Brain Tumor Segmentation using Deep Learning - Project Report

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1. Introduction

Segmenting brain tumors from the 3D MRI Scans has never been more necessary than before. As noted from various medical surveys, brain tumor is leading cause of death in the world causing 10 Million deaths world wide. MRI(Magnetic Resonance Imaging) is currently used to generate 3D Scans of the brain for the tumor identification. Tumors when identified properly and segmented can be used to plan the operational procedures by the doctor. In this project, I have tried to use existing deep learning models such as U-Net and Attention U-Net on the Brain Tumor Dataset 2018 of MSD Decalthon to effectively detect regions of tumours. As a part of course project, I am able to get competitive results with the methods showing both the quantitative and the qualitative results.

2. Methodology

We will first have a look at dataset in section 2.1, Model architectures in 2.2, experimental setup in 2.3, results in 2.4, analysis and discussion of results in section 3 and conclude.

2.1. Dataset

The dataset for the method was used from the MSD BraTS Dataset. The dataset consists of 465 3D Volumes of MRI Scans annotated with 3D Segmentation Masks. Each Volume is 240 x 240 x 155 x 4 with 240 x 240 x 155 Segmentation Masks. Data is split into 400 for training, 65 for validation. Along with the 3-D Dataset, 2-D Dataset was created consisting of 62000 Images for training and 10000 Images for Validation. Filenames used for training and validation are available in the github repository. According to the dataset, label 0 is Background, Label 1 - Non Enhancing Tumor , Label 2 - Peritumoral Edema, Label 4 - GD Enhancing Tumor. Figure 1 shows sample 2D Image and corresponding masks. the output will be 128 x 128 x 128 x 4

2.2. Model

In this project, I have tried to use 4 models, while 2 models applied on 2D Data, 2 models are applied on 3D Data.

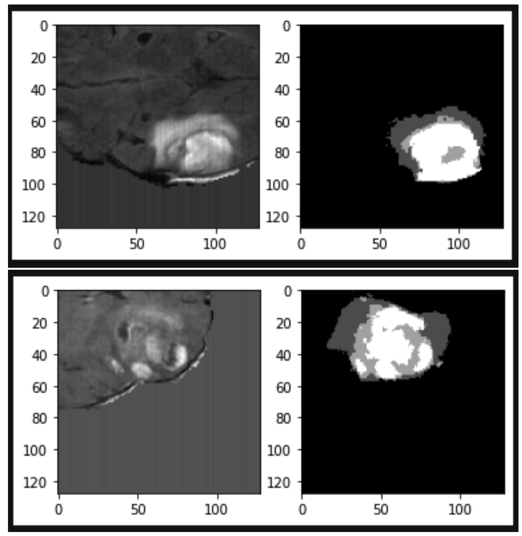

Figure 1. Input and Mask

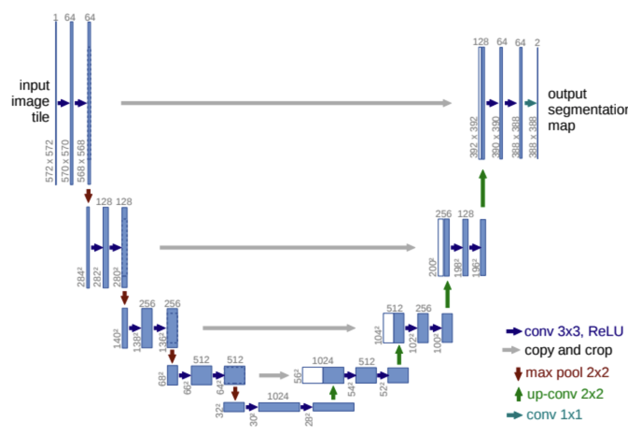

Figure 2. 2-D Unet

Initially, 2D Unet 2 [3] architecture is used as a baseline to compare results. Following 2D-UNet, 3D-UNet 3 model which uses 3D volumes to segment the regions is taken. The method strictly follows the 3D-UNet architecture proposed by Özgün Çiçek et al[1]. Input to this network is cropped region of 128 x 128 x 128 x 4, Segmentation masks. Each 3D

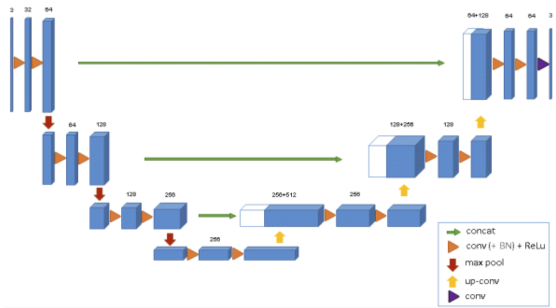

Figure 3. 3-D Unet

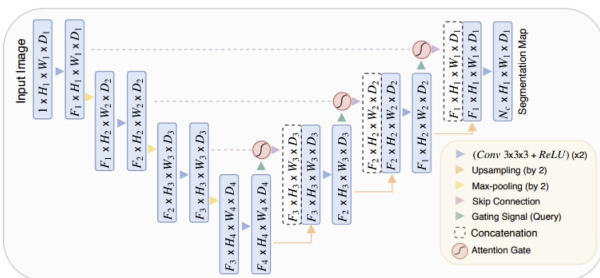

Figure 4. Attention Unet

Volume and mask will have Extensive data augmentations applied on both the train and validation as used by TransBTS [4]. Additionally, attention unet model 4 proposed by [2] is tested on 2d and 3d. The crux of attention-unet is that in the decoder stage, the features of finer layers can be used as a query on the features maps of coarser layers to perform attention and get effective representations. Such methodology can be improve the results. I have followed the architectures closely as stated in their respective papers.

3. Experimental Setup

All the models are trained using softmax dice loss using adam optimizer on GPU's of various capacities. 3D-Unets in particular take up larger memory gpu's than 2d variants and this phenomenon is directly related to added parameters of 3d convolutions. All the models are trained for 100 epochs with an inital learning rate of 0.001 and decrease the learning rate according to cosine learning rate decay with a minimum learning rate upto 0.00001. Thus, the resulting architectures are compared. Quantitative results are shown in the Table 1. Qualitative results are showin in figure 5.

4. Discussion

From the results shown above, both quantitative and qualitative, it is clear that using refined versions of U-net certainly helps. It is evident that using attention in the decoder can lead to better results. Figure 5 shows the masks of the outputs from the respective models. From the quantitative results. It can be seen that the results improved progressively as expected across all the labels of Enhanced Tumor, Tumor Core and Whole Tumor.

Model	Loss	ET	TC	WT
2D-UNet	0.92	71.2	62.1	65.2
2D-Attention-UNet	0.85	73.5	64.3	67.6
3D-UNet	0.75	74.2	66.12	70.12
3D-Attention-UNet	0.64	75.24	69.34	74.34

Table 1. Results of UNet using Dice Coeffecient on the BraTS Datasets

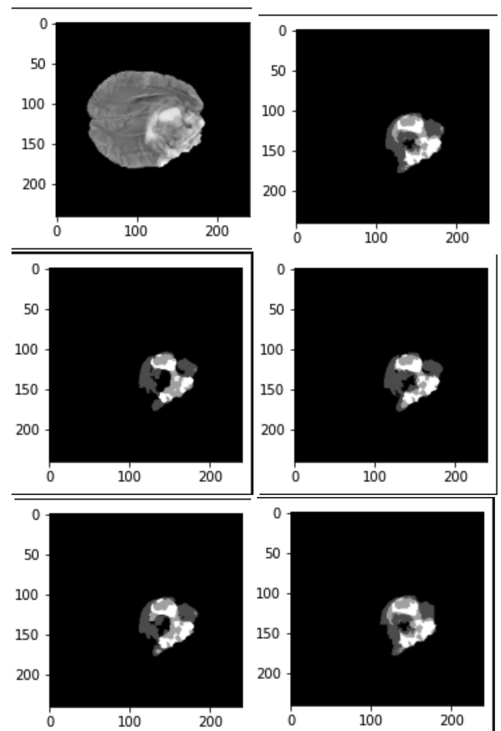

Figure 5. Qualitative Results (a) Input, (b) GT, (c) UNet, (d) Att-UNet, (e) 3D-Unet, (f) Att-3D-UNet

5. Conclusion, Limitations, Findings

In conclusion, In this project, I have used various segmentation models such as U-Net and It's variants for brain tumor segmentation. The results of the models seemed satisfactory qualitatively and quantitatively. While the architectures are powerful, techniques such as transformers can be employed for future work for better performance.

The following are my core takeaways from this course project,

- I have for the first time learned developed segmentation networks.
- I have developed the ability to train models by reading

research papers

- I have developed abilities to read code from other people and write code both on single gpu's and multiple gpu's(Distributed Training)

6. Code

GitHub: https://github.com/saruCRCV/CourseProjectBraTS

References

[1] Özgün Çiçek et al. "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation". In: *CoRR* abs/1606.06650 (2016). arXiv: 1606.06650. URL: http://arxiv.org/abs/1606.06650.

[2] Ozan Oktay et al. "Attention U-Net: Learning Where to Look for the Pancreas". In: *CoRR* abs/1804.03999 (2018). arXiv: 1804.03999. URL: http://arxiv.org/abs/1804.03999.

[3] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. "U-Net: Convolutional Networks for Biomedical Image Segmentation". In: *CoRR* abs/1505.04597 (2015). arXiv: 1505.04597. URL: http://arxiv.org/abs/1505.04597.

[4] Wenxuan Wang et al. "TransBTS: Multimodal Brain Tumor Segmentation Using Transformer". In: *CoRR* abs/2103.04430 (2021). arXiv: 2103.04430. URL: https://arxiv.org/abs/2103.04430.