Introduction

The problem that we are investigating is how to effectively track healthy organs in medical scans in order to improve cancer treatment. Cancer takes enough of a toll, and solving the problem will enable radiation oncologists to safely deliver higher doses of radiation to tumors while avoiding the stomach and intestines. This will make cancer patients' daily treatments faster and allow them to get more effective treatment with less side effects and better long-term cancer control.

Datasets & Metrics

The data we use is anonymized MRIs of patients treated with MRI guided radiotherapy provided by the UW-Madison Carbone Cancer Center. We then use U-Net and Mask R-CNN methods to obtain predicted segmented areas of patients' MRI scans with labels for "stomach", "large bowel", and "small bowel".

Problem Statement

For this project, we are building a model to accurately segment the stomach and intestines on MRI scans. The model takes in inputs of MRI scan images from cancer patients by the UW-Madison Carbone Cancer Center. We then use U-Net and Mask R-CNN methods to obtain predicted segmented areas of patients' MRI scans with labels for "stomach", "large bowel", and "small bowel".

Model I: U-Net

The U-Net model consists of two main subnetworks: down and up. The down subnetwork consists of 4 growing step down layers. The up subnetwork consists of 4 corresponding step up layers, which are similar to the step down layers except MaxPool layer is replaced by a UpSample layer, and the convolutional layer is getting smaller. We added dropout layers between convolutional layers.

Model II: Mask R-CNN

We use a ResNet-50-FPN as our backbone in the Mask R-CNN:

Experiments & Analysis

For U-Net, we experiment with the following hyperparameter combinations; bolded column results in the highest Dice score.

For Mask R-CNN, following is the best performing Mask R-CNN specific hyperparameter combination:

Conclusion & Future Work

In this project, we implement and modify the U-Net model and the Mask R-CNN model, and apply them to the GI tract image segmentation problem. Our best U-Net model and Mask R-CNN model achieve Dice scores of 0.51 and 0.73 on the validation set respectively, which both are significant improvements compared to the baseline Dice score result of 0.33. Mask R-CNN performs better than the U-Net model with potential reason of higher complexity in loss function.

We hypothesize several future directions may further improve our results and network design:

- Formulate a more sophisticated loss function for U-Net
- Ensemble the U-Net architecture with Mask R-CNN, potentially using U-Net as the backbone
- Incorporate data augmentation procedure