DETECTING BRAIN TUMORS FROM INCOMPLETE MRI DATA

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OUTLINE

Introduction

Brain tumors are a cancerous/non-cancerous mass or growth of abnormal cells in the brain

Gliomas are the most common brain tumors

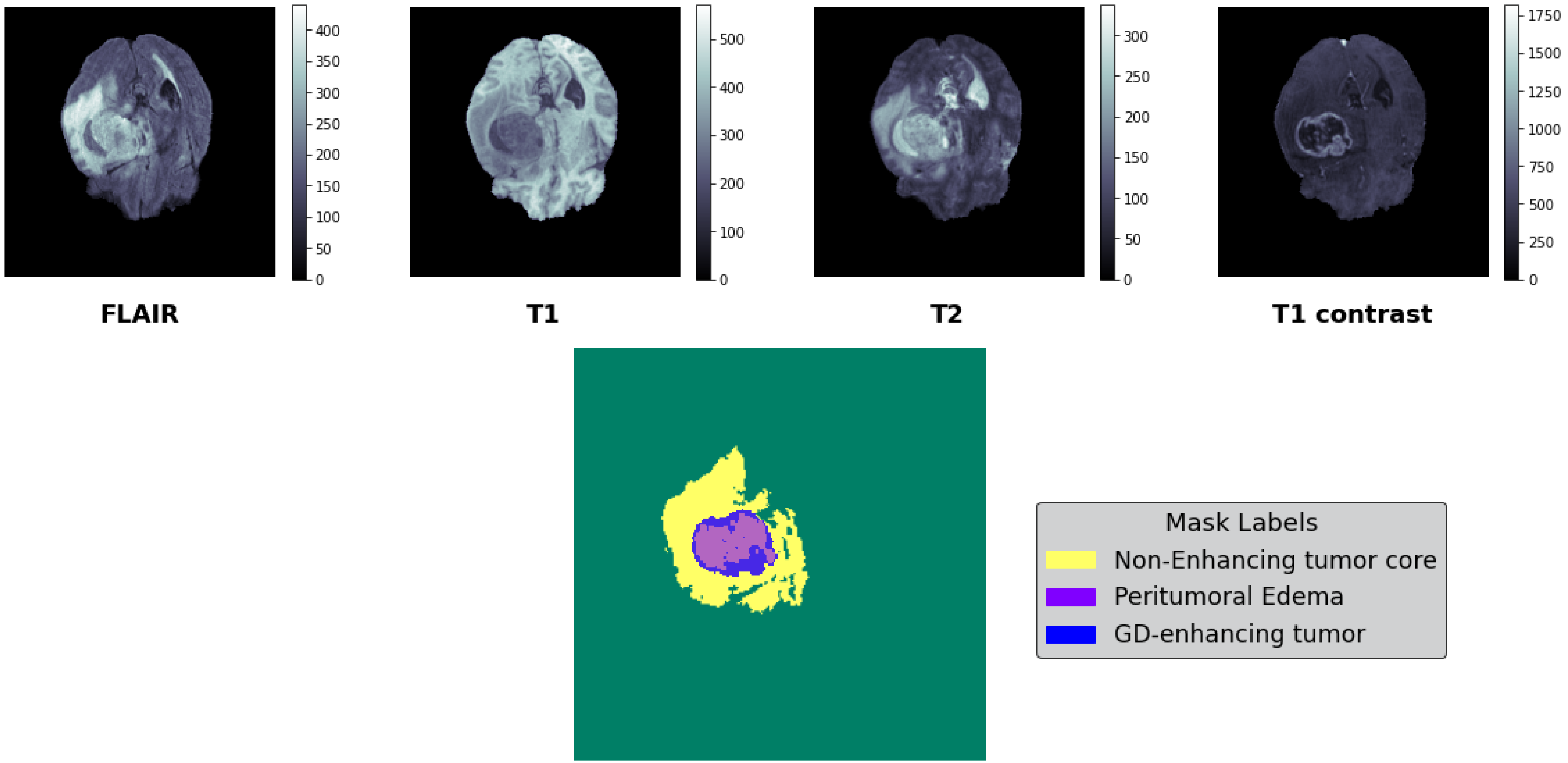
- Glioblastoma- GBM (Higher Grade Glioma-HGG)
- Lower Grade Glioma (LGG)

Multimodal Magnetic Resonance Imaging (MRI) is commonly used in radiology to portray the heterogeneity of gliomas

Multimodal brain MRI scans consist of,

- T1-weighted
- Contrast enhanced T1-weighted
- T2-weighted
- Fluid Attenuation Inversion Recovery (FLAIR)

Multimodal Scans - Data | Manually-segmented mask - Target



Research Problem

Challenging task due to the irregular form and confusing boundaries of tumors.

Segmentation of gliomas using all the modalities would consume more time

Brain tumor segmentation necessitates expert knowledge to identify unhealthy from healthy tissues, those tasks are both costly and time-consuming

In some clinical scenarios all the modalities cannot be obtained through MRI machines

Research Objectives

Identifying Neural Network models available for brain tumor image segmentation

Extracting handcrafted features or image segments of MRI data which can be used to identify brain tumors

Combination of MRI modalities having a significant impact on the accuracy

Techniques to be used to reconstruct the missing MRI modalities to mitigate the accuracy drop

Literature Review

Glioblastoma Multiforme Prognosis: MRI Missing Modality Generation, Segmentation and Radio genomic Survival Prediction

Brain Tumor Segmentation on MRI with Missing Modalities

Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions

Context Aware 3D UNet for Brain Tumor Segmentation

Brain Tumor Segmentation and Survival Prediction Using Multimodal MRI Scans With Deep Learning _ Enhanced Reader

Dataset

Utilized the MICCAI BraTS 2020 dataset to evaluate the performance the used methods

The dataset contains the brain MRIs, patient age, survival days and resection status

Training dataset contains 369 images with 293 High Grade Gliomas and 76 Low Grade Gliomas

Validation set contained 125 scans of patients with brain tumors

Test set contained images from 191 patients with a brain tumor, in which 119 patients had a resection state of Gross Total Resection (GTR)

Data Pre-Processing

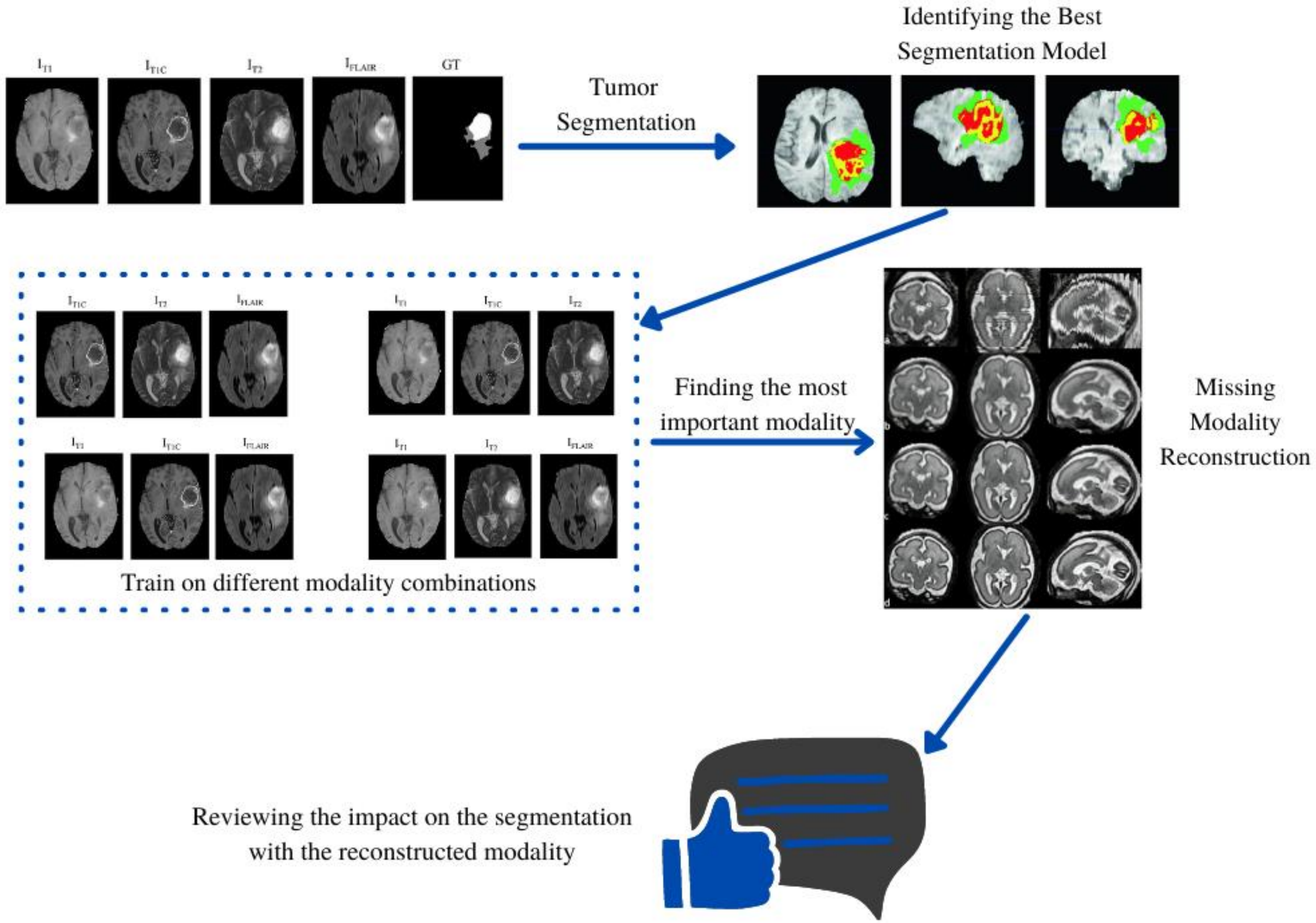
Images were skull stripped and re-sampled to an isotropic 1mm3 resolution

Data augmentations to increase images

Segmentation annotations comprise of the following tumor subtypes

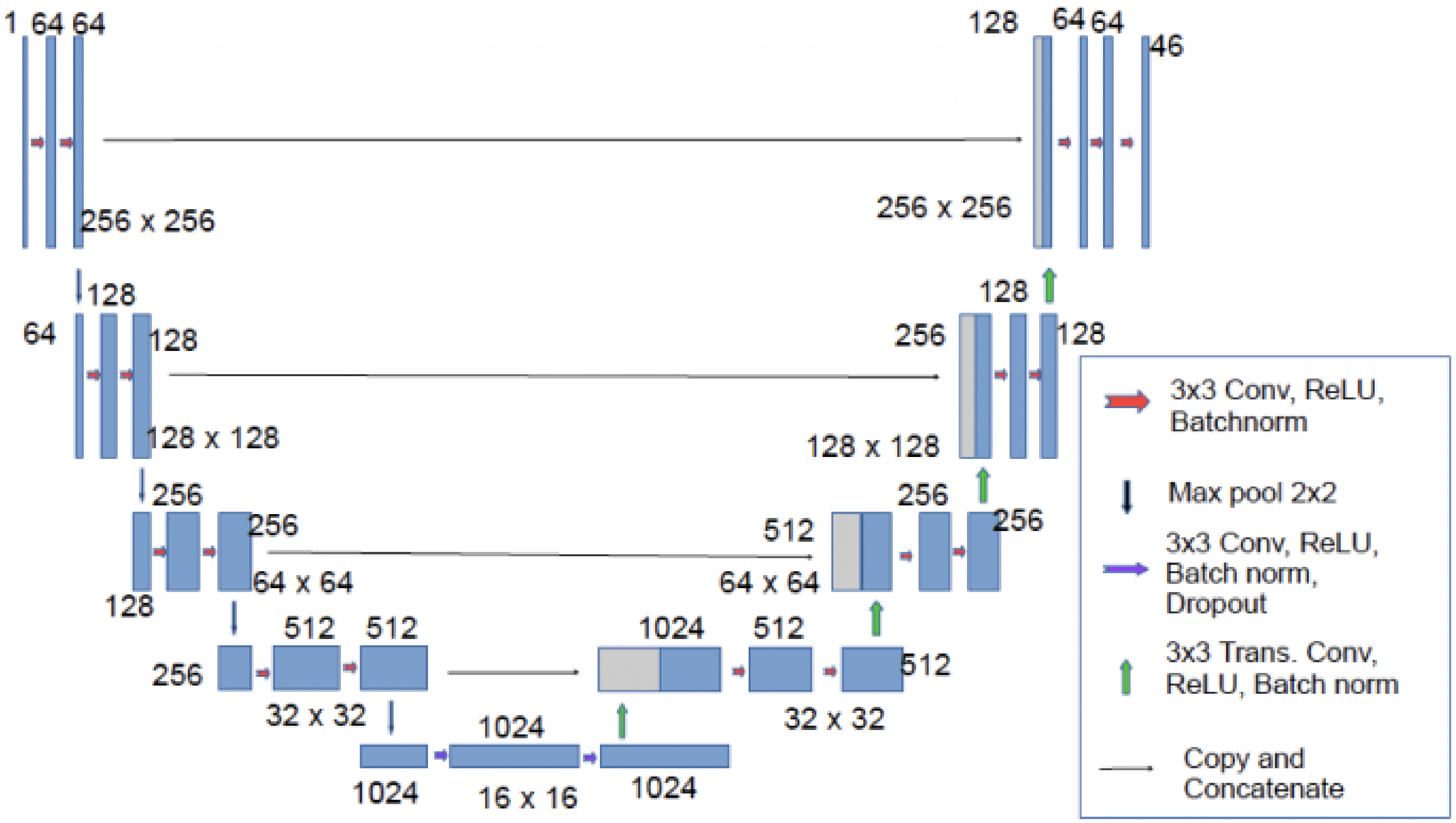
- Necrotic/non-enhancing tumor(NCR)
- Peritumoral edema (ED)
- Gd-enhancing tumor (ET)

Methodology

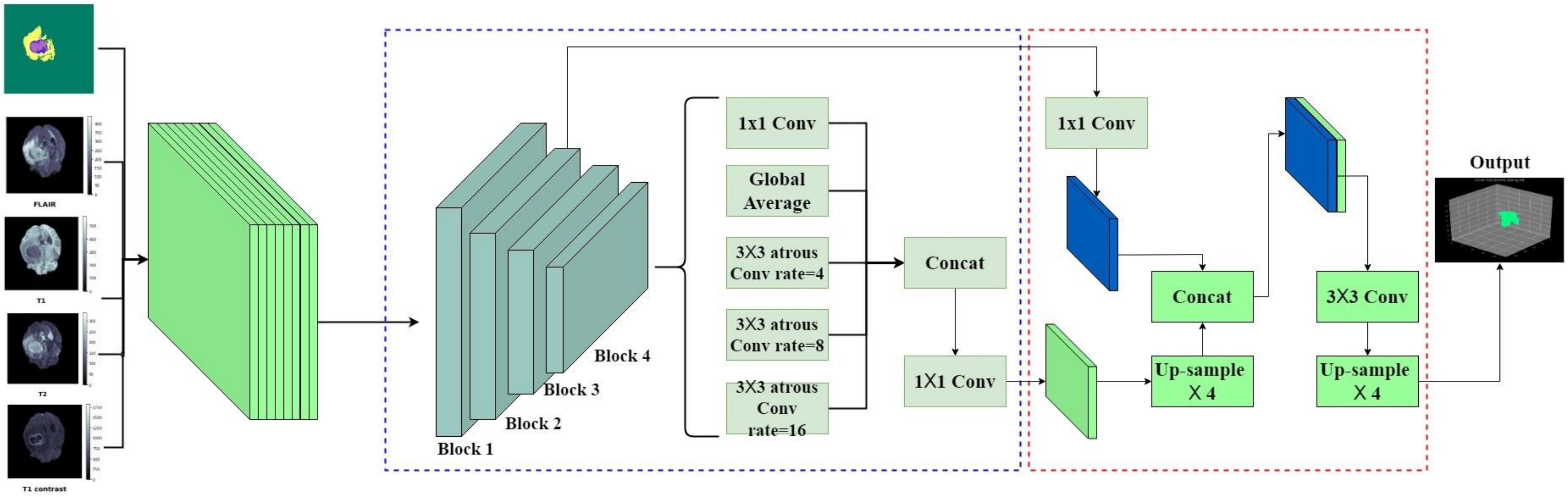


Identifying the Best Segmentation Model
GT
Tumor Segmentation
Finding the most important modality
Missing Modality Reconstruction
Train on different modality combinations
Reviewing the impact on the segmentation with the reconstructed modality

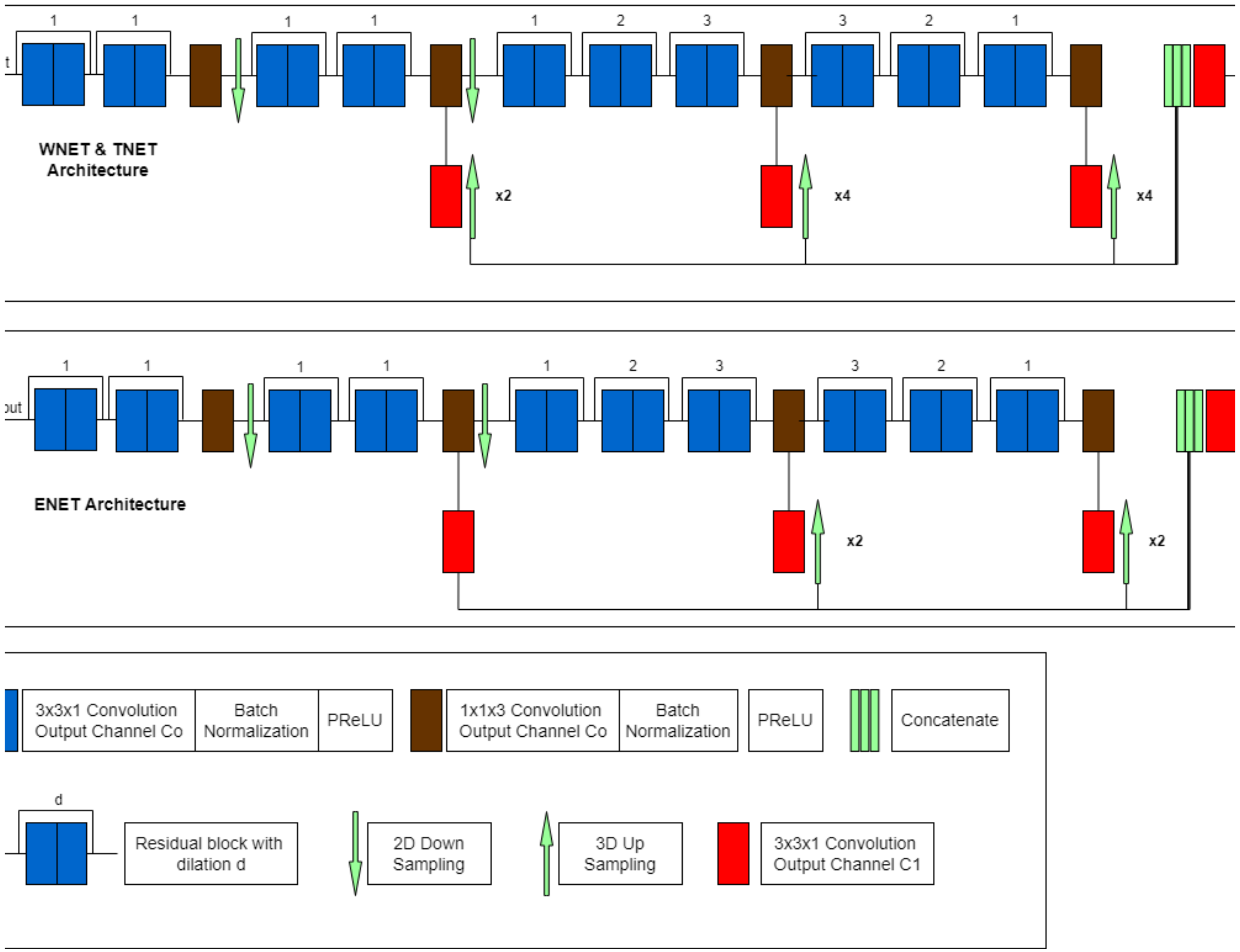
3D U-net Architecture



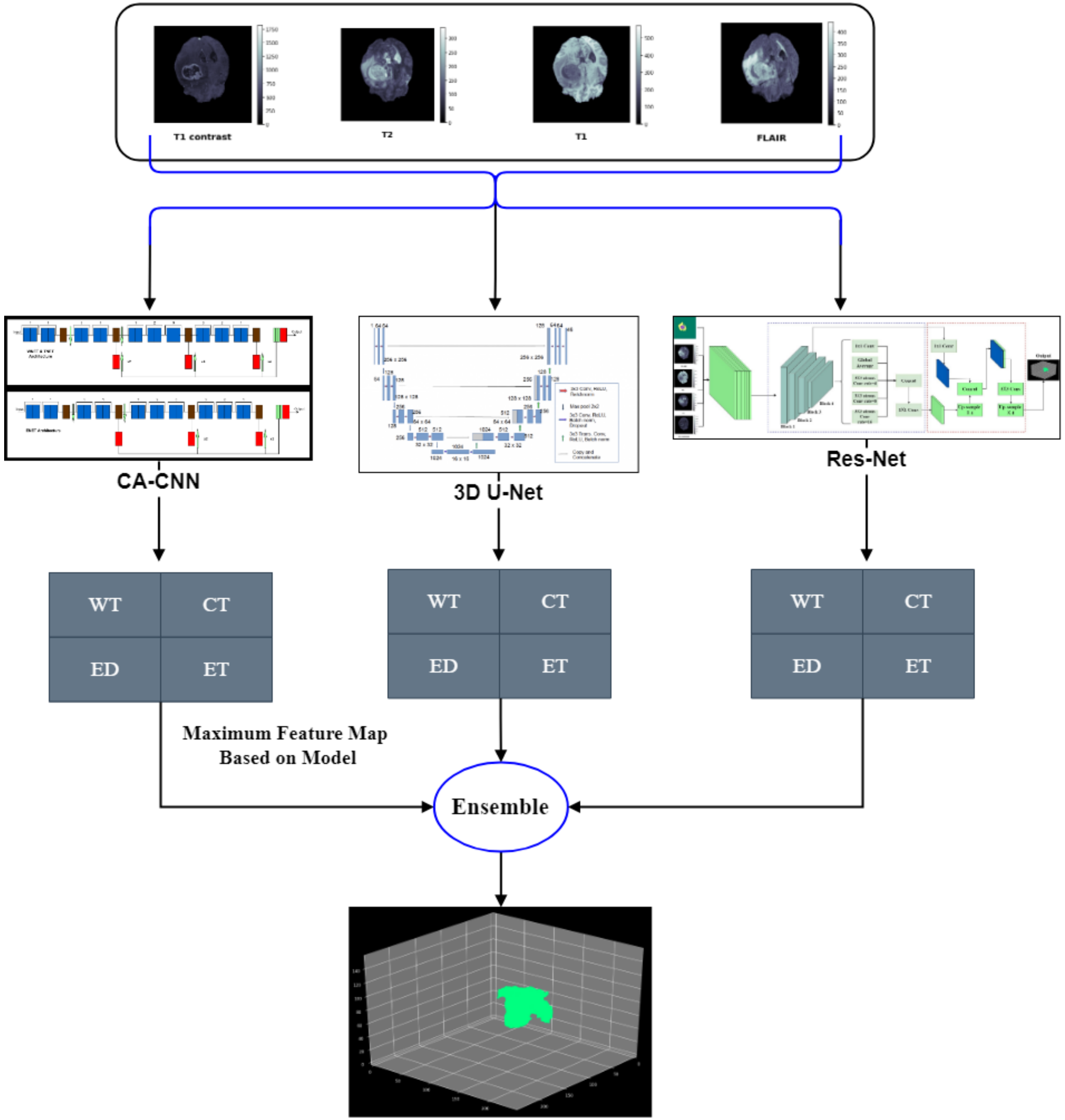
ResNet50 Architecture



Cascaded Anisotropic Convolutional Networks Architecture



Ensemble Architecture

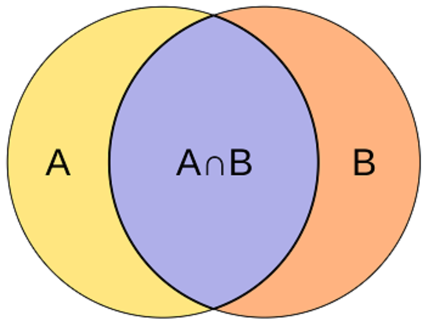


Final Output: 3D Cross Section of the Segmented Tumor

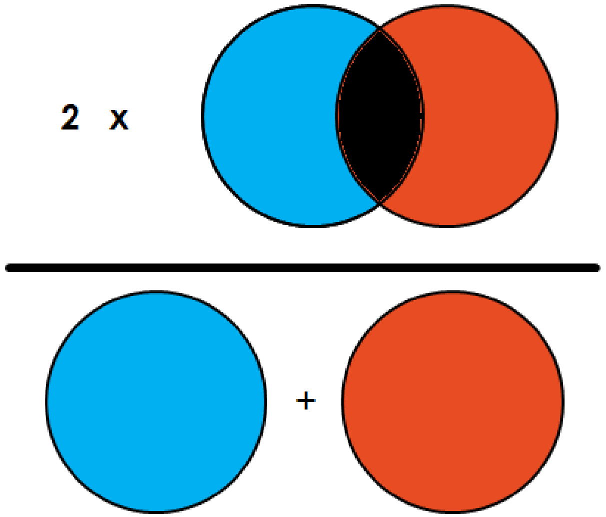
Results

Evaluation Metrics

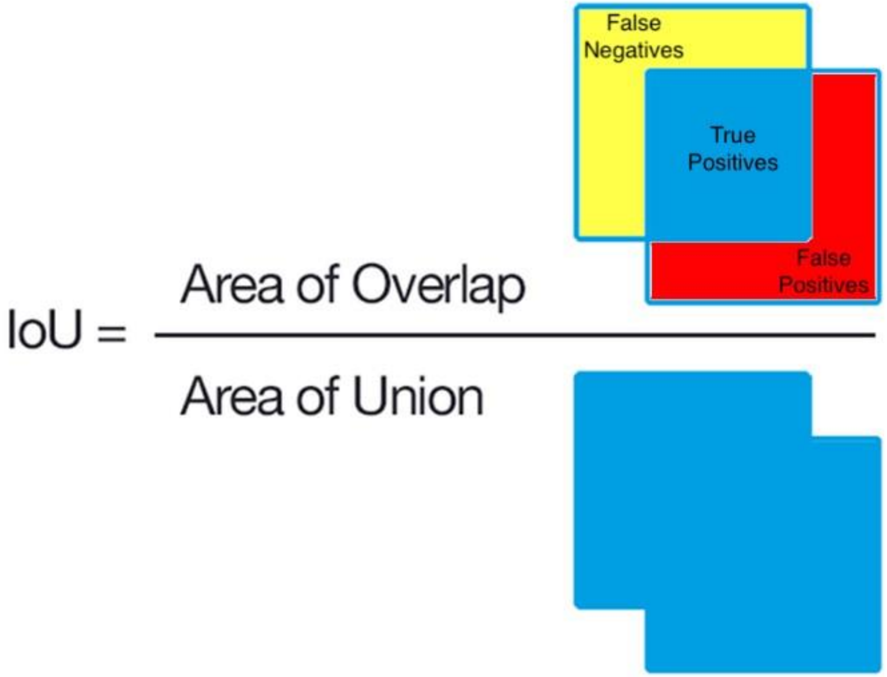
Dice Coefficient
(F1 Score)



$$\text{Dice coefficient}(A, B) = \frac{2 \times |A \cap B|}{|A| + |B|}$$



Intersection Over Union
(Jaccard Index)



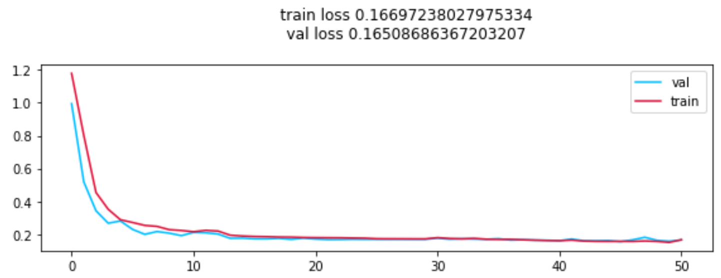
Finding the CNN Architecture with a Higher Accuracy

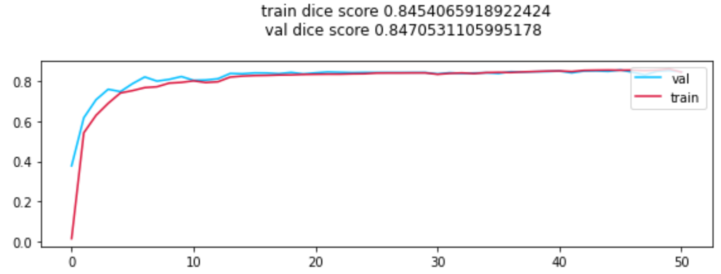
Model	Metric	Enhancing Tumor (ET)	Whole Tumor (WT)	Tumor Core (TC)
CA-CNN	Mean Dice	0.72682	0.80282	0.78343
	Sensitivity	0.81258	0.93045	0.85305
	Specificity	0.99807	0.99336	0.99786
3D Attention U-Net	Mean Dice	0.72088	0.88762	0.82567
	Sensitivity	0.84281	0.90188	0.81913
	Specificity	0.99743	0.99416	0.99813
ResNet50	Mean Dice	0.70524	0.86485	0.82531
	Sensitivity	0.87452	0.88864	0.79658
	Specificity	0.83243	0.91056	091069
Ensemble Model	Mean Dice	**0.74687**	**0.89152**	**0.85392**
	Sensitivity	0.83064	0.90688	0.83156
	Specificity	0.99815	0.99549	0.99863

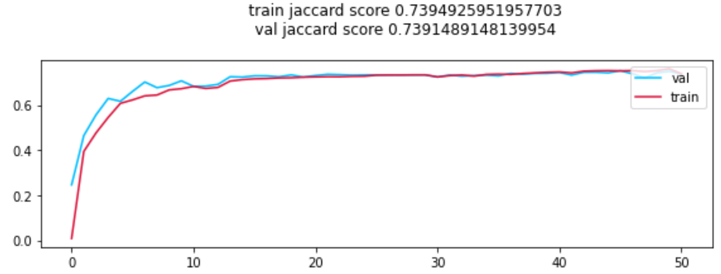
Segmentation Results on all 4 modalities using the Ensemble Model

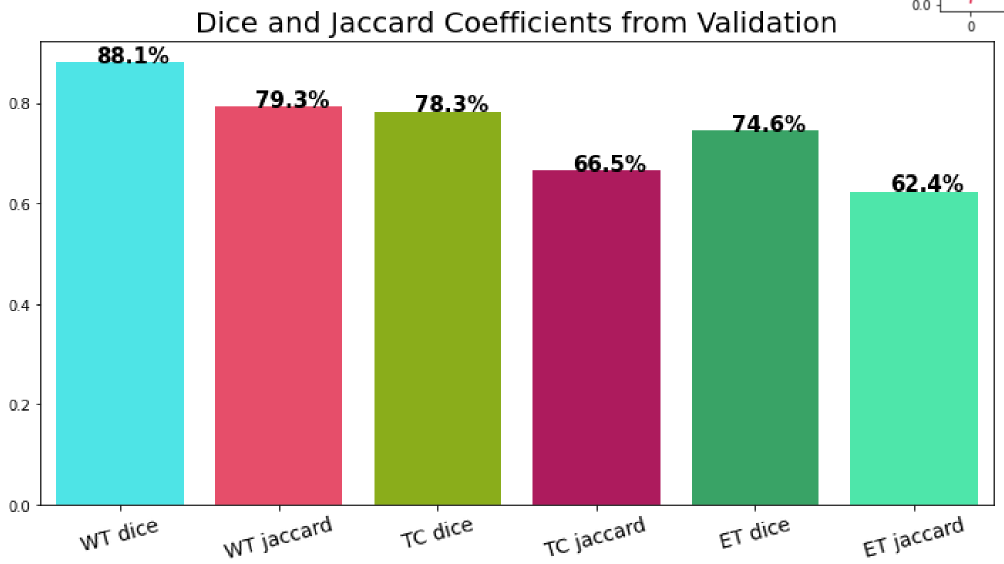
Training Results on the Segmented Tumor

Metric	Score
Training Loss	0.1669
Training Dice	84.54%
Training Jacaard	73.94%



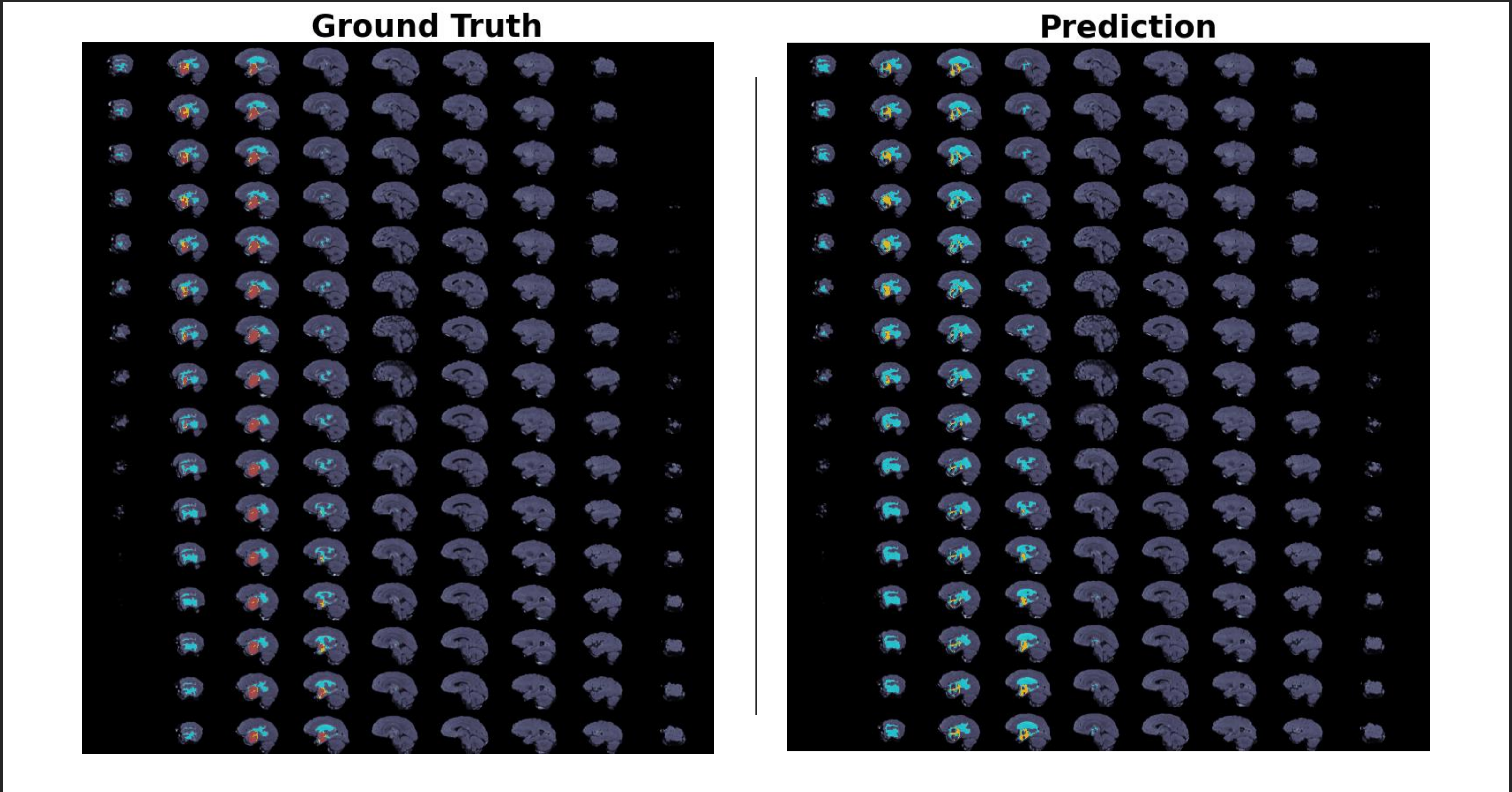






3D Cross Section of a Segmented Brain Tumor using the Ensemble Model

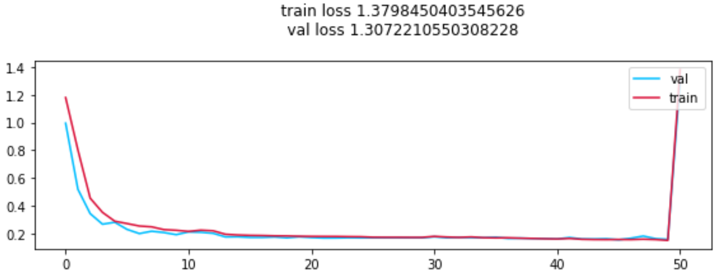
Ground Truth vs Predictions of the Ensemble

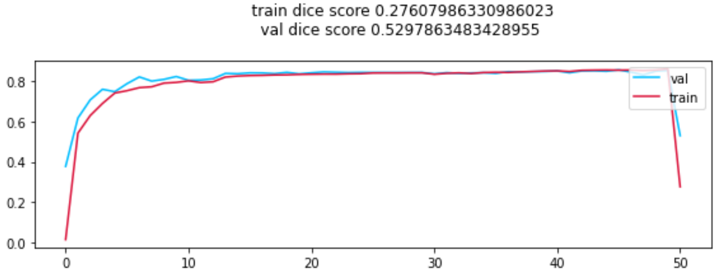


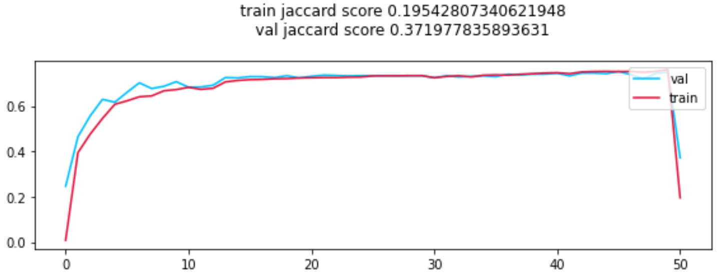
Segmentation Results on missing T2 Modality

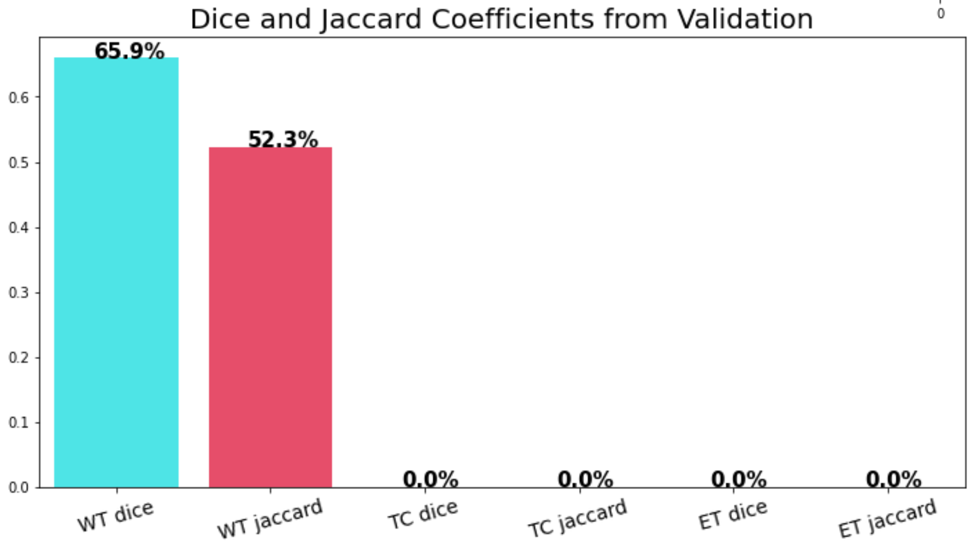
Training Results on the Segmented Tumor

Metric	Score
Training Loss	1.379
Training Dice	27.6%
Training Jacaard	19.54%





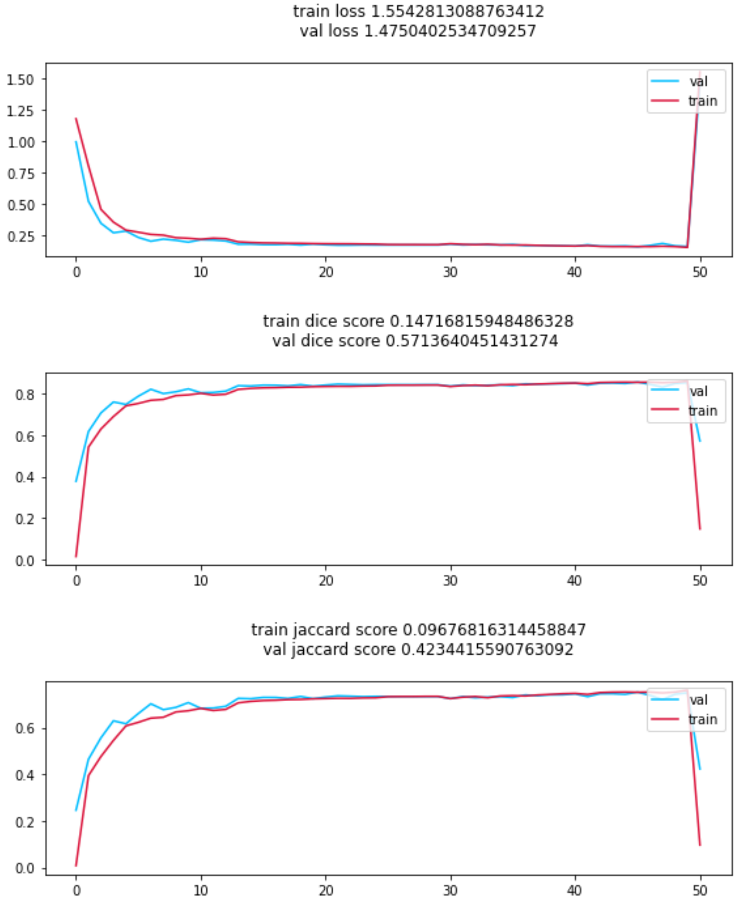


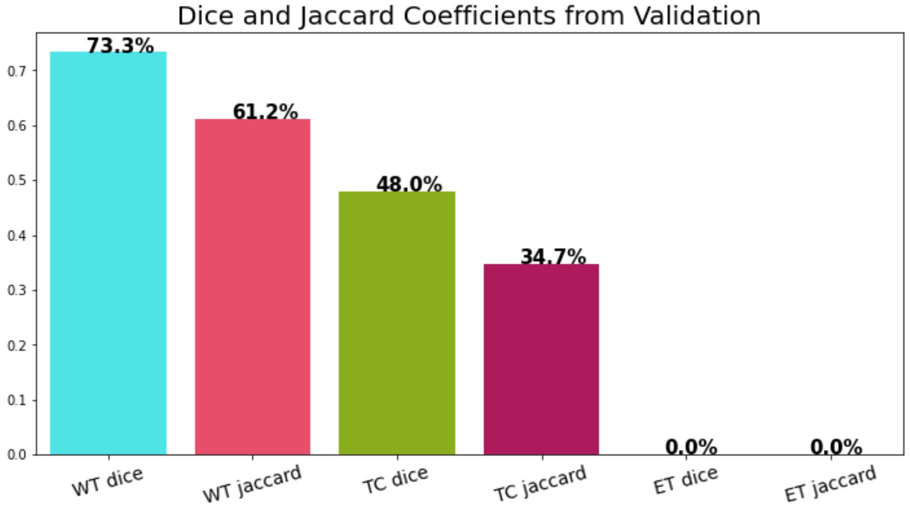


Segmentation Results on missing Post Contrast T1-weighted (T1ce) Modality

Training Results on the Segmented Tumor

Metric	Score
Training Loss	1.554
Training Dice	14.71%
Training Jacaard	9.67%

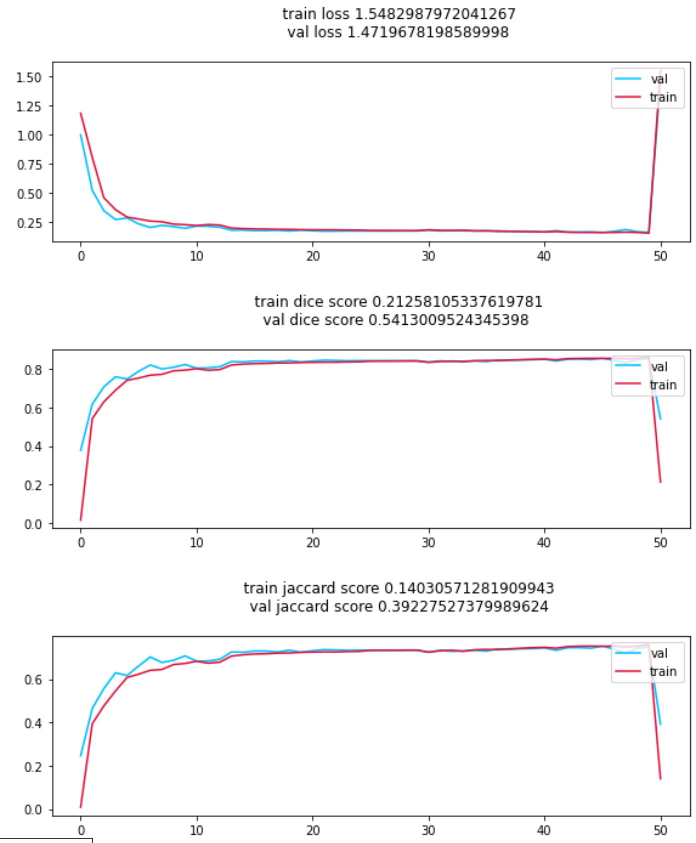




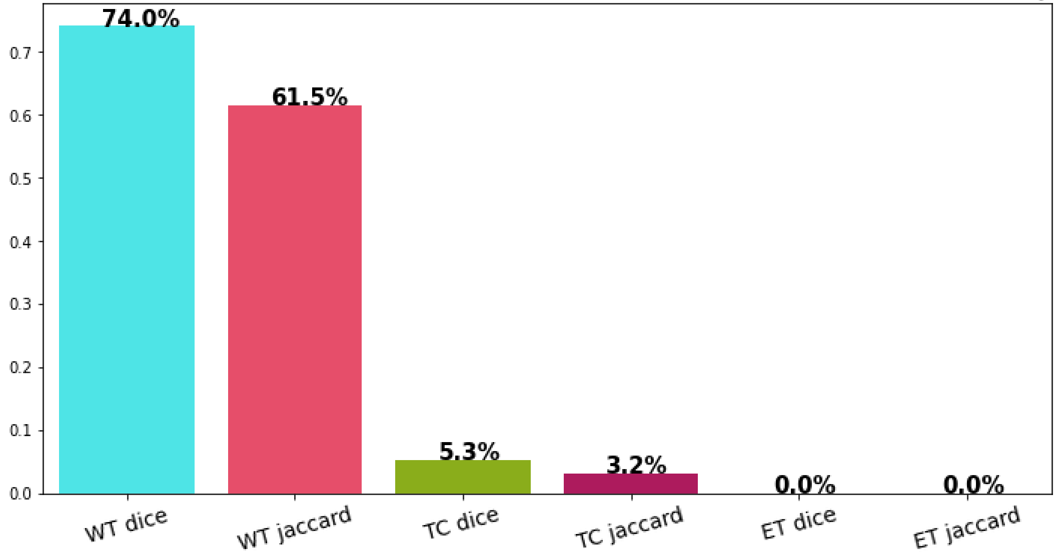
Segmentation Results on missing T1 Modality

Training Results on the Segmented Tumor

Metric	Score
Training Loss	1.548
Training Dice	21.25%
Training Jacaard	14.03%



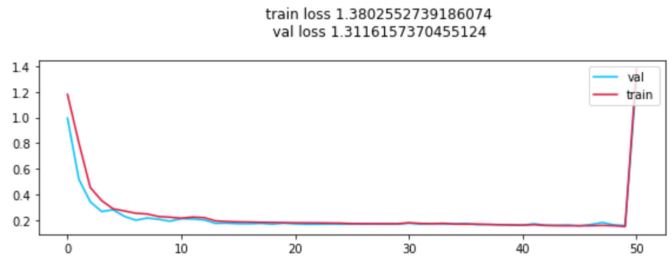
Dice and Jaccard Coefficients from Validation

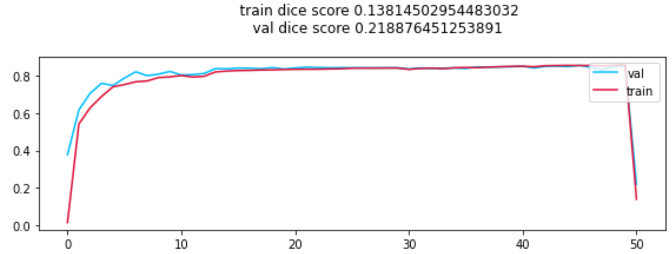


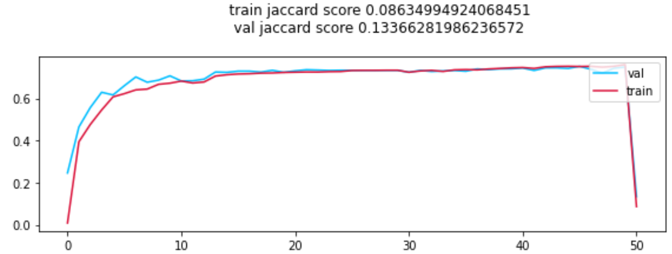
Segmentation Results on missing FLAIR Modality

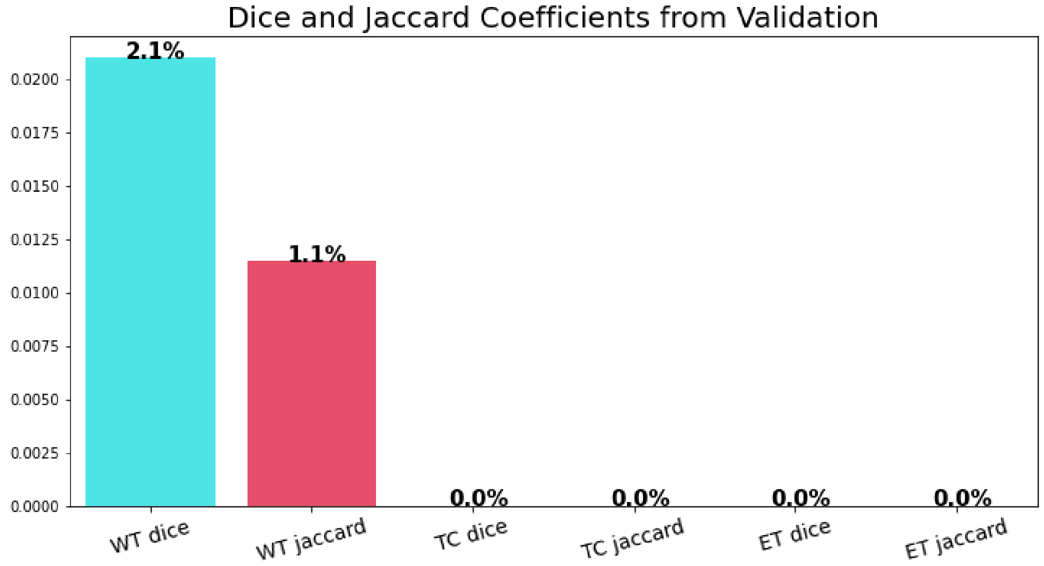
Training Results on the Segmented Tumor

Metric	Score
Training Loss	1.3802
Training Dice	13.81%
Training Jacaard	8.63%

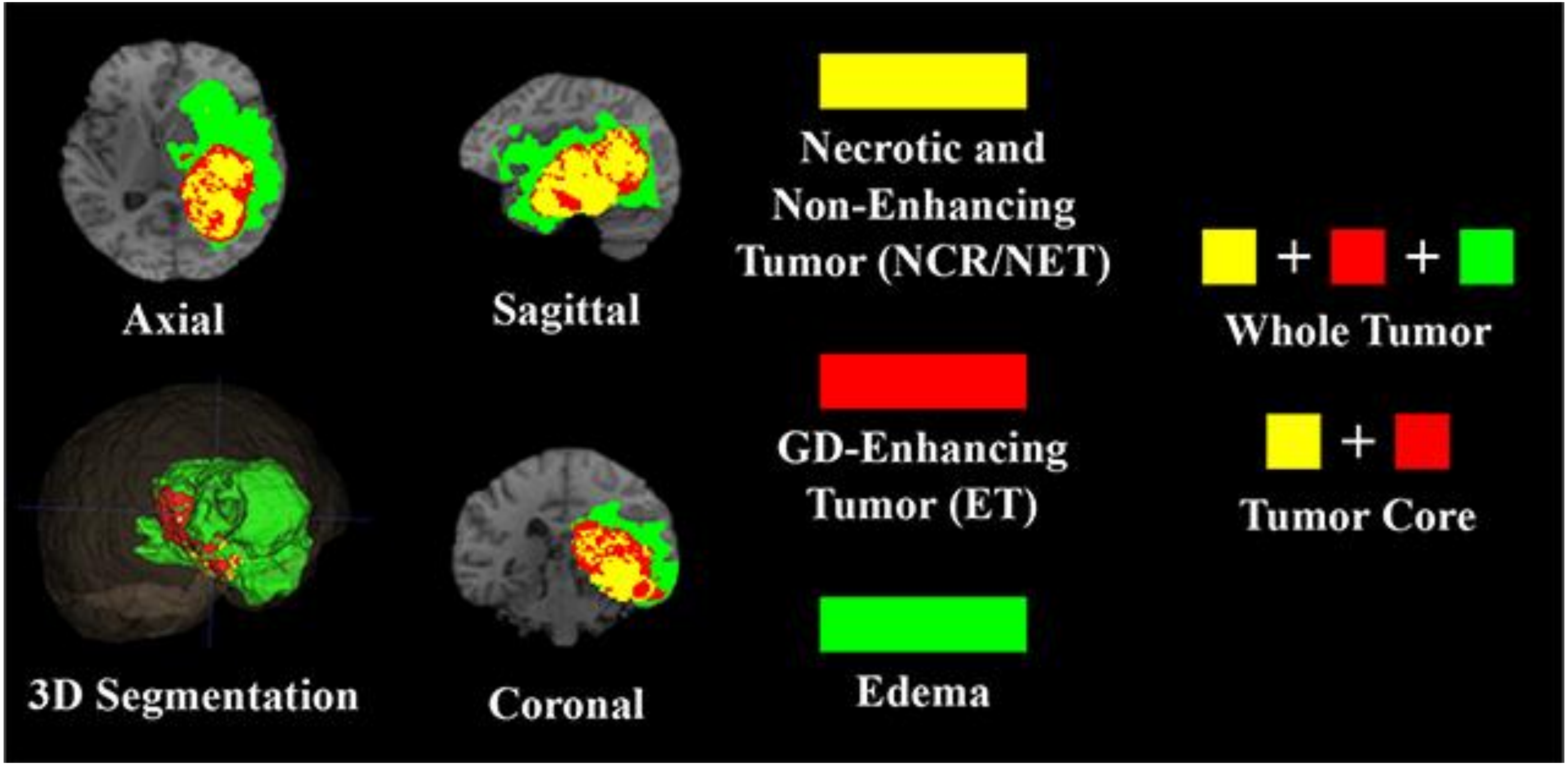








Sub Regions of a Brain Tumor



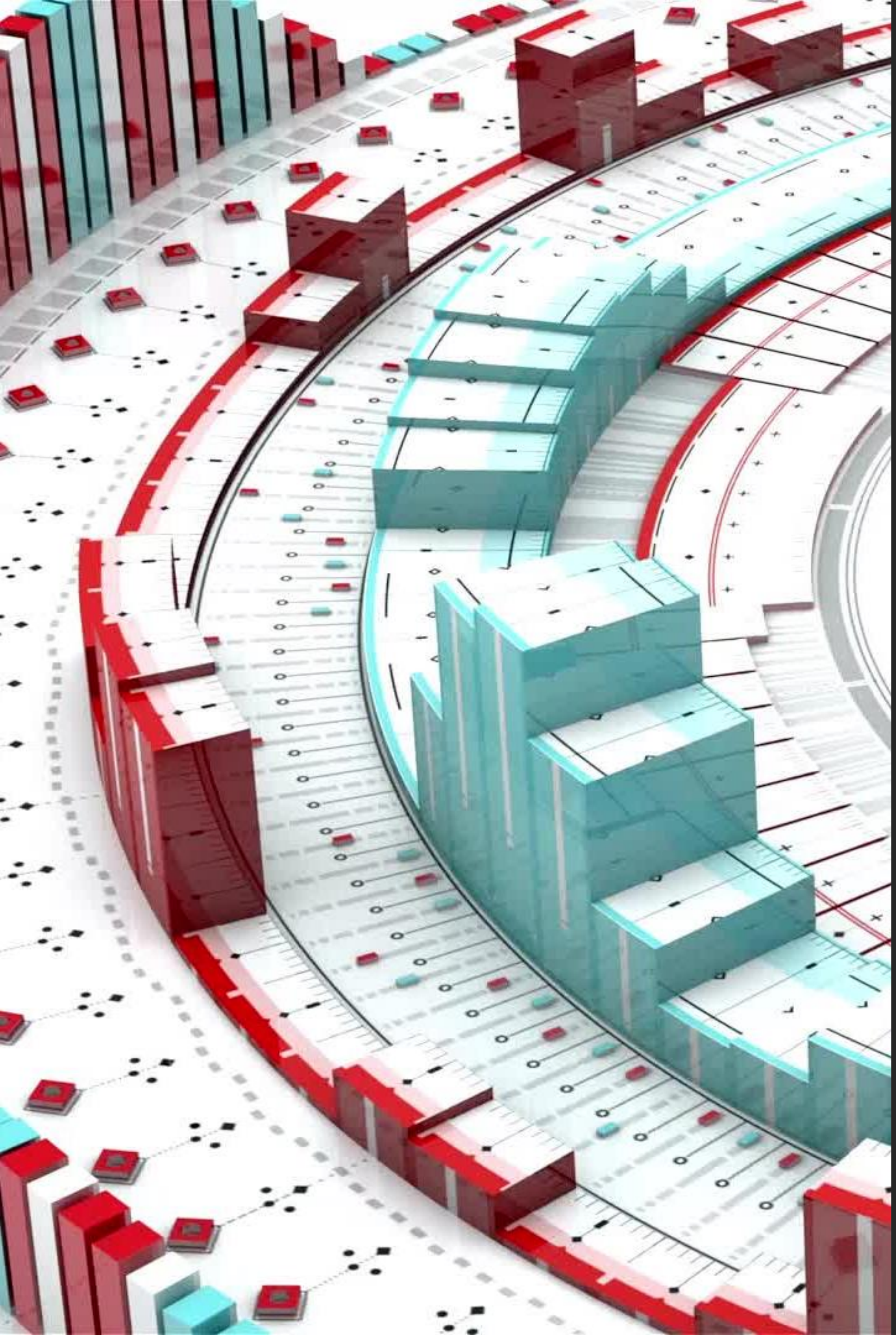
Challenges and Deviations

Configuring the dataset for each segmentation and classification model used in the research.

Downloading and loading the image dataset for training and testing.

Finding pre trained segmentation models with better accuracies for MRI scans.

Missing modality generation using GANs



Limitations of the Interpretation of Results

Number of images were insufficient for training.

Lack of GPU power.

Time constraint on developing a GAN.

CONCLUSION

Missing FLAIR modality and the T2-weighted modalities had a greater impact on the segmentation

Missing FLAIR modality significantly shows a very low percentage of Dice and Jaccard coefficients of the whole tumor and no score from the Tumor core and Enhancing Tumor

T2 modality shows a slight drop in Dice and Jaccard coefficients of the whole tumor and no score from the Tumor core and Enhancing Tumor

T1ce modality has a lower impact on the segmentation and is important in detecting the Enhancing Tumor

FUTURE WORK

Reconstruction of missing FLAIR and T2 modalities using a Generative Adversarial Network

Survival Prediction of patients with Higher Grade Gliomas

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Thank You

ANY QUESTIONS?