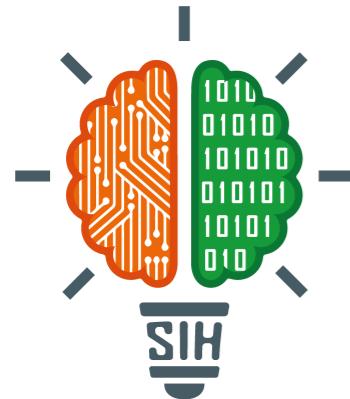


Organizers



MHRD



SMART INDIA
HACKATHON
2019

Department of Atomic Energy

NeuralNets

Indian Institute of Information Technology Kalyani



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DEVNET

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KPIT

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Problem Statement

Brain Image Segmentation using Machine Learning



Department of Atomic Energy

MR Brain Segmentation 2018

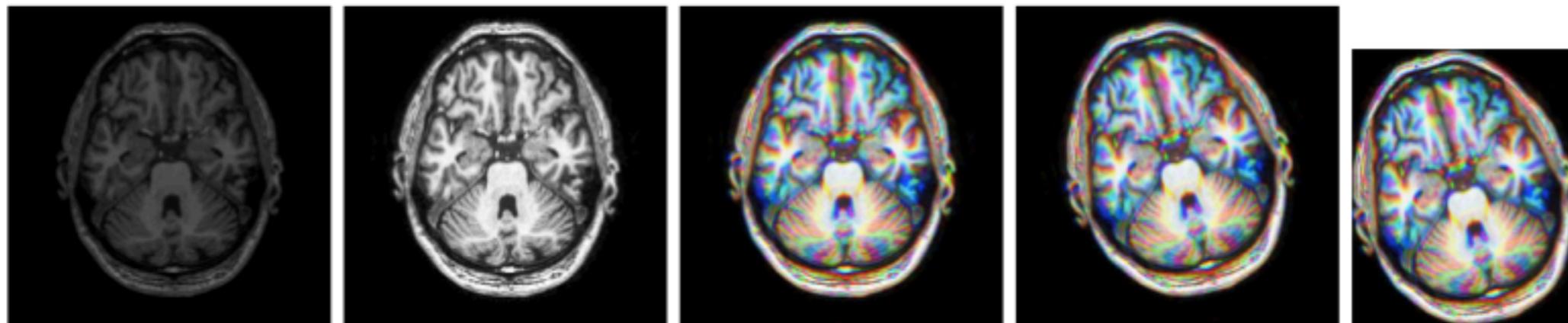
Approach used:

- Our method segments 3D brain MR images into different tissues using fully convolutional network (FCN) and **transfer learning**.
- As compared to existing deep learning-based approaches that rely either on 2D patches or on fully 3D FCN, our method is much faster.

In order to take the 3D information into account, all 3 successive 2D slices are stacked to form a set of 2D “colour” images.

Preprocess:

- 1) histogram equalization(only for T1);
- 2) stack 3 continue slices as a RGB image;
- 3) flip and rotate for $[0, \pm 5, \pm 10, \pm 15]$ for data augmentation;
- 4) crop to reduce background in image and ensure width and height can be devided by 16;



(a) source

(b) hist equalized

(c) stack 3 imgs

(d) rotate

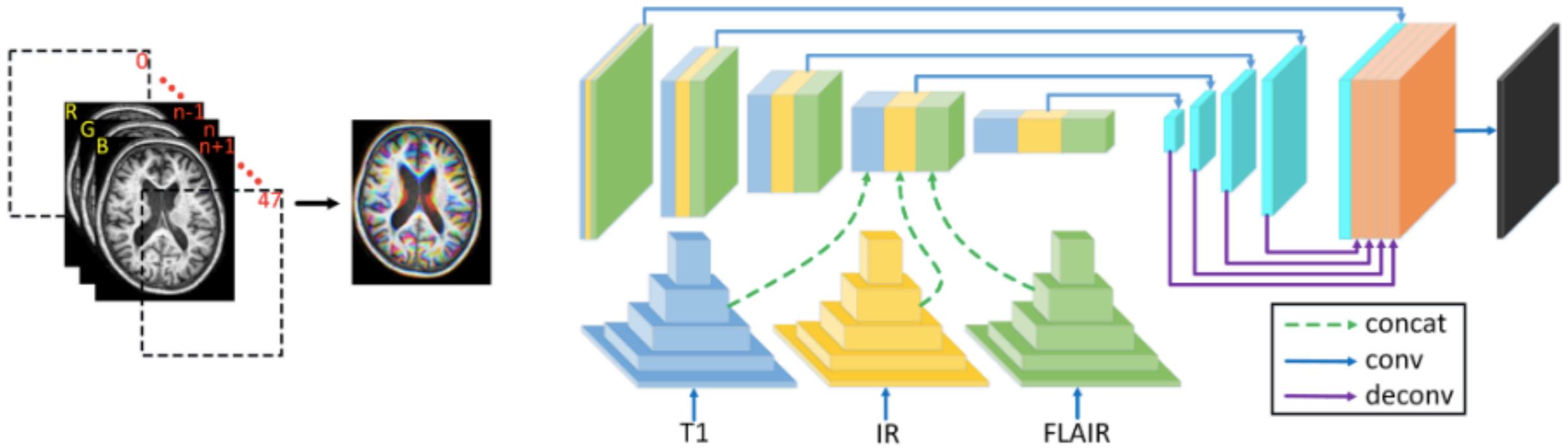
(e) crop

- This stack serve as input for the FCN(Fully Connected Network) pre-trained on ImageNet for natural image classification.
- To the best of our knowledge, **this is the first method that applies transfer learning** to segment brain 3D MR images.

Architecture

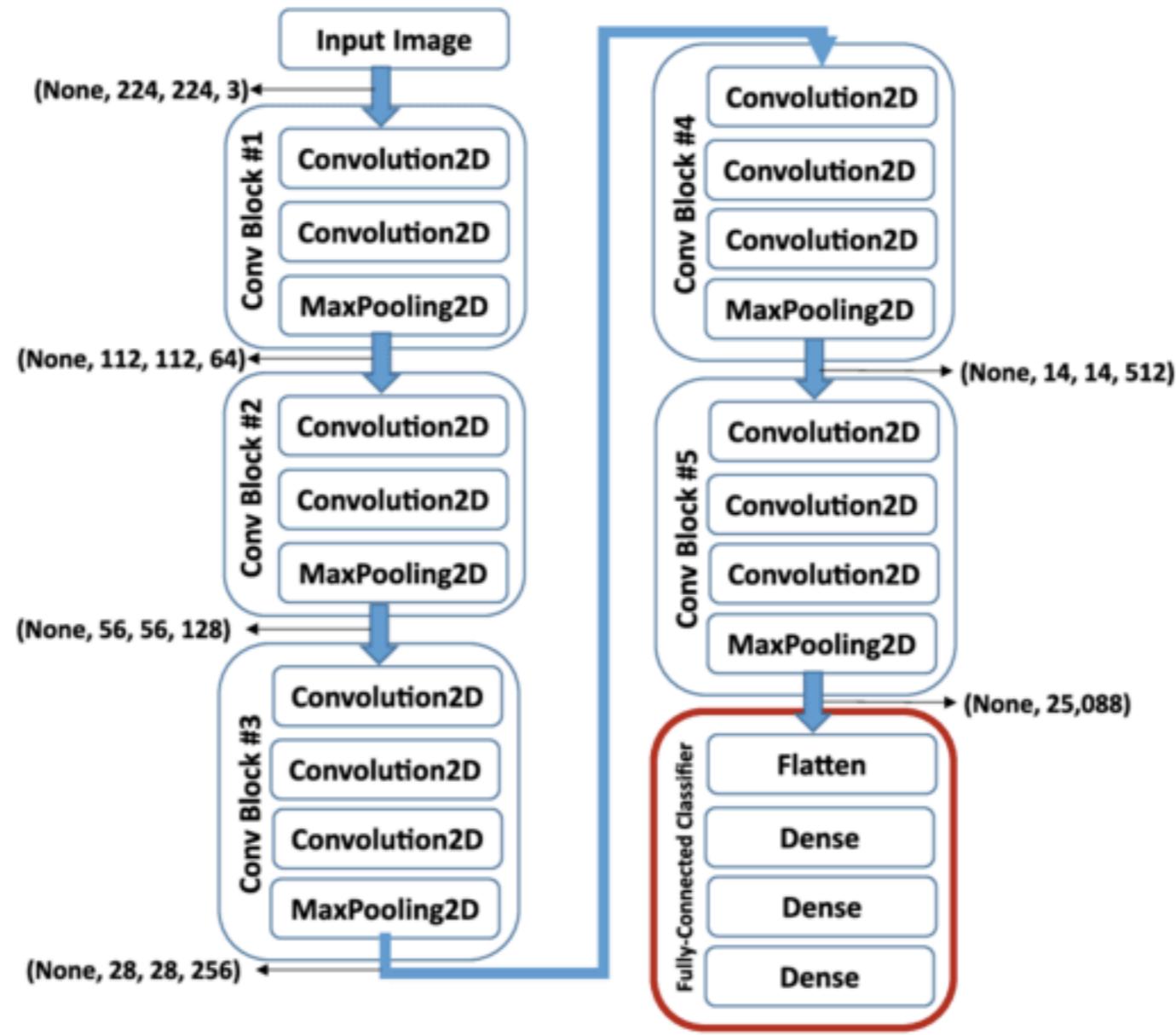
Network

Simply pass image in 3 modalities through 3 streams of VGG, and concat them in every stage.



The architecture basically consists of 5 VGG16 layers combined together.

VGG 16 architecture



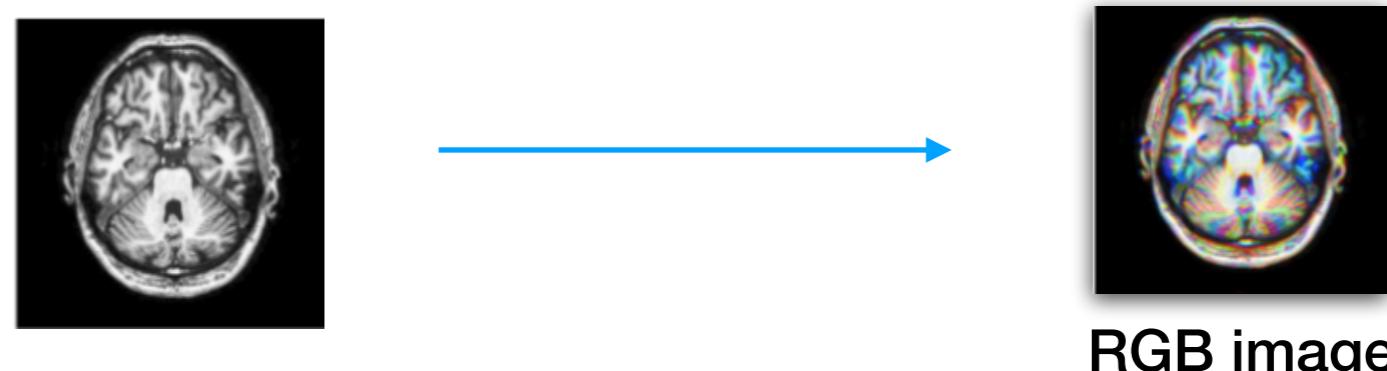
We discard the fully connected layers, and add specialised convolutional layers at the end of each of the five convolutional stages in VGG network.

- For our application, we discard the fully connected layers at the end of VGG network, and keep the 5 stages of convolutional parts called “base network”.
- We add specialised convolutional layers (with a 3×3 kernel size) with K feature maps after the convolutional layers at the end of each VGG16 layer.

- A last convolutional layer with kernel size 1×1 is appended at the end that combines linearly the fine to coarse feature maps in the concatenated specialised layers, to produce the final segmentation result.
- A linear combination of these specialised layers (i.e. fine to coarse feature maps) results in the final segmentation.

Why our model?

- Since we are using **transfer learning**, a novel approach in this field, so we do not need to train our model from scratch which makes it **very fast** in training in comparison to other models.
- Stacking 3 successive 2D slices allows us to make a **RGB image**, another novel idea. This representation enables us to incorporate some 3D information, while **avoiding the expensive computational and memory requirements** of fully 3D FCN.

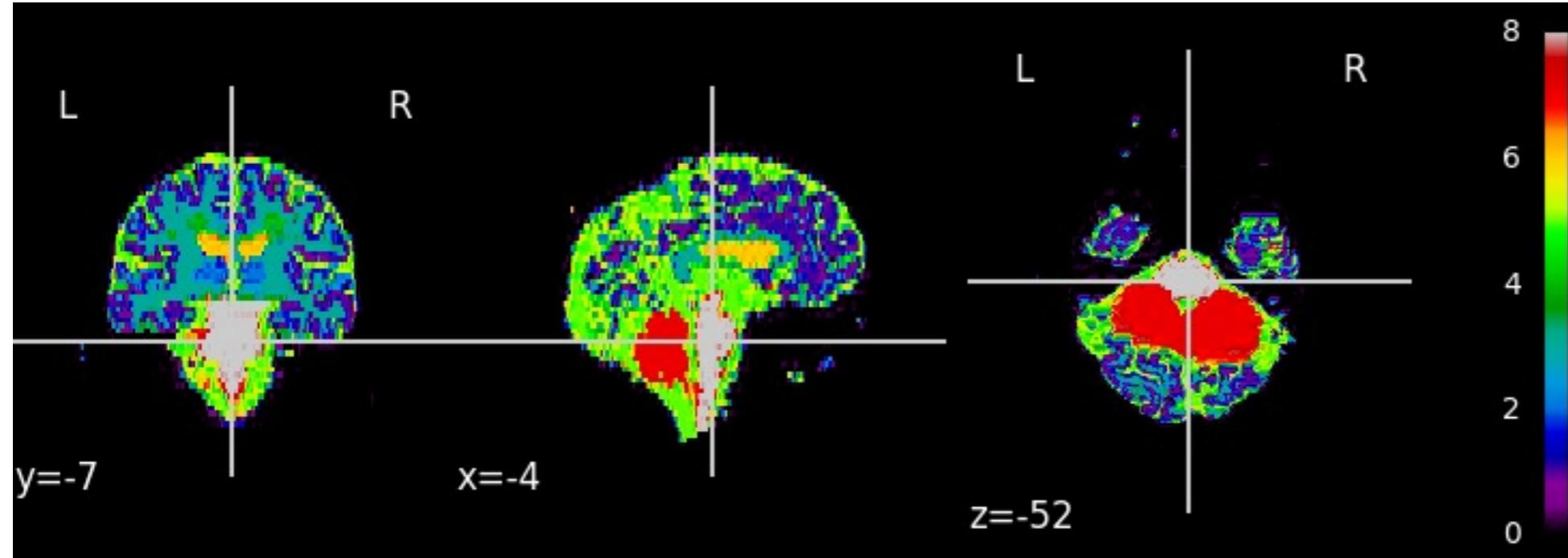


- Using Transfer Learning we do not need many training images, so we could **train** our model very well only on a **few training images**.
- We are also using traditional data augmentation methods like **rotating, cropping and flipping** the images in training set for improving our model.
- This technique helped in achieving very good dice scores on the validation set of images.

Eight Label Segmentation Results

Label	Dice Coefficient	95% Hausdorff	Volume Similarity
Cortical gray matter	0.826449	1.916664	0.979693
Basal ganglia	0.746008	19.805929	0.913474
White matter	0.820702	2.874997	0.991316
White matter lesions	0.738680	5.749998	0.760392
Cerebrospinal fluid in the extracerebral space	0.807224	2.710574	0.990537
Ventricles	0.915846	3.686733	0.946286
Cerebellum	0.921235	23.338083	0.987430
Brain stem	0.813145	14.648693	0.873004

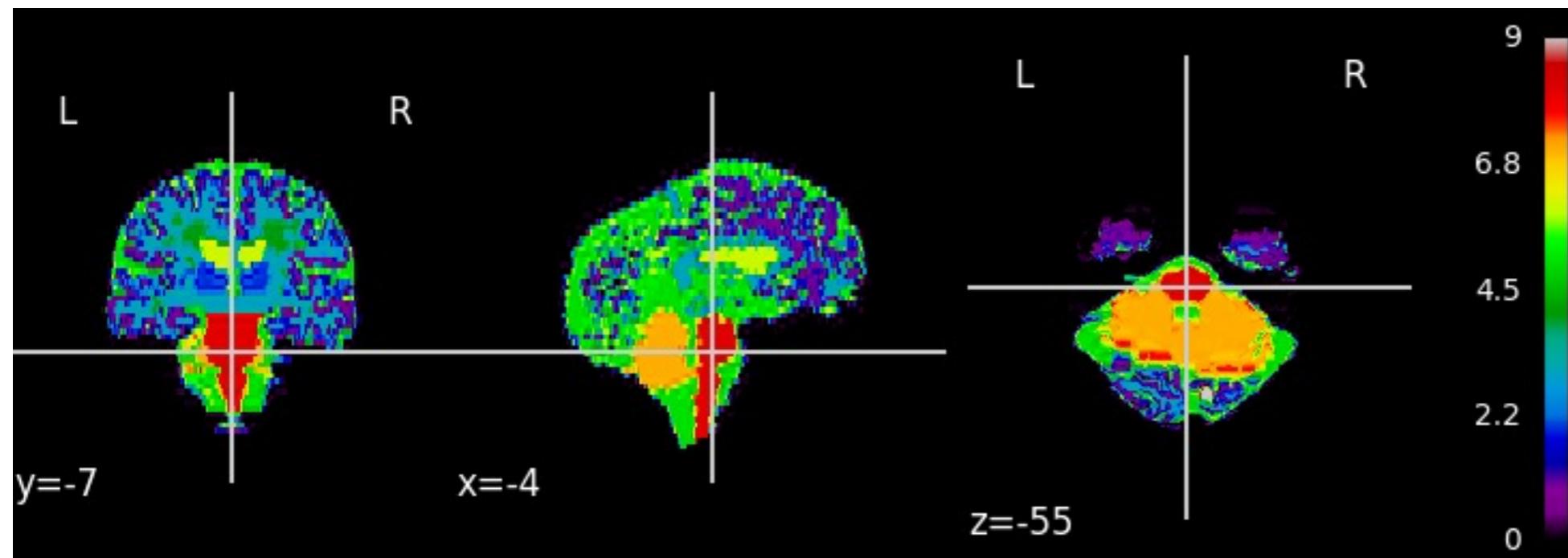
Ground Truth



Color Chart

Brain Stem
Cerebellum
Ventricles
CSF
WM lesions
WM
Basal ganglia
Cortical GM

Predicted



BraTS Dataset

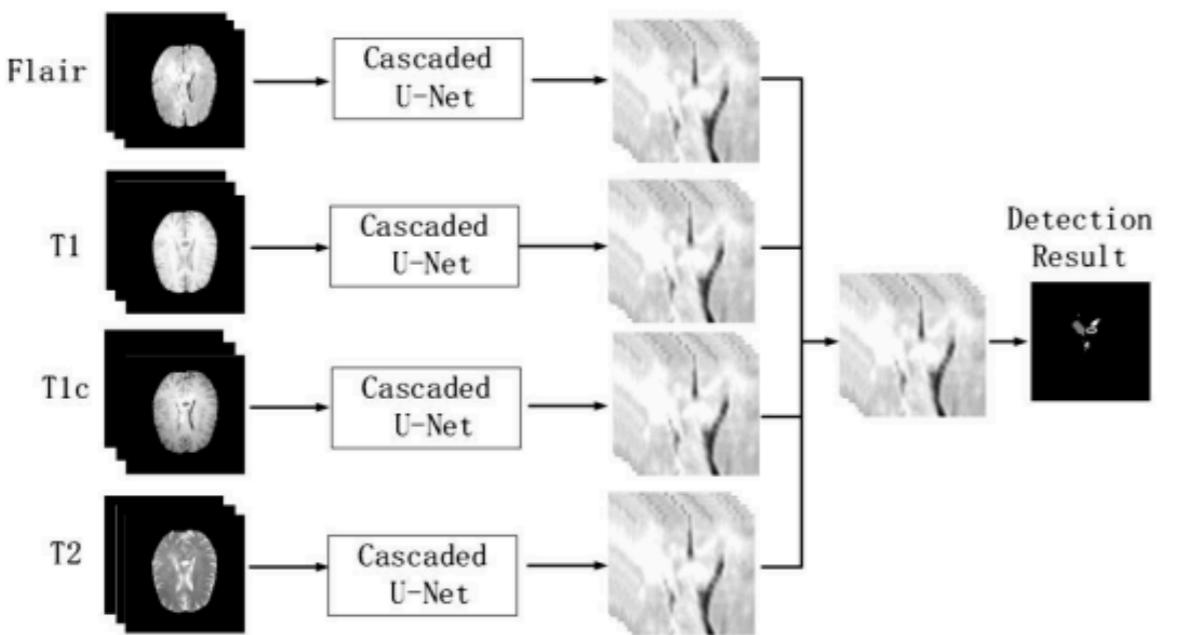


Fig 1. Architecture of the Tumor Detection Module

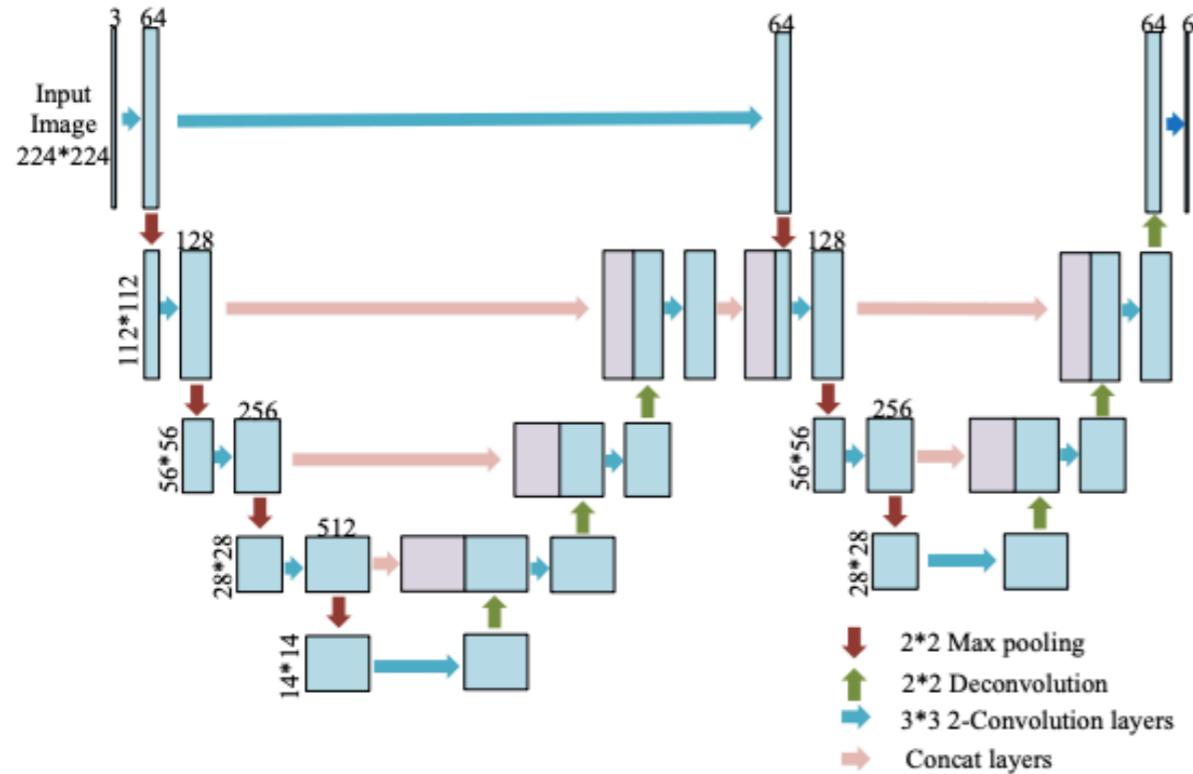
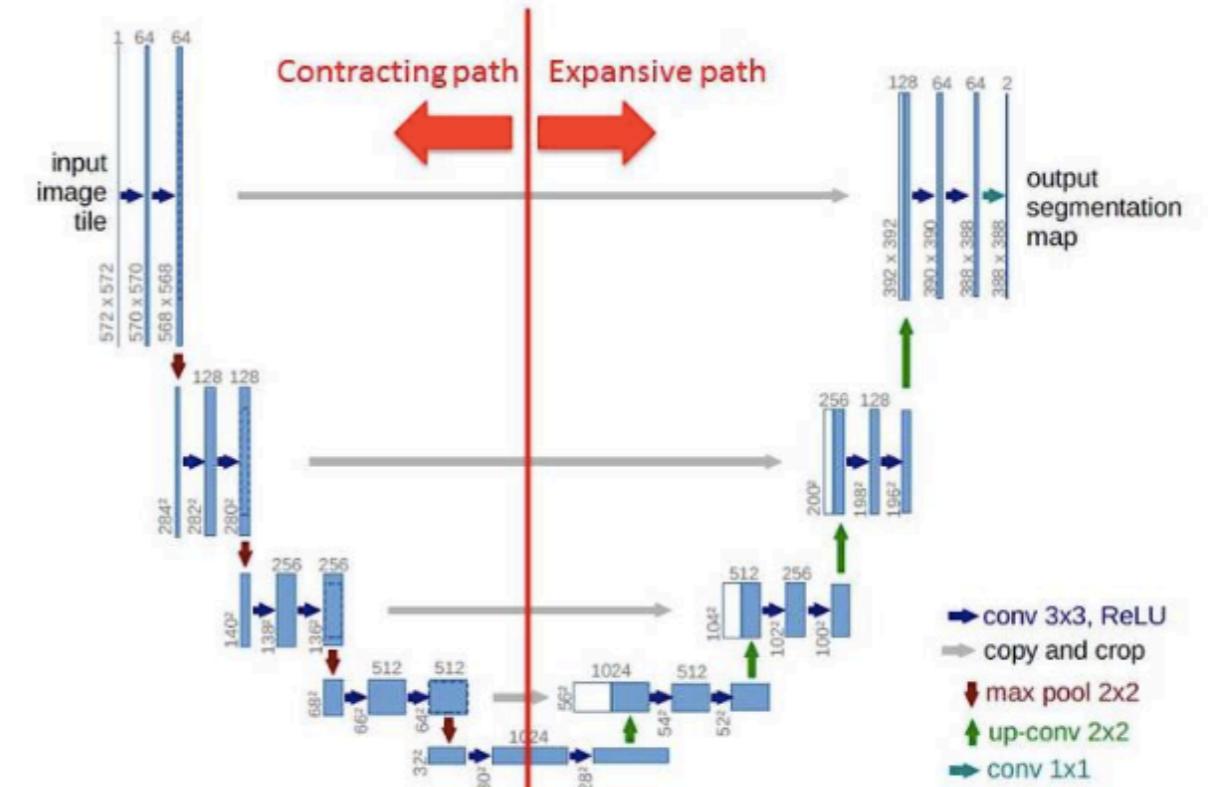


Fig 2. Architecture of the Cascaded U-Net

Network Architecture



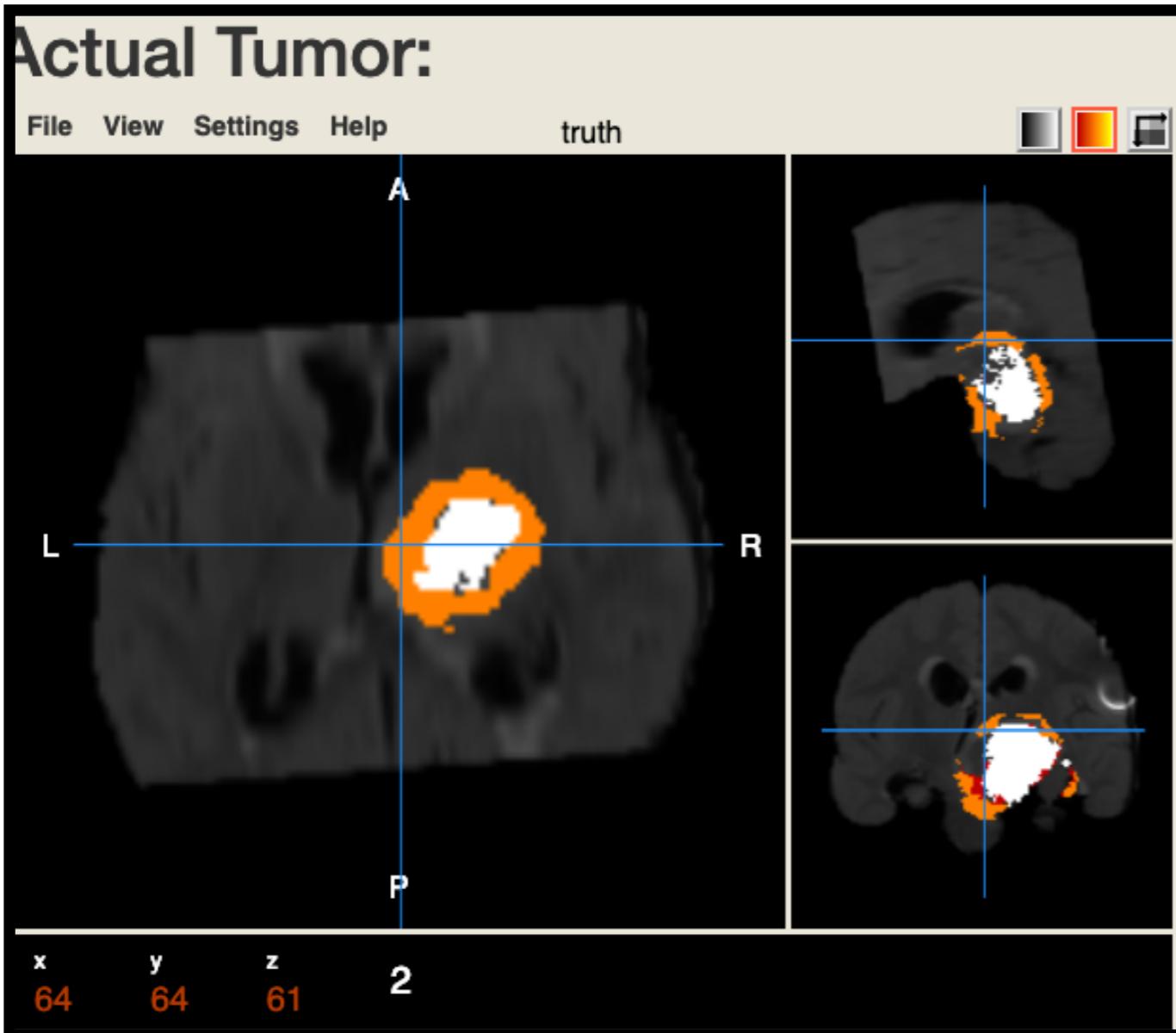
UNet Model

Our Modified Model

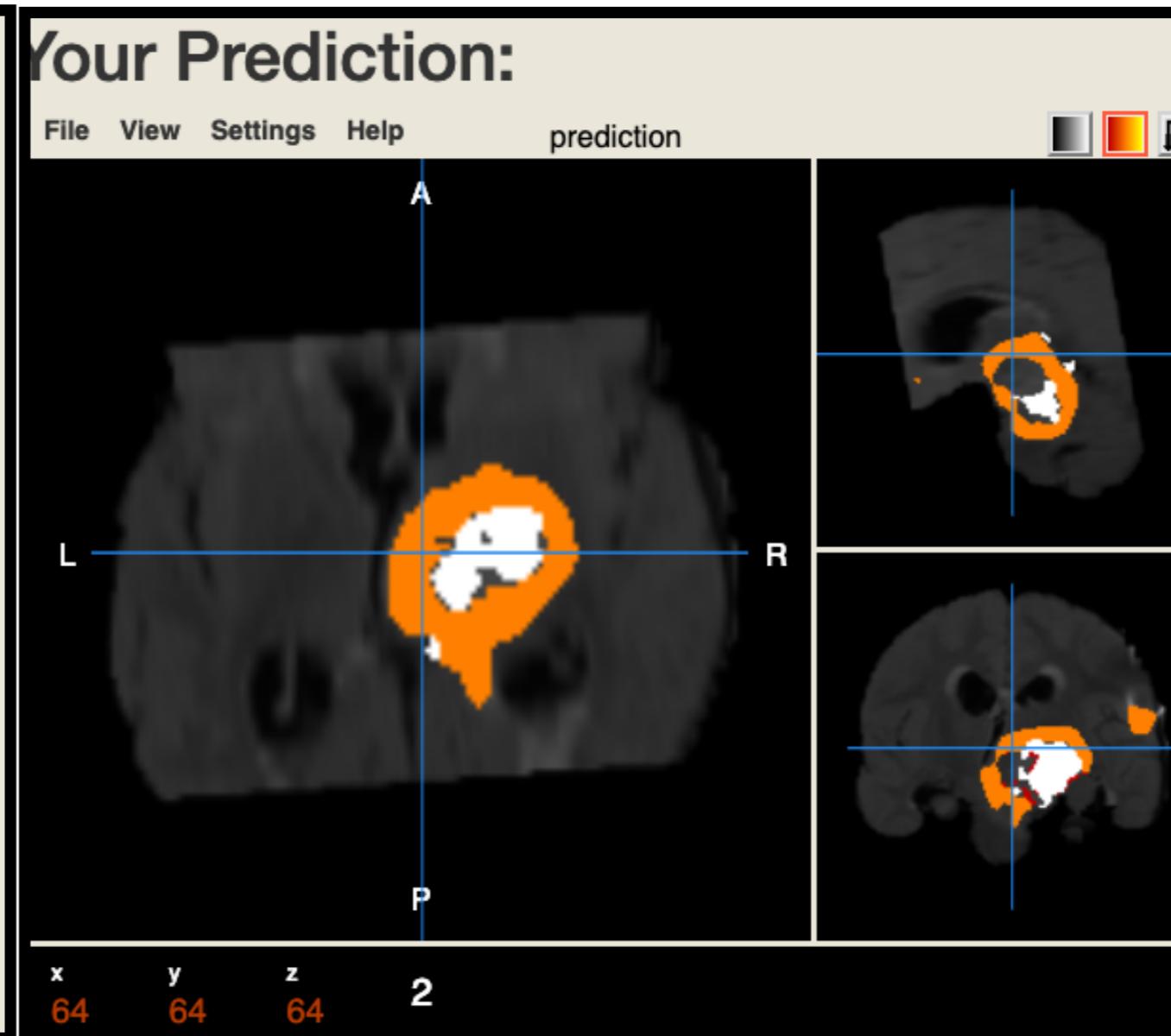
This architecture employs a number of changes to the basic UNet including an **equally weighted dice coefficient**, **residual weights**, and **deep supervision**.

BraTS Dataset Validation Set Prediction

Actual Tumor:

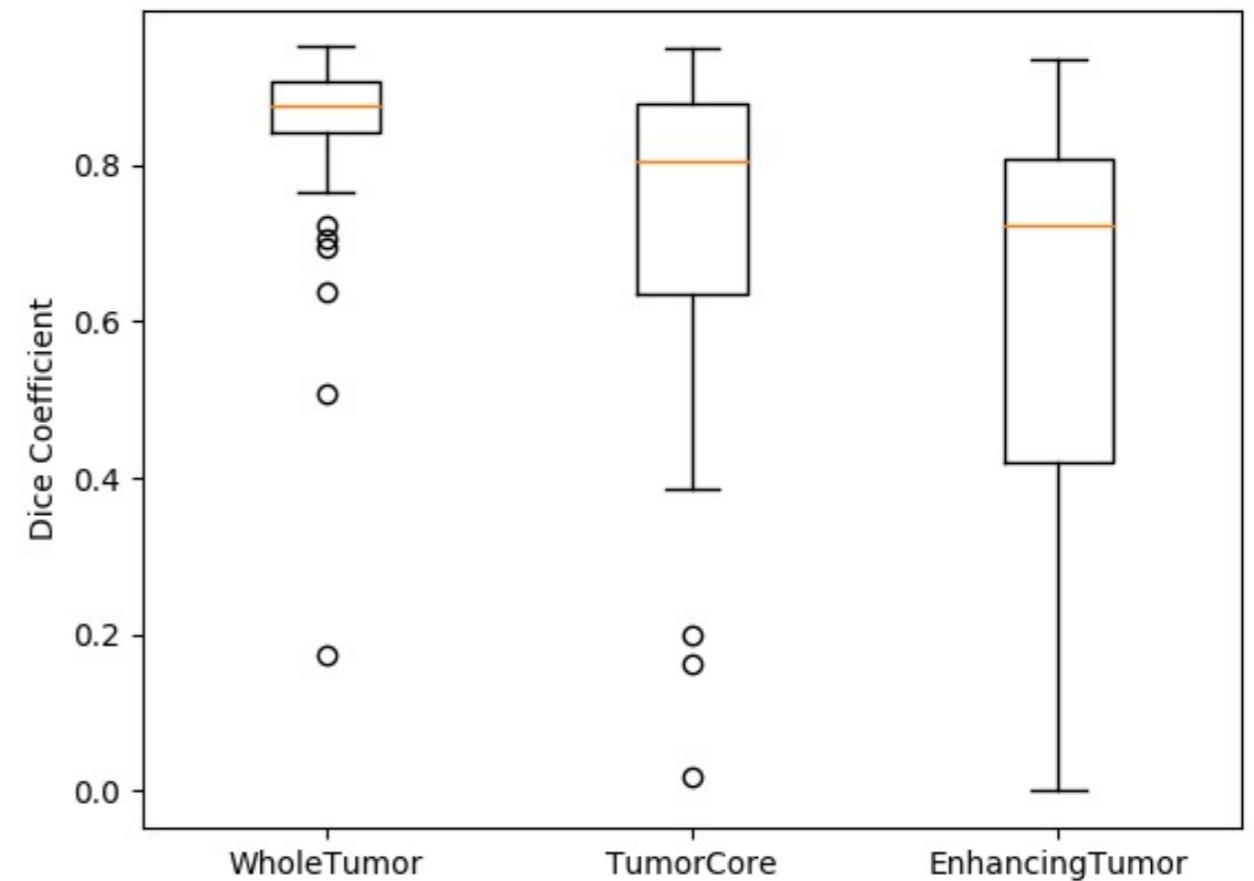
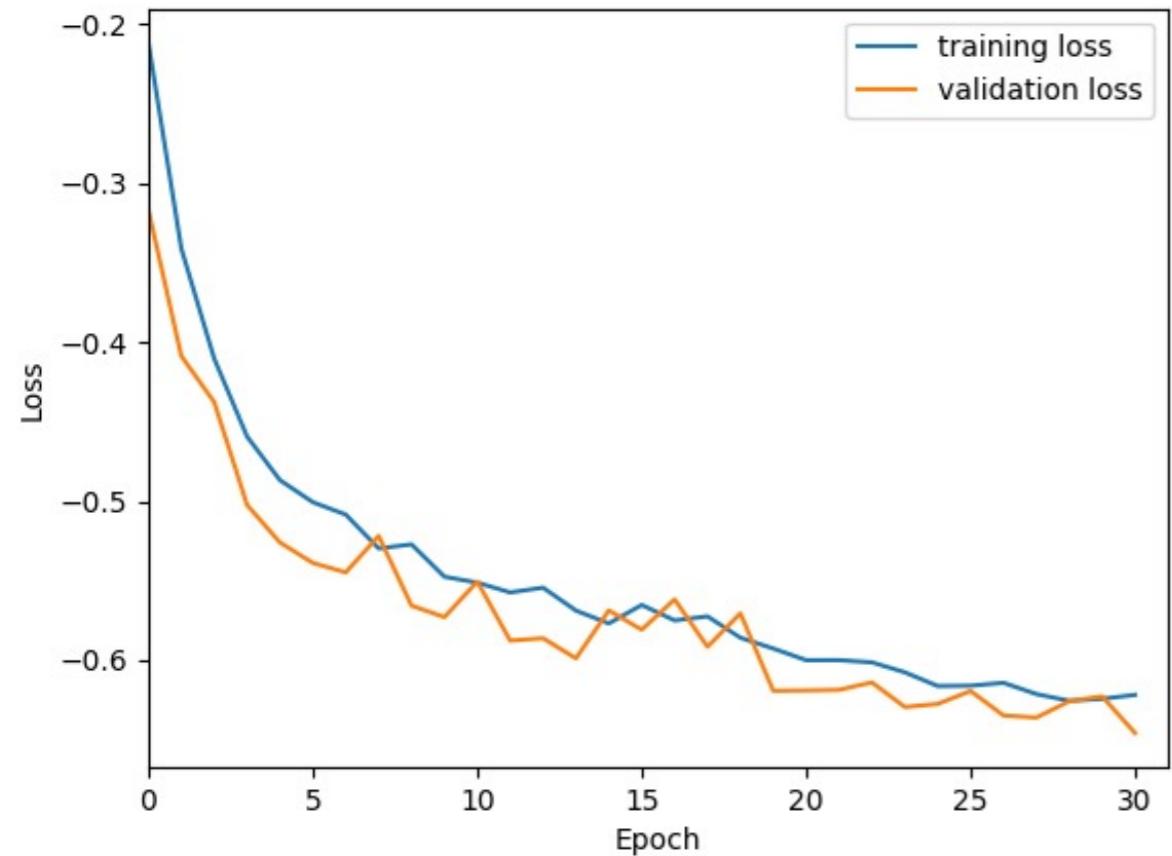


Your Prediction:



Results on BraTS 2018 Training Dataset

Whole Tumour	Core Tumour	Active Tumour
0.81	0.77	0.60



Thank You