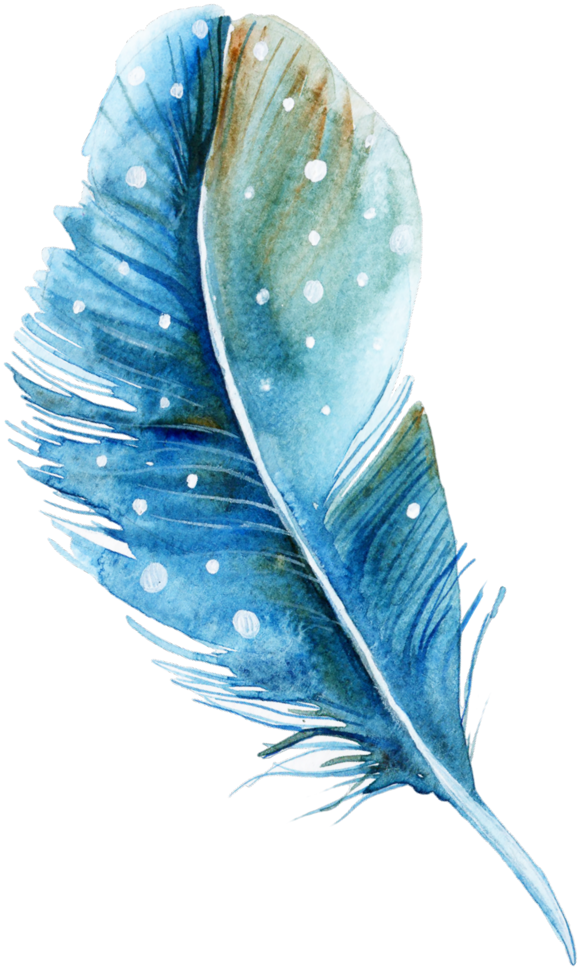
Beijing University of Posts and Telecommunications
Queen Mary University of London

# An Algorithm For 3D MRI Brain Tumor Segmentation

## Final Viva

Speaker: Dong Wanqi
Student No: 2018213196
Affiliation: BUPT & QMUL



# CONTENT

Part 01

# Project overview

# Project overview

## 1. Brain tumor

- ✓ Brain tumor is a mass of malicious cells in the brain.
- ✓ Claimed millions of lives of human beings

## 2. Why automated brain tumor segmentation?

- ✓ Pinpoint the exact location of the tumor.
- ✓ Identify different tumor areas and tissue properties.

- ✓ Manual delineation can be expensive, time consuming, inaccurate.
- ✓ Save time, provide suggestions for tumor analysis and resection.

## 3. Objectives & Tasks

- ✓ Propose an algorithm for 3D MRI brain tumor segmentation.
- ✓ Compare with other methods
- ✓ Improve segmentation performance

Part 02

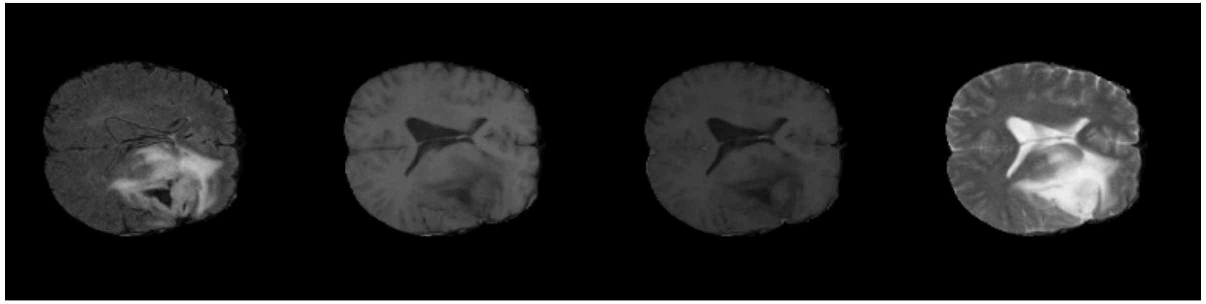
# Background

# Dataset, labels, and segmentation targets

**Source**:
Multimodal Brain Tumor Segmentation Challenge 2020 (BraTS 2020)

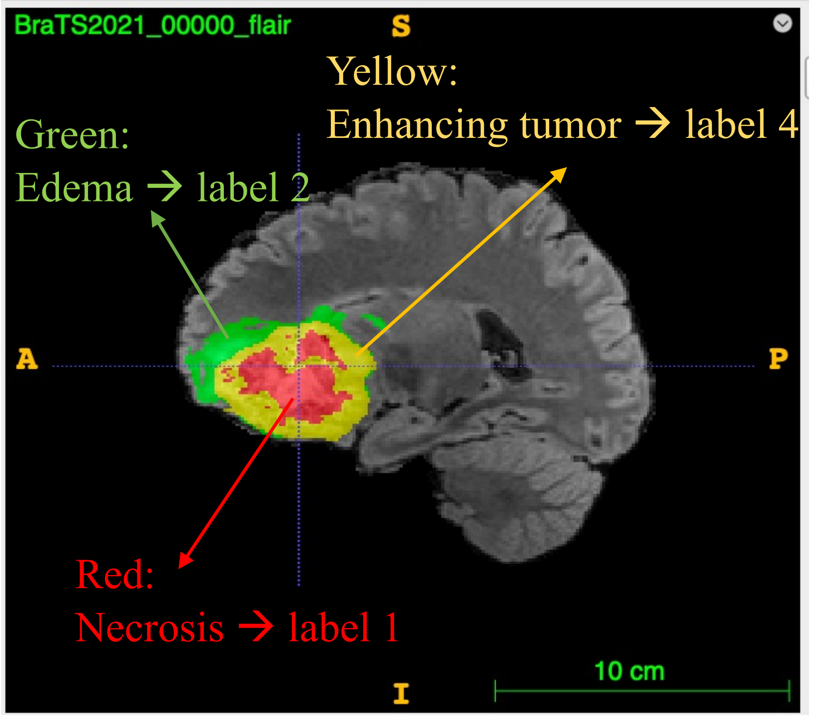
**Details of the dataset :**

- ✓ **File format:** nii.gz
- ✓ **Modalities:** FLAIR, T1, T1c, T2 (4 modalities)
- ✓ **Image Size:** 240(Slide height)×240(Slide width)×155(Number of slides)×4(Modality number)
- ✓ **Used dataset size:** 200 Volumes




<Four modalities for each 3D data volume>

**Labels:**




**Segmentation target (Tumor regions):**

- ✓ ET (Enhancing tumor) → label 4
- ✓ TC (Tumor core) → label 4 + label 1
- ✓ WT (Whole Tumor) → label 4 + label 1 + label 2

ET, TC, WT are three overlapping parts!!

Part 03

# Design & Innovation

# Data pre-processing & Data augmentation

## Data Normalization:

Minmax normalization + Remove outliers → Scaled to 0~1

Minmax normalization: $x_{new} = \frac{(x_{old} - X_{min})}{(X_{max} - X_{min})}$

## Data cropping and padding:

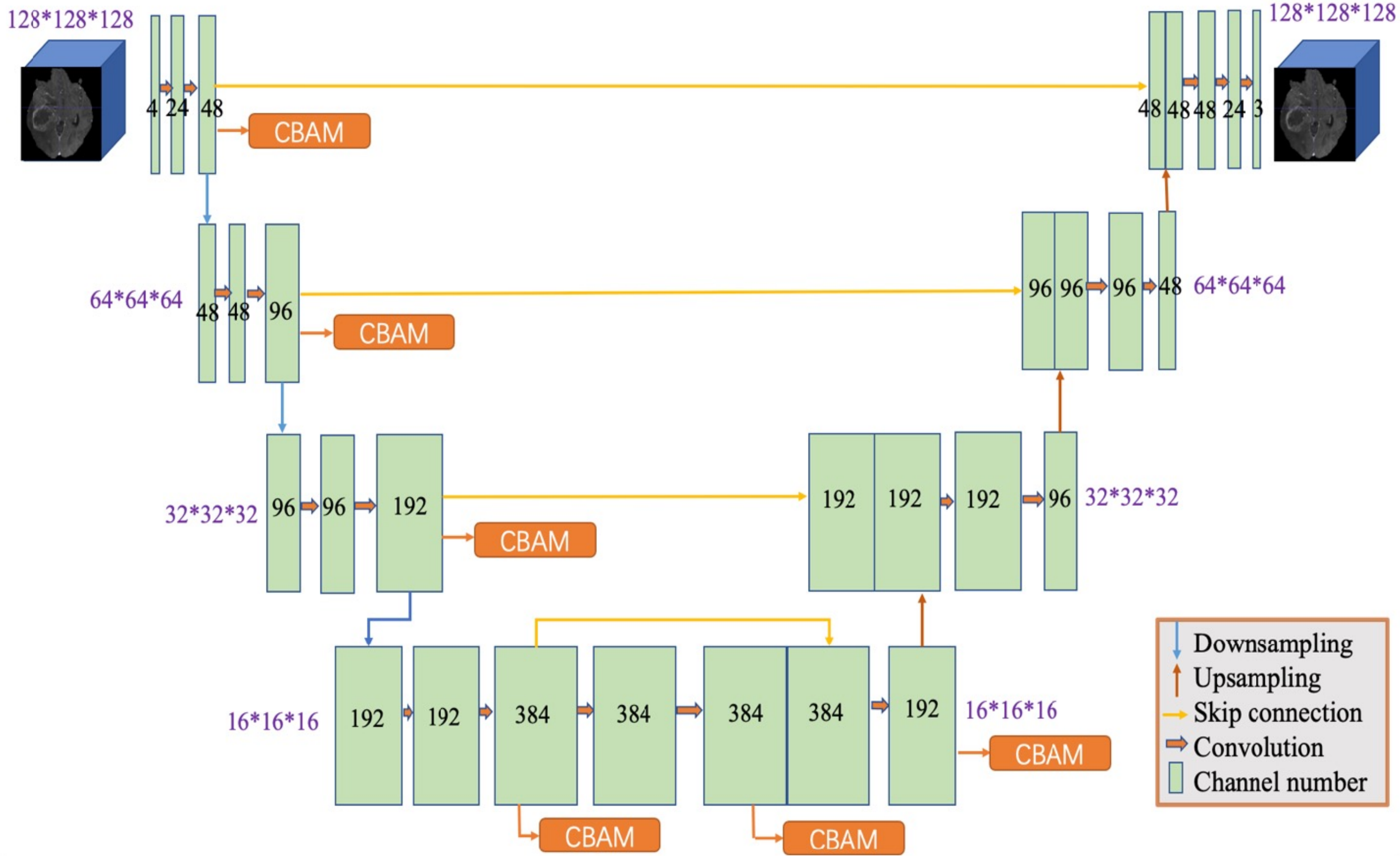
Minimal bounding box strategy → 128*128*128

## Data augmentation strategies:

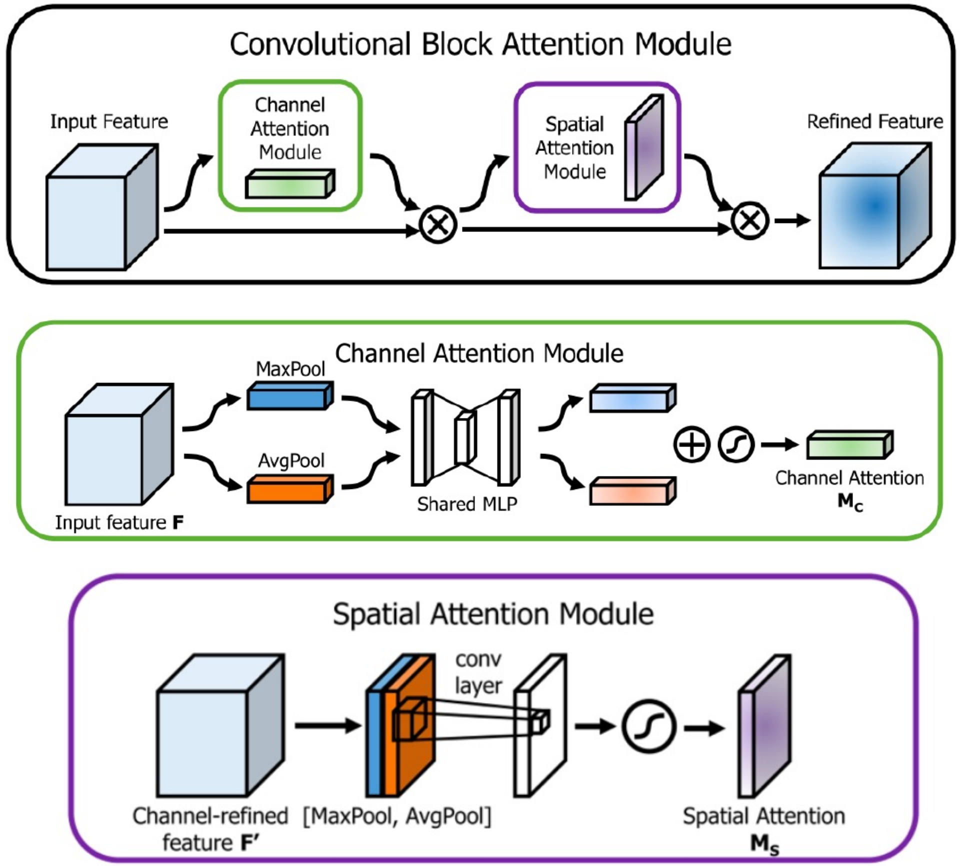
| Strategy | Rescaling | Noise | Transposing | Flipping | Channel dropping |
|---|---|---|---|---|---|
| Probability | 0.8 | 0.8 | 0.8 | 0.8 | 0.2 |

# Proposed model: Atten_Unet

## Proposed model: Atten_Unet




## CBAM (Convolutional Block Attention Module)

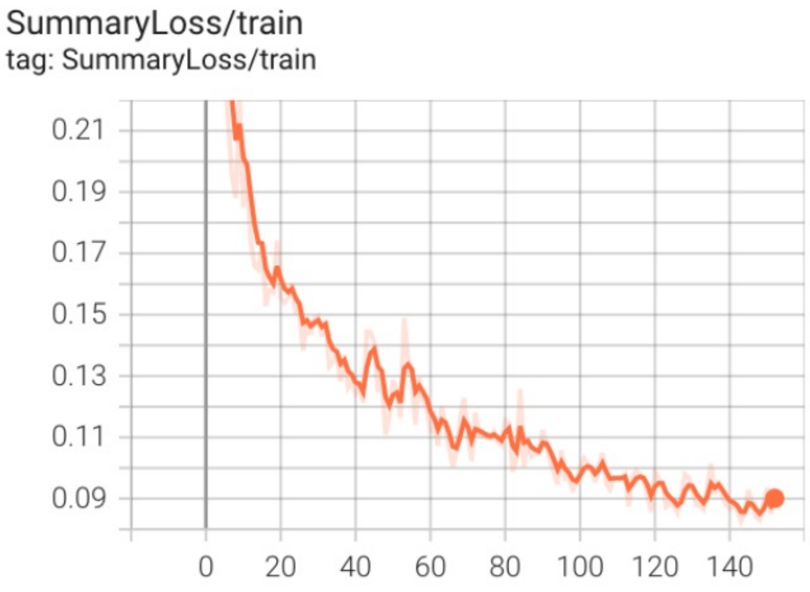


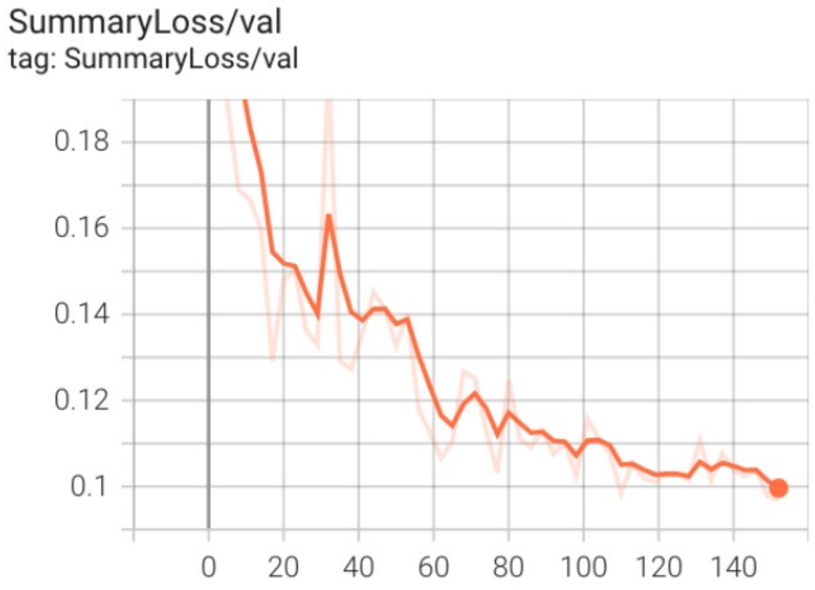
# Loss function & Training procedure

- **Loss:** Dice Loss

$$L_{dice} = 1 - \frac{2 * \sum p_{true} * p_{pred} + \varepsilon}{\sum p_{true}^2 + \sum p_{pred}^2 + \varepsilon}$$

- **Optimizer:** Adam (Initial learning rate = 0.0001)
- **Device:** Google Colab Pro, Telsa V100 GPU
- **Training:** 150 epochs, 17 hours
- **5-fold cross validation** (4/5 Training, 1/5 Validation)



# Evaluation metrics

**1. Dice similarity coefficient (DSC Score) → To replace accuracy**

$$DSC = \frac{2TP}{2TP + FP + FN}$$

- DSC indicates the extent of overlap between the predicted tumor regions and actual tumor regions

**2. Hausdorff distance**

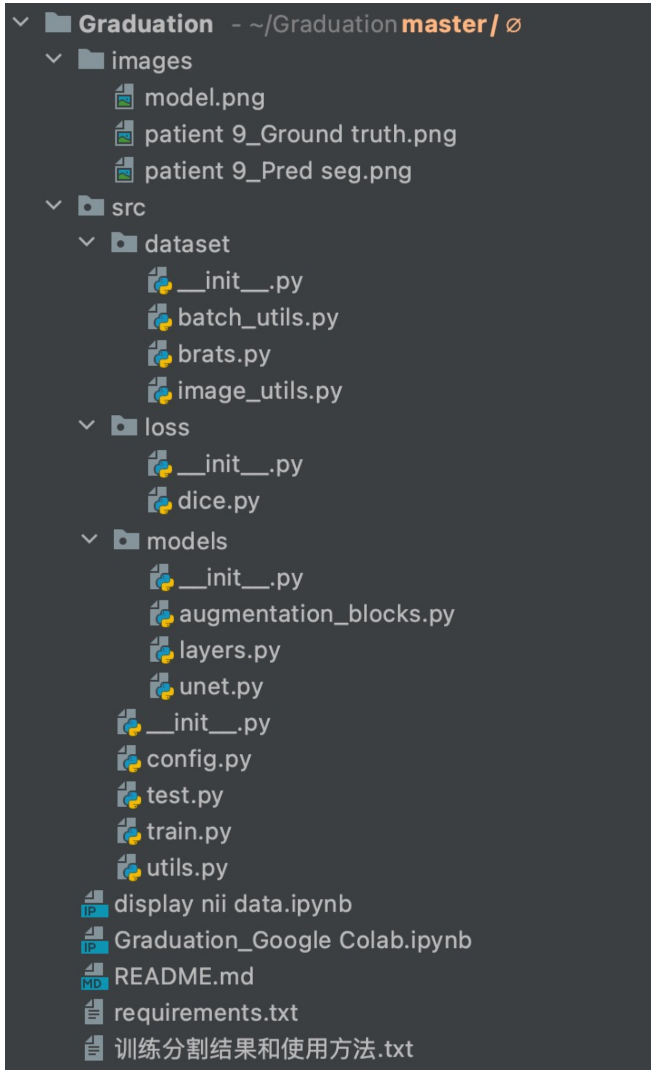
$$h(A,B) = \max_{a \in A} \left\{ \min_{b \in B} d(a,b) \right\}$$

- Hausdorff distance is a complement to the DSC
- Can be used to measure the maximum distance between two contour edges
- Used to present the severity of outliers for segmentation

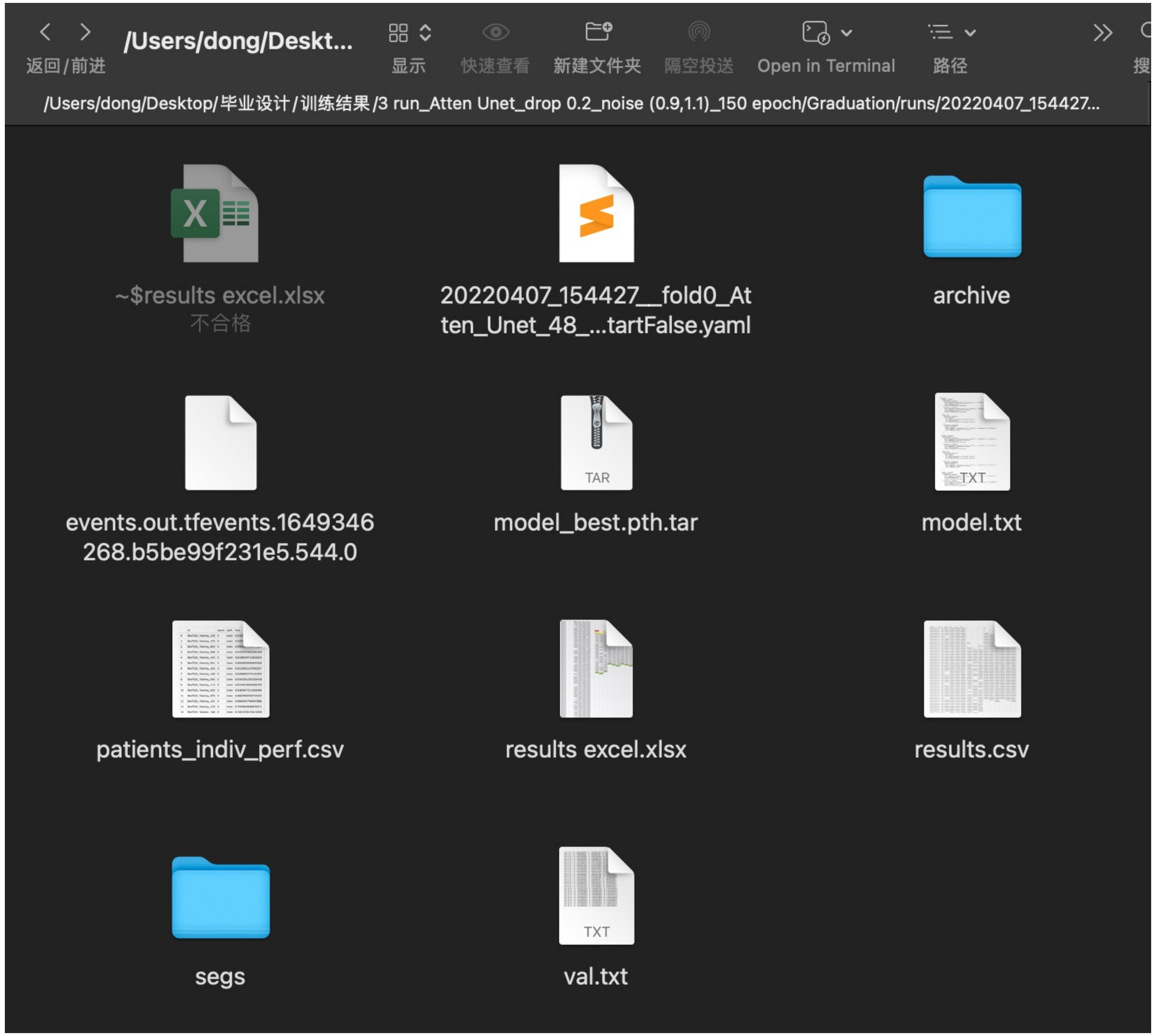
# Code and logs

## Code on Github: https://github.com/sea-comet/Graduation

Overall structure of the code:




## Logs for training



# Code and logs

```
Epoch 113 :Val : ['ET : 0.8499204516410828', 'TC : 0.8979440927505493', 'WT : 0.8637707829475403']
Epoch 116 :Val : ['ET : 0.8520125150680542', 'TC : 0.8950595855712891', 'WT : 0.8769645690917969']
Epoch 119 :Val : ['ET : 0.8518754839897156', 'TC : 0.8986184000968933', 'WT : 0.8769129514694214']
Epoch 122 :Val : ['ET : 0.8516132235527039', 'TC : 0.8979402780532837', 'WT : 0.8717659115791321']
Epoch 125 :Val : ['ET : 0.8499546051025391', 'TC : 0.8973857760429382', 'WT : 0.8730329275131226']
Epoch 128 :Val : ['ET : 0.8494693636894226', 'TC : 0.8980101346969604', 'WT : 0.8792937994003296']
Epoch 131 :Val : ['ET : 0.8539274334907532', 'TC : 0.8984575271606445', 'WT : 0.8414308428764343']
Epoch 134 :Val : ['ET : 0.8536598086357117', 'TC : 0.8981119990348816', 'WT : 0.8737003207206726']
Epoch 137 :Val : ['ET : 0.8512079119682312', 'TC : 0.895054817199707', 'WT : 0.8577709197998047']
Epoch 140 :Val : ['ET : 0.8503589630126953', 'TC : 0.8977636098861694', 'WT : 0.8699328303337097']
Epoch 143 :Val : ['ET : 0.8515545725822449', 'TC : 0.8987848162651062', 'WT : 0.8706623315811157']
Epoch 146 :Val : ['ET : 0.8537999987602234', 'TC : 0.9003745913505554', 'WT : 0.8631355166435242']
Epoch 149 :Val : ['ET : 0.8533316850662231', 'TC : 0.901594340801239', 'WT : 0.8825992345809937']
Epoch 152 :Val : ['ET : 0.8538955450057983', 'TC : 0.9004379510879517', 'WT : 0.8864582180976868']
```

**Val.txt**: DSC scores for three tumor regions

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | patient_id | label | haussdorf | dice | sens | spec |
| 2 | BraTS20_Training_005 | ET | 2.82842712 | 0.83202777 | 0.82226961 | 0.99981339 |
| 3 | BraTS20_Training_005 | TC | 2.82842712 | 0.92377067 | 0.89562804 | 0.99992977 |
| 4 | BraTS20_Training_005 | WT | 75.3126815 | 0.74599071 | 0.77516733 | 0.99925264 |
| 5 | BraTS20_Training_009 | ET | 21.7715411 | 0.81397963 | 0.74674368 | 0.99949511 |
| 6 | BraTS20_Training_009 | TC | 19.2613603 | 0.89731446 | 0.88943089 | 0.9991988 |
| 7 | BraTS20_Training_009 | WT | 24 | 0.91797891 | 0.93050564 | 0.99797356 |
| 8 | BraTS20_Training_011 | ET | 4.47213595 | 0.7956476 | 0.98146865 | 0.99968573 |
| 9 | BraTS20_Training_011 | TC | 4.35889894 | 0.91731714 | 0.91731714 | 0.99990379 |
| 10 | BraTS20_Training_011 | WT | 8.54400375 | 0.91607586 | 0.95156902 | 0.99921762 |
| 11 | BraTS20_Training_012 | ET | 3.74165739 | 0.83924051 | 0.77699648 | 0.99995001 |
| 12 | BraTS20_Training_012 | TC | 2.23606798 | 0.92719645 | 0.90748792 | 0.99995359 |
| 13 | BraTS20_Training_012 | WT | 5.65685425 | 0.8694556 | 0.8069951 | 0.99982228 |
| 14 | BraTS20_Training_016 | ET | 5.09901951 | 0.64147306 | 0.99585604 | 0.99837891 |
| 15 | BraTS20_Training_016 | TC | 3.31662479 | 0.79799633 | 0.67667105 | 0.99991099 |
| 16 | BraTS20_Training_016 | WT | 4.12310563 | 0.90106505 | 0.91993804 | 0.99823755 |
| 17 | BraTS20_Training_023 | ET | 2.44948974 | 0.87748421 | 0.86998263 | 0.9998615 |
| 18 | BraTS20_Training_023 | TC | 1.41421356 | 0.95323646 | 0.92639507 | 0.999966 |

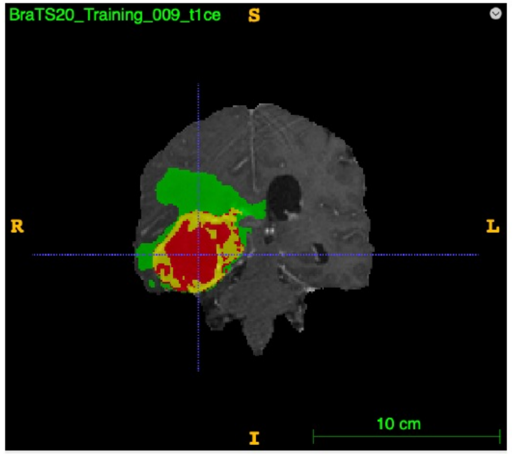
**Patients_indiv_perf.csv**

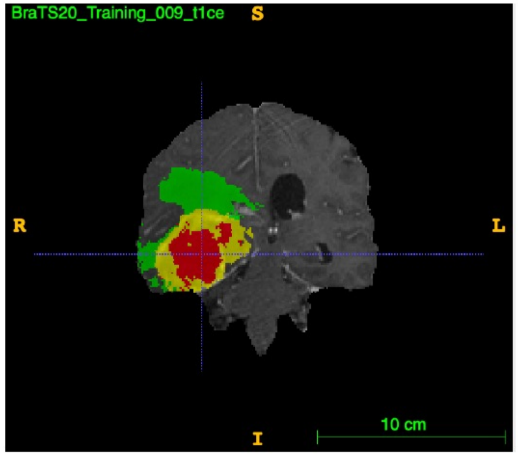
Part 04

# Results

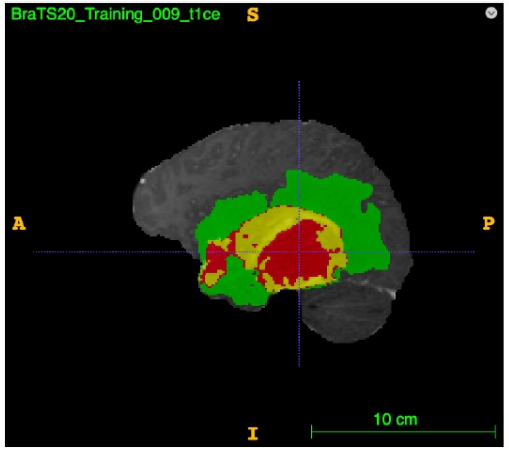
# Segmentation results

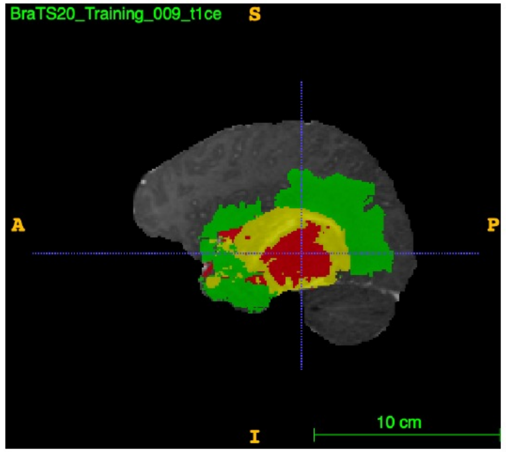
**Predicted segmentation result:** **Ground Truth label:**



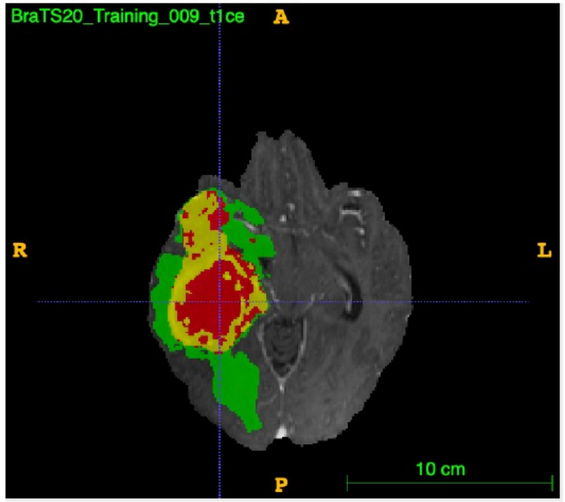



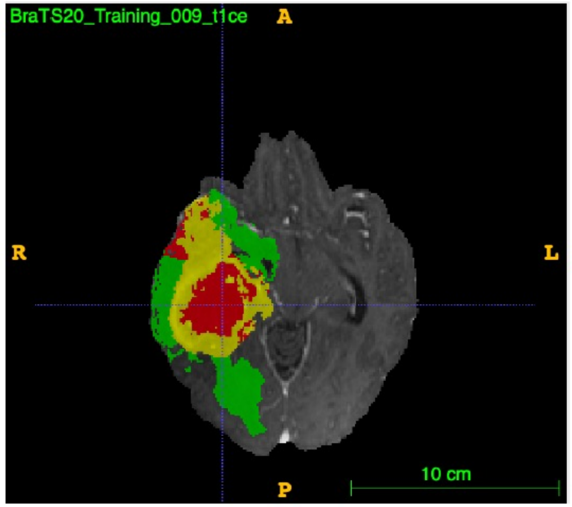

**Predicted segmentation result:** **Ground Truth label:**




**Predicted segmentation result:** **Ground Truth label:**



# Qualitative results and comparison

## Qualitative results of my algorithm

| | ET | TC | WT |
|---|---|---|---|
| **DSC** | 0.8539 | 0.9004 | 0.8865 |
| **Hausdorff** | 7.599 | 4.882 | 21.612 |

## Comparison between my method and the winner solution nn-Unet in BraST 2020

| nn-Unet / My Method | ET | TC | WT |
|---|---|---|---|
| **DSC** | 82.03 / **85.39** | 85.06 / **90.04** | 88.95 / 88.65 |
| **Hausdorff** | 17.805 / **7.599** | 17.337 / **4.822** | 8.498 / 21.612 |

My method ***outperforms*** nn-Unet regarding tumor regions ET and TC. The results for WT is ***close*** to nn-Unet.

## Comparison of my method and the method with model replaced with 3D-Unet

| 3D-Unet / My Method | ET | TC | WT |
|---|---|---|---|
| **DSC** | 84.83 / **85.39** | 89.91 / **90.04** | 87.14 / **88.65** |
| **Hausdorff** | 9.47 / **7.599** | 8.53/ **4.822** | 33.57 / **21.612** |

My method ***outperforms*** 3D-Unet in every metrics for three tumor regions ET, TC and WT

Part 05

# Conclusion & Future work

# Conclusion & Future work

## Conclusion

- ✓ My algorithm provides better performance for 3D MRI brain tumor segmentation
- ✓ Pave the way for automated tumor segmentation in medical field

## Future work

- ✓ Train more epochs
- ✓ Train on the whole dataset when computational resource is sufficient

## Future work

- ✓ Try other networks
- ✓ Try other data augmentation strategies

# Thank you for listening