Brain Tumor Segmentation

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Introduction

Gliomas are types of tumors that occur in the brain and spinal cord. There are two main challenges with automatic segmentation. First, the size, shape, and localization of brain tumors vary significantly between patients. Second, the boundaries between parts of a tumor structure are often unclear. Given these challenges, deep learning is widely being applied to automatic brain image segmentation.

Data

Dataset:

- BraTs 2018 dataset from UPenn
- GD-enhancing tumors, peritumoral edemas, necrotic and non-enhancing tumor cores
- Glioblastomas (HGG) and lower grade gliomas (LGG)
- Each patient scanned with four MRI modes: T1, T1c, T2, Flair
- "Ground truth" segmentation files manually created by clinicians

Data Split:

- Training Set: 10,455 images
- Test Set: 1,260 images

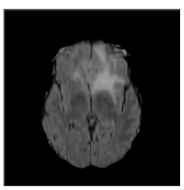

Figure 1: Axial view of HGG Flair image

Figure 2: Sagittal view of HGG T1c image and label

Mask RCNN

Model:

Our first method used the Mask RCNN built on FPN and ResNet101 which is used for image detection [3]. This network was implemented using the Stochastic Gradient Descent optimizer. An average binary cross-entropy loss was used for this model. Transfer learning was utilized by using the pre-trained weights from the MS COCO dataset of generic images.

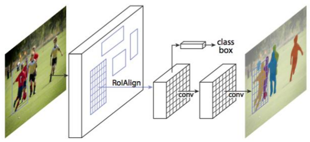

Figure 3: Mask RCNN Model

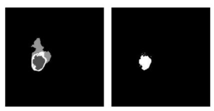

Figure 4: Segmentation and Mask

Results:

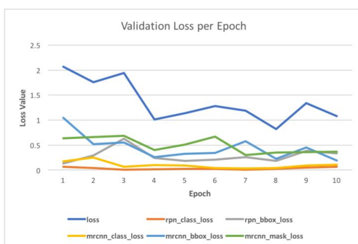

Figure 5: Validation Loss Results

WNet and UNet

Model:

Our second method combined WNet, the first network of the model created by Wang et al [1], and UNet from Akereta et al [2]. For both networks Adaptive Moment Estimation (Adam) was used as the optimizer for training. We used softmax cross entropy as our loss function.

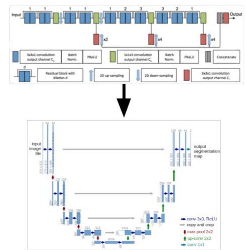

Figure 6: WNet and UNet Model

Results:

View	Training Accuracy
Axial	88.117
Coronal	86.627
Sagittal	97.317

Table 1: Table caption

Through the training process we observed that the model performed worse for axial and coronal view images compared to sagittal view images. We computed a test error rate of 47.570 percent for the training performed on sagittal-view images.

Discussion

- We tried Mask RCNN because it is a object detection algorithm that also generates segmentation masks.
- Since the enhanced tumor core is not well contained within one region, it was hard to train an accurate model.
- We wanted to implement UNet because it is the standard architecture for segmenting 3D images.
- Our model produced good accuracy but with extreme over fitting, so the results are not comparable to previous methods.

Future Work

- Use pre-existing medical segmentation weights instead of COCO weights
- Try ResNet50 as the backbone of RCNN
- Implementing UNet for the whole model and not just one network
- Use pretrained models for segementation during pre-processing instead of using the ground truth

References

[1] Guotai Wang, Wenqi Li, SEbastien Ourselin, and Tom Vercauteren *Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks*.

[2] Joel Akereta, Chihway Changa Aurelien Lucchib, Alexandre Refregiera *Radio frequency interference mitigation using deep convolutional neural networks*

[3] Kaiming He,Georgia Gkioxari,Piotr Dollar,Ross Girshick *Mask R-CNN*