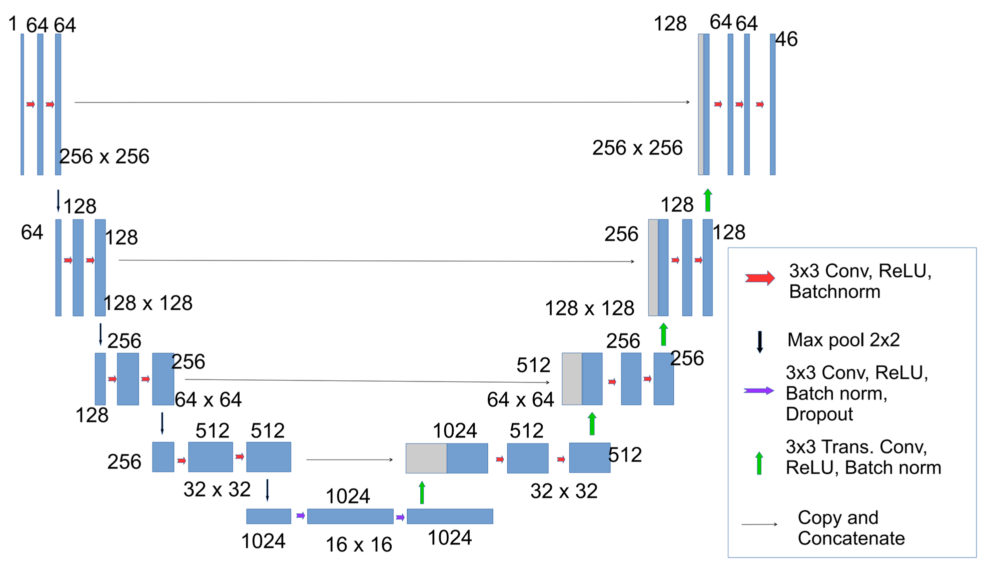
- Accurate brain structural segmentation is central to nearly all neuroimaging analyses.
- Freesurfer and other traditional tools take 2-4 hrs to segment a volume.
- Freesurfer also has systematic biases.
- Deep Learning based models can increase the efficiency and quality of segmentation.

CONTRIBUTION

- Novel training methodology of scheduling dice and cross entropy loss to optimally train segmentation models.
- Revealed systematic biases in Freesurfer tool and built model free of those biases.
- Inference time < 20 secs / MRI volume

MODEL ARCHITECTURE AND DATA

- Vanilla U-Net architecture



- Pre-trained the model using Human Connectome Project (HCP) Data: Healthy Individuals (# = 1113), Ground Truth = Freesurfer Segmentation.
- Fine-tuned using manually annotated MICCAI challenge train dataset (train = 15 subjects and test = 20 subjects).

TRAINING METHODOLOGY

- Xavier initialization for model parameters.
- Augmented data using Gaussian blurring, contrast adjustment, rotation and translation.
- Experimented with different loss function schedule:
  - Only dice loss for the entire training period.
  - Only cross entropy loss (CEL) for the entire training period.
  - Both CEL and dice loss for the entire training period.
  - CEL and dice loss for 30 epochs then switched to pure dice loss (Loss scheduling).
- Pre-trained on HCP with Freesurfer labels as the ground truth.
- Fine-tuned on MICCAI train data.

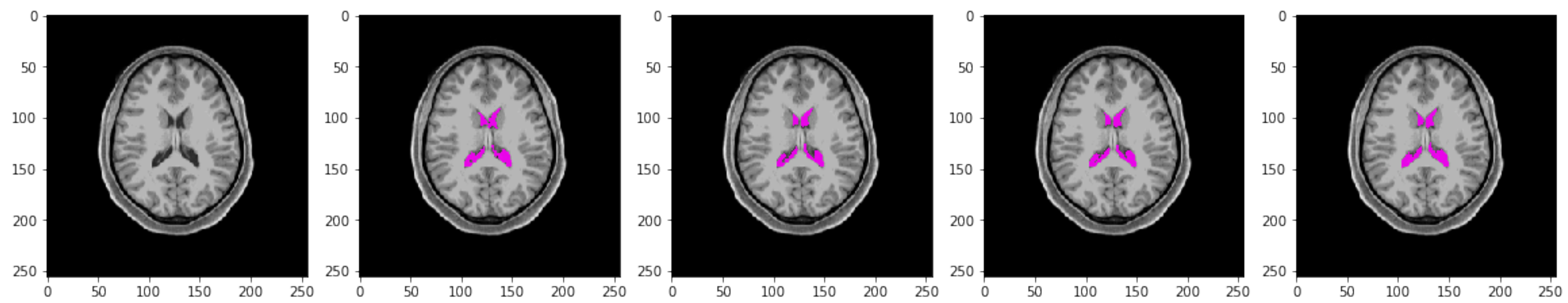
RESULTS

- Evaluated on MICCAI Test Data:

Models			
Name	Loss Function	Pre-Trained	Fine-Tuned
U-Net	Fixed (w-Dice Loss)	Did not converge	
U-Net	Fixed (w-Cel)	0.7602 ± 0.085	
U-Net	Fixed (w-Cel + w-dice loss)	0.7819 ± 0.072	
U-Net	Loss scheduling	$\mathbf{0.8049 \pm 0.067}$	0.885 ± 0.042
QuickNAT	Fixed (w-Cel + dice loss + Boundary Loss)	0.798 ± 0.097	$\mathbf{0.901 \pm 0.045}$
U-Net	Fixed (w-Cel + dice loss + Boundary Loss)	0.681 ± 0.193	0.857 ± 0.079

Performance on MICCAI test data. Pre-Trained refers to results when training on auxiliary (Freesurfer) labels, and Fine-Tuned refers to results of fine-tuned model on MICCAI training set

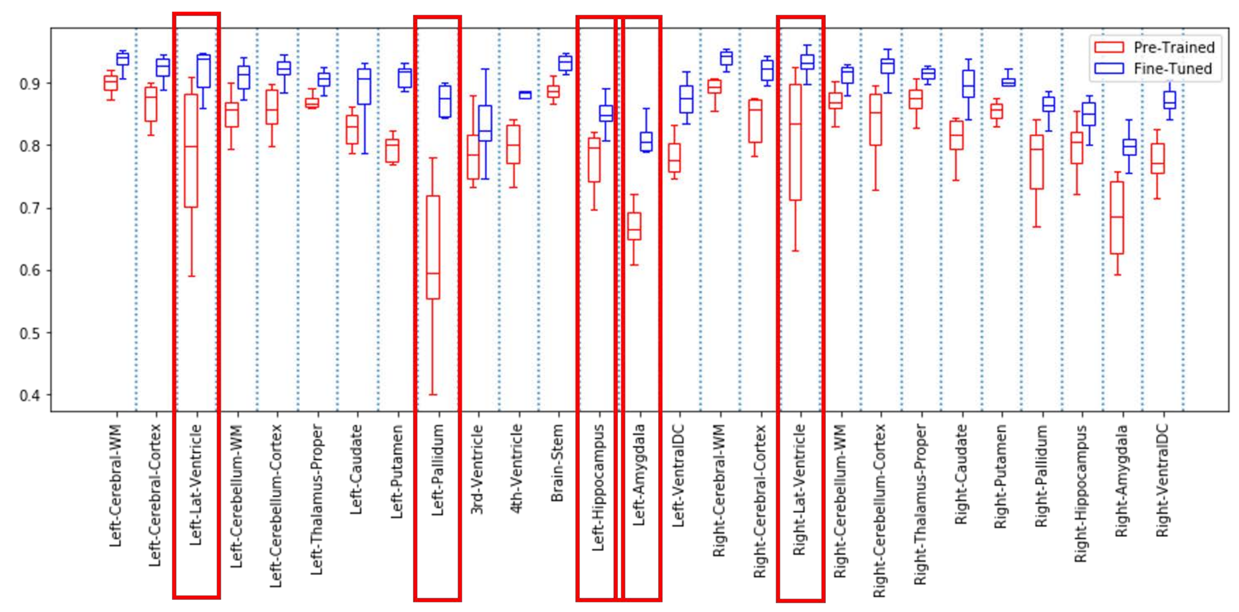
- Vanilla U-Net trained with loss scheduling performed better than the state-of-the-art QuickNAT for the pre-trained model.
- A sample segment is visualized below for all the different pre-trained models.
- Visualization shows the loss scheduling helps the model to get close to Ground Truth (i.e. Freesurfer)
- Coordinated U-net's performance was same as vanilla U-net



(L-R: Original, Freesurfer, Only CEL, Both CEL and Dice, Loss Scheduling)

SYSTEMATIC BIAS IN FREESURFER

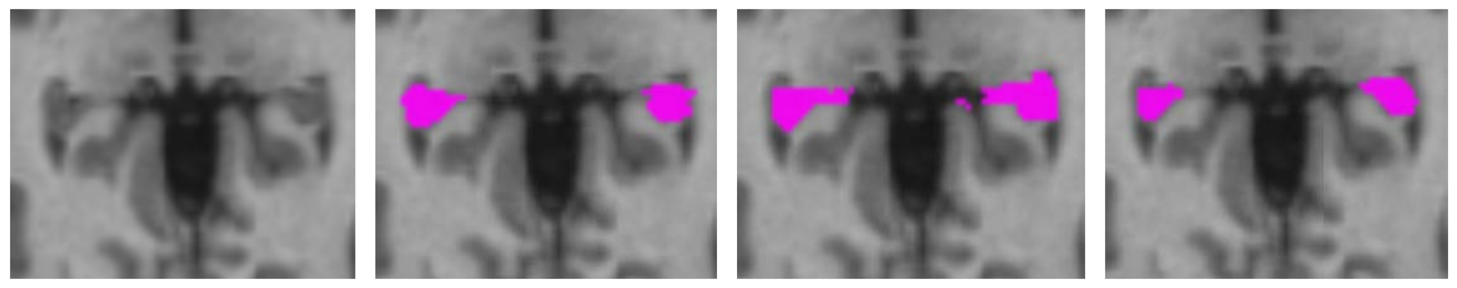
- Difference in performance of pre-trained and fine-tuned model can be seen below:



- Reveals systematic bias of Freesurfer.
- Large bias for Lat-Ventricle, Pallidum, Hippocampus and Amygdala.

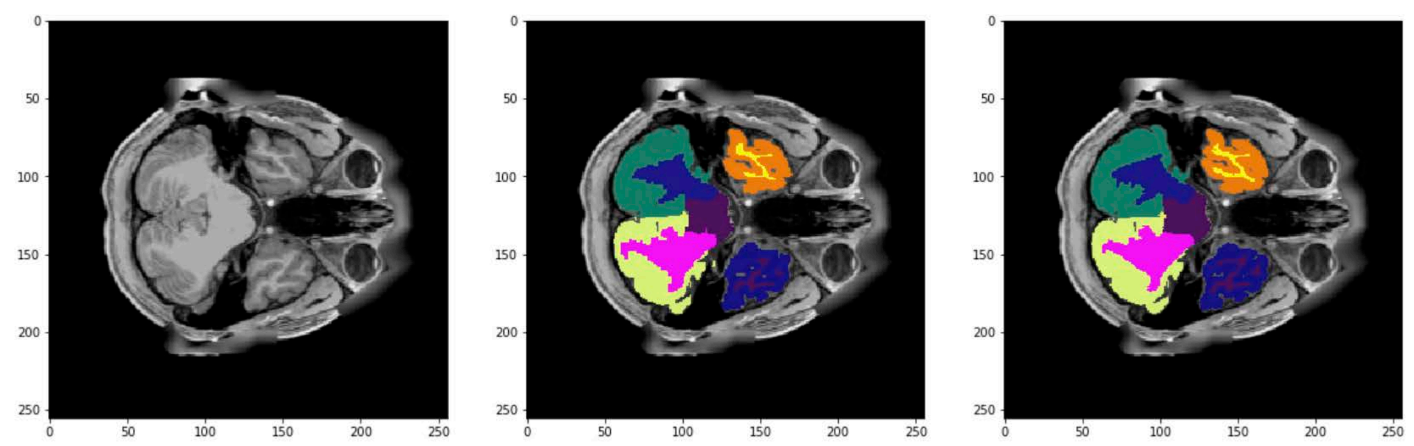
MODEL FREE OF SYSTEMATIC BIAS

- Visualization of fine-tuned and pre-trained model on the MICCAI test data.



(L-R : Original, Manual Ground Truth, Pre-trained Model, Fine-tuned Model)

- Pre-trained model is very liberal for
- Hippocampus. This implies Freesurfer is also liberal while segmenting it.
- Freesurfer being the tool based on template matching mechanism, doesnt emphasize on the edges- hence, rough edges and over predictions. Where as our model, segments the tissue based on edge detection



(L-R:MRI, Freesurfer ground truth, Pretrained U-net output)

CONCLUSION AND FUTURE WORK

- Loss function and training methodology are as important as the model architecture.
- Deep learning models can overcome biases and inference time is low.
- Future work: Experiment with other data sets and segmentation models to conclusively prove that loss scheduling is a helpful training methodology.
- Future work: Build an open source tool and release models for ~190 segments

References

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2. Abhijit Guha Roy, Sailesh Conjeti, Nassir Navab, and Christian Wachinger. Quicknat: Segmenting MRI neuroanatomy in 20 seconds. CoRR, abs/1801.04161, 2018
3. Bennett A. Landman and Simon K. Warfield. Miccai 2012 workshop on multi-atlas labeling (volume 2). CreateSpace Independent Publishing Platform(EDS), 2012