University at Buffalo
School of Engineering and Applied Sciences

CSE 700: Independent Study

Instructor

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U-Net for Brain Tumor Segmentation

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Abstract

Convolution Neural Networks are widely used in Image Segmentation especially in Biomedical Image Segmentation. U-Net is a Convolution Network Network which has an architecture with contracting path to capture context and a symmetric expanding path to capture localization. It has proven to be highly effective and faster in segmentation tasks. In this study, a U-Net proposed in the paper[1] is adapted for Brain Tumor Segmentation using the BraTS 2013 dataset[2]

1 Timeline of Study

Period	***Workdone***
Jan 29 - Feb 23	Literary Review - studied papers on Generative Networks, Adversarial Training procedures and dilated convolutions, semantic segmentation of brain tumors, conditional GANs for train tumor segmentation and CNN for brain tumor segmentation
Feb 23 - March 05	Studied the BraTS 2013 dataset on how to load them using Medpy package in Python and preprocessed them for adaptations later in both Python and Matlab
March 05 - March 11	Studied and familiarized the U-Net architecture before beginning implementation
March 11 - March 25	Set up environments for designing U-Net Model and started with the implementation of U-Net
March 25 - April 04	Pre-processed and prepared dataset for inputting to U-Net
April 04 - April 16	Adapted a basic U-Net and trained a fully working model on the source code's native Transmission Electron Microscopy dataset
April 16 - April 22	Modified U-Net Model for BraTS dataset - partially working
April 22 - April 30	Trained the first fully working model and extracted results
April 30 - May 07	Modified input to U-Net: Tested model with different number of epochs and input channels
May 07 - May 11	Final Analysis of the U-Net Model and Documentation

2 Literature Review

On reading a wide variety of papers, a plethora of methods are found to be available for Segmentation task in Computer Vision. The paper[3] proposes a fully convolutional networks for semantic segmentation. It suggests that transforming the fully connected layers of the network into convolution layers, enables the classification net to output a heatmap - an approach for segmentation tasks.

The most recent Adversarial training method is highly effective and some of the effective approaches are outlined in the papers[4] and [5] for Brain Tumor Segmentation. In these processes, a generative model is trained to segment tumors from the data distribution alongside a discriminator that learns to differentiate between generated and ground truth images.

3 U-Net

This idea of U-Net for Brain Tumor Segmentation is heavily adapted from this paper [6]. The architecture of the U-Net (Figure 1) proposed in the network in replicated exactly. The network start with the input size of 512×512 and 64×64 convolution layer. In out adaptation, each convolution step in the contracting path is followed by a ReLU activatation function followed by a max-pooling layers of size 2×2. The number of feature channels is doubles in each down sampling step In the expansive path, each convolution layer is followed by ReLU activation and then followed by up sampling of convolution output. The number of channels are reduced in half in each of step of expanding path. In total the network at 23 convolution layers including the final 1×1 convolution layers at the final layer

4 Training

BraTS dataset consists of MRI scans of around 30 patients with different channels (flair,t1,t1c,t2) along with the ground truth (ot). Some of the image samples are shown in Figure 2

MedPy package is used to load the input data present in .mha format. In our training, image padding is done to make the input of arbitary size and the pre-processed input data that is fed to the network is of shape $N \times 512 \times 512 \times 4$, which consists of N samples each containing 4 channels.

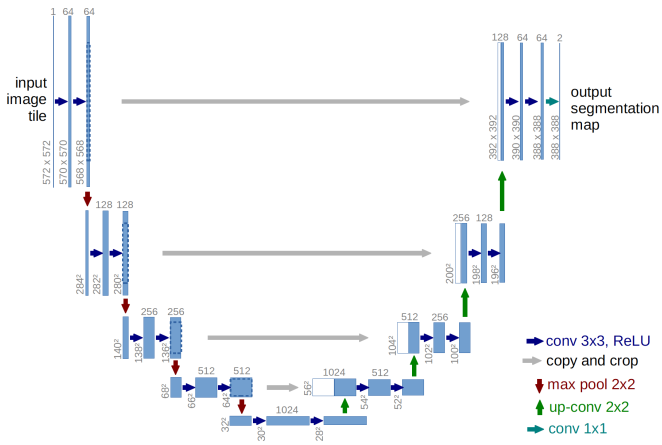

Figure 1: U-Net Architecture.

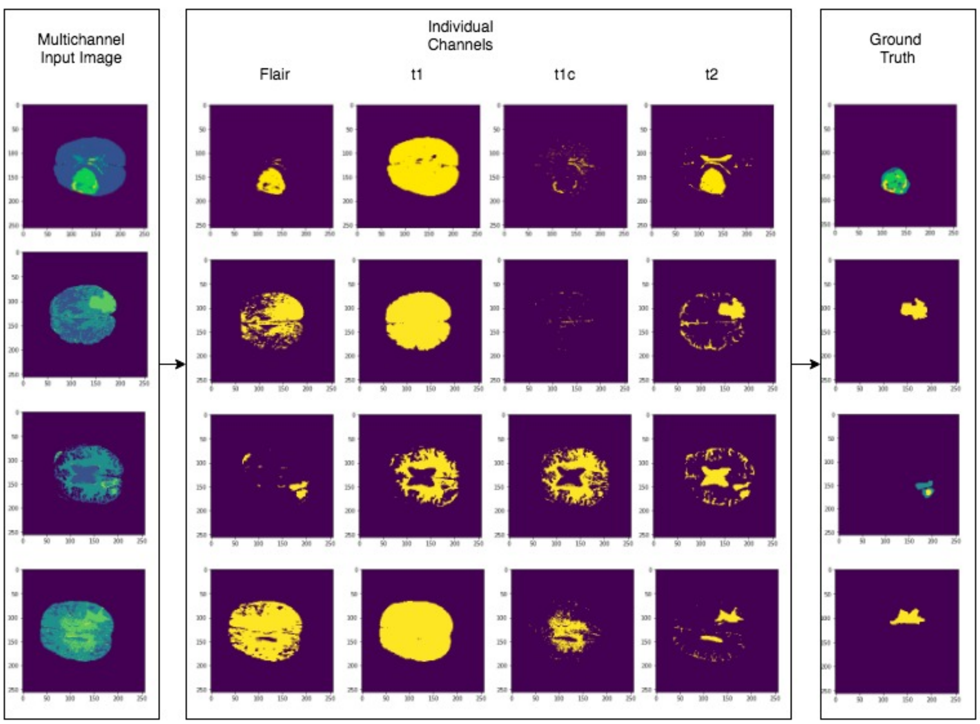

Figure 2: BrATS dataset of MRI Scans

Keras is used to design the U-Net Model using 2D convolution function. The source code for U-Net model is adapted from [6]. In the training, the model is trained for 50 epochs with a batch size of 5. The model had a training time of 1 min/epoch, in the CUDA server. ReLU activation function is used in each convolution layer. Adam Optimizer is used in the model for optimization.

5 Experimental Results

Some of the outputs segmented from the testing data is shown in Figure 3.The result of the training is as follows.
Though the network was able to segment images successfully in many cases, there are a significant samples for which the segmented image grossly different from the ground truth. On analyzing some of the input data and the ground truth, tumors in certain segments of images are hard to do distinguish and are not clearly visible across the four channels. Hence the dataset needs further preprocessing to identify such case and modfify dataset to match them accordingly.

Training accuracy = 0.9859
Validation accuracy = 0.9809
Testing Accuracy = 0.9823

Training loss = 0.0673
Validation loss = 0.05322
Testing loss = 0.05205

Dice Co-efficient = 0.4107

6 Future Work

1. Explore the GAN framework proposed in Figure 4 and integrate the UNET designed as the Generator in the GAN framework and using a Markovian GAN as a Discriminator, as proposed by Conditional Generative Adversarial Network for Brain Tumor Segmentation.

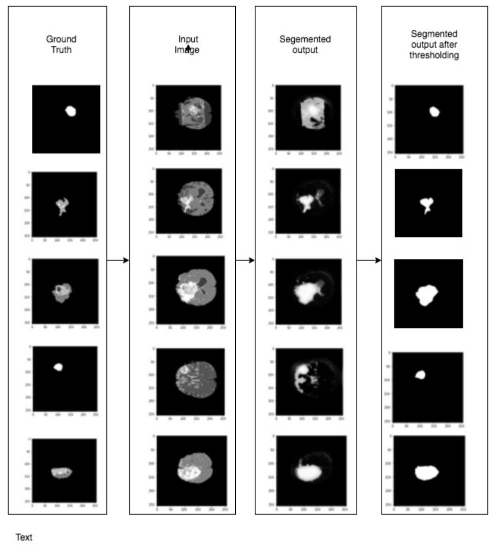

Figure 3: Tumors segmented from U-Net

2. Experiment with different pre-processing techniques for the input images - data augmentation and interpolation techniques
3. Use 3D Convolution Network in Keras to train the model
4. Find an alternative to remove the thresholding used on the output from UNet

References

[1] Olaf Ronneberger, Philipp Fischer, Thomas Brox, *U-Net: Convolutional Networks for Biomedical Image Segmentation*,CoRR,abs/1505.04597,2015, http://arxiv.org/abs/1505.04597.

[2] Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, Burren Y, Porz N, Slotboom J, Wiest R, Lanczi L, Gerstner E, Weber MA, Arbel T, Avants BB, Ayache N, Buendia P, Collins DL, Cordier N, Corso JJ, Criminisi A, Das T, Delingette H, Demiralp, Durst CR, Dojat M, Doyle S, Festa J, Forbes F, Geremia E, Glocker B, Golland P,

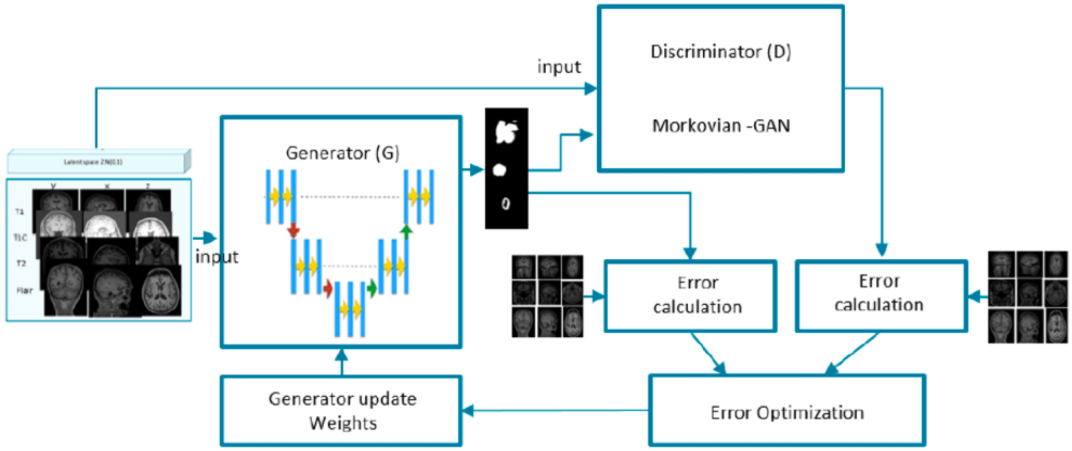

Figure 4: Future Work: GAN Framework.

Guo X, Hamamci A, Iftekharuddin KM, Jena R, John NM, Konukoglu E, Lashkari D, Mariz JA, Meier R, Pereira S, Precup D, Price SJ, Raviv TR, Reza SM, Ryan M, Sarikaya D, Schwartz L, Shin HC, Shotton J, Silva CA, Sousa N, Subbanna NK, Szekely G, Taylor TJ, Thomas OM, Tustison NJ, Unal G, Vasseur F, Wintermark M, Ye DH, Zhao L, Zhao B, Zikic D, Prastawa M, Reyes M, Van Leemput K, *"The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)"*, IEEE Transactions on Medical Imaging 34(10), 1993-2024 (2015) DOI: 10.1109/TMI.2014.2377694

[3] Jonathan Long, Evan Shelhamer. Trevor Darrell *Fully Convolutional Networks for Semantic Segmentation.*

[4] Pim Moeskops and Mitko Veta and Maxime W. Lafarge and Koen A. J. Eppenhof and Josien P. W. Pluim *Adversarial training and dilated convolutions for brain MRI segmentation*,http://arxiv.org/abs/1707.03195.

[5] Mina Rezaei, Konstantin Harmuth, Willi Gierke, Thomas Kellermeier, Martin Fischer, Haojin Yang, Christoph Meinel, *Conditional Adversarial Network for Semantic Segmentation of Brain Tumor*,

[6] U-Net, *source code*, https://github.com/zhixuhao/unet.