BIOMEDICAL IMAGE ANALYSIS FINAL PROJECT:

AUTOMATIC BRAIN TUMOR SEMANTIC SEGMENTATION

TEAM 8

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OUTLINE

- Introduction
- Related Works
- Dataset
- Proposed Method
- Experimental Results
- Conclusions & Future Work

INTRODUCTION

National Brain Tumor Society

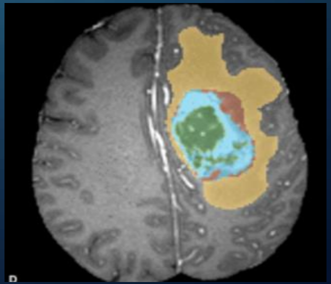
- **Cell origin or not / Benign → Malignent**
- **Symptoms:** Headaches, Vision problems, Speech difficulties and Unexplained nausea, …etc.
- **Survival rate:** For the most malignant brain tumors, the five-year relative survival rate is :

	5-Year Relative Survival Rate		
Brain Tumor Type	**Age**		
	20-44	**45-54**	**55-64**
Glioblastoma	22%	9%	**6%**

INTRODUCTION

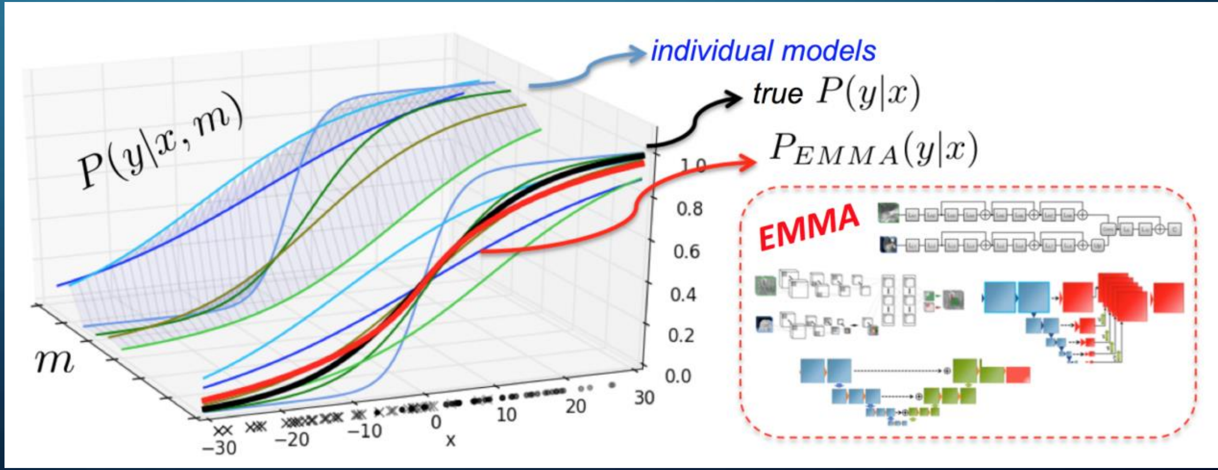
National Brain Tumor Society

- Quantitative assessment of brain tumor is an essential part of diagnose procedure.
- Automatic segmentation:
    - Faster and more objective.
    - However, due to the irregular nature of tumor, the development of method for segmentation remains challenging.



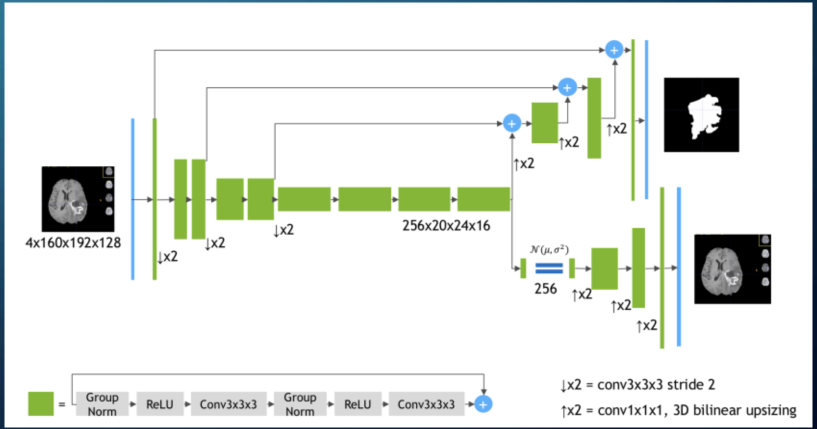
RELATED WORKS

- Kamnitsas et al. (BraTS 2017)
  - Ensembles of Multiple Models and Architectures (EMMA)
    - DeepMedic (Fully 3D, multi-scale CNN)
    - 3D U-Net
    - 3D FCN



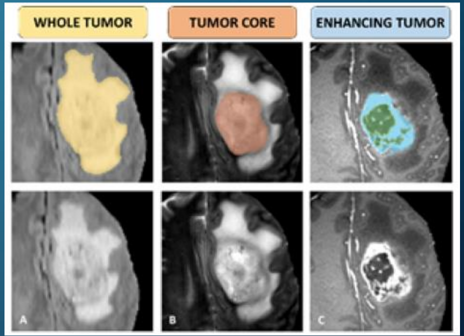
RELATED WORKS

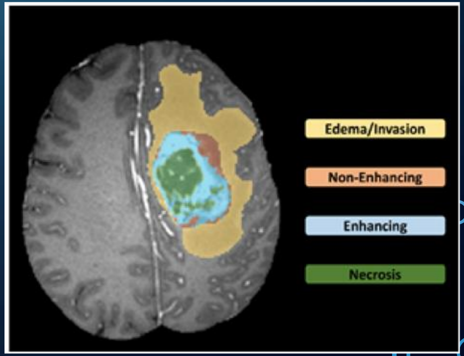
- Myronenko (BraTS 2018)
  - Autoencoder Regularization
    - Encoder: ResNet + Group Normalization
    - Decoder: 1x1x1 Convolution + 3D bilinear upsampling
    - VAE: Gaussian distribution (128, 128)



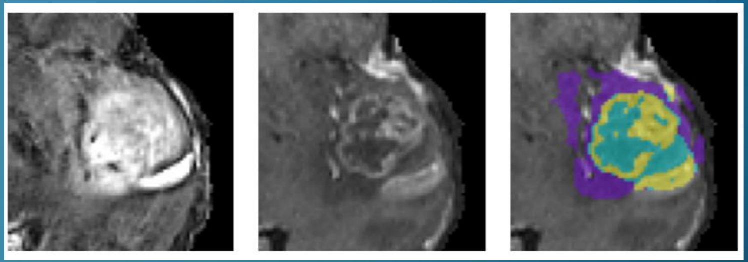
DATA COLLECTION

- Miccai - Multimodal Brain Tumor Segmentation Challenge
  - Pre-operative multimodal MRI scans:
    - 210 glioblastoma (GBM/HGG) and 75 lower grade glioma (LGG).
  - Available as NIfTI files (.nii.gz)
    - native (T1)
    - post-contrast T1-weighted (T1CE)
    - T2-weighted (T2)
    - T2 Fluid Attenuated Inversion Recovery (T2-FLAIR)
- Annotations comprise
    - peritumoral edema (ED)
    - GD-enhancing tumor (ET)
    - necrotic and non-enhancing tumor core (NCR/NET)





DATA COLLECTION



Flair T1CE Segmentation result

We used:

- Data from 210 glioblastoma (GBM/HGG)
- T2-FLAIR:
  - Fluid Attenuated Inversion Recovery
  - Whole tumor is brighter on T2-FLAIR compared to T2
- T1CE:
  - Infusing Gadolinium (GD).
  - Tumor core is very bright on T1-weighted images

DATA PREPROCESSING

We used:

- Min-max normalization:

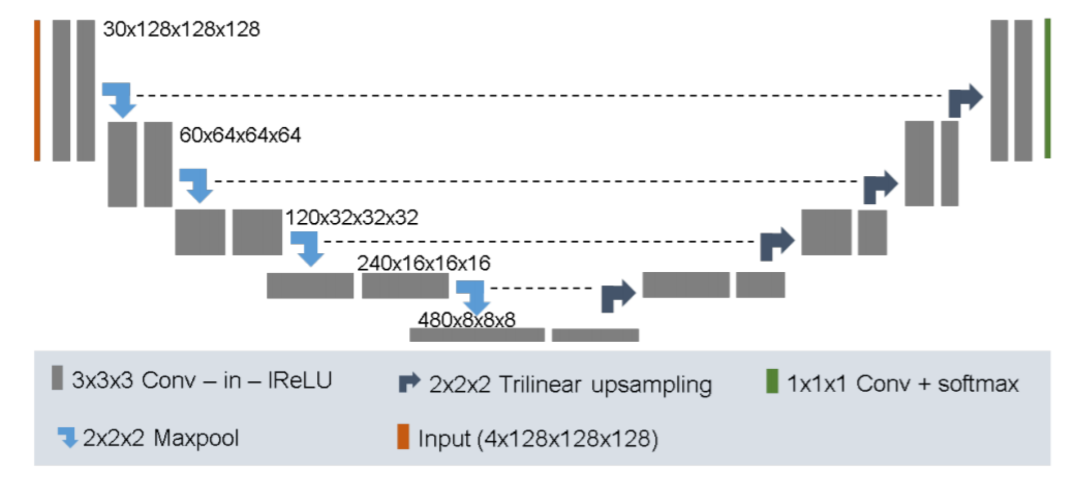
$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \in [0, 1]$$

- 3D-recaled:
  - 115,240,240 → 128,128,128
  - Spline interpolation

PROPOSED METHOD

3D-UNet

1. It consists of encoder part (left) and decoder part (right).
2. Repeated application of Two 3x3 convolutions. Each followed by a leaky rectified linear unit (lReLU) and a 2x2 max pooling.



TRAINING PROCEDURE

- **35** training sample data of size 128∗128∗128 and batch size is 1.
- In every **5** training epoch, Validating with 5 validating sample data.
- Training optimizer: **ADAM** with an fixed learning rate $LR = 1 \times 10^{-4}$.
- Loss function: **Weighted-Mean square error (W-Mse)**

$$p_k(x) = \frac{exp(a_k(x))}{\sum_{k'=1}^{K} \exp(a_{k'}(x))}$$

pixel-wise softmax over the final feature map

$$Weighted - MSE = \omega_k * (p_k(x) - y_k(x))^2$$

EXPERIMENTAL RESULTS

- Evaluate Dice score and Hausdorff distance on two types of model trained with different MRI data.
  - 3D-Unet + only FLAIR
  - 3D-Unet + FLAIR + T1CE

$$\mathrm{Dice}(P,T) = \frac{|P_1 \wedge T_1|}{(|P_1| + |T_1|)/2}$$

$$\mathrm{Haus}(P,T) = \max\{ \sup_{p \in \partial P_1} \inf_{t \in \partial T_1} d(p,t), \sup_{t \in \partial T_1} \inf_{p \in \partial P_1} d(t,p)\}$$

Model	Statistics			
	Dice mean	Dice std	Hausdorff mean	Hausdorff std
3D-Unet + Only FlAIR	0.6820	0.4033	1.0595	1.3743
3D-Unet + Flair + T1CE	0.7325	0.3558	0.9361	1.2250

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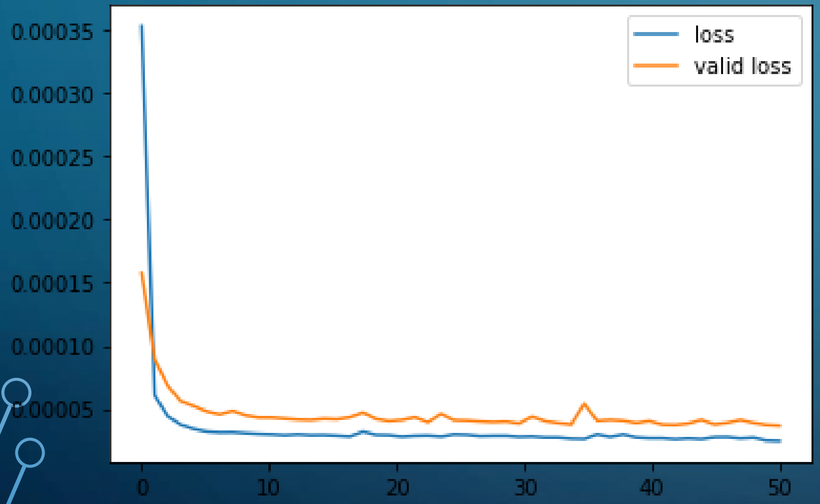
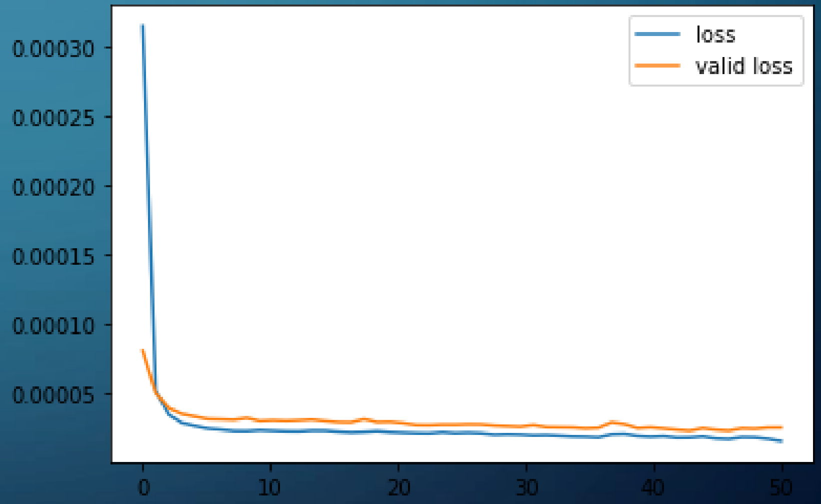
EXPERIMENTAL RESULTS

- Analysis on Weighted-MSE loss for two models.



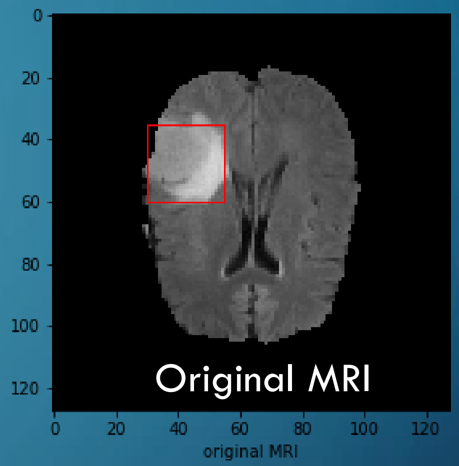
3D-Unet + Flair

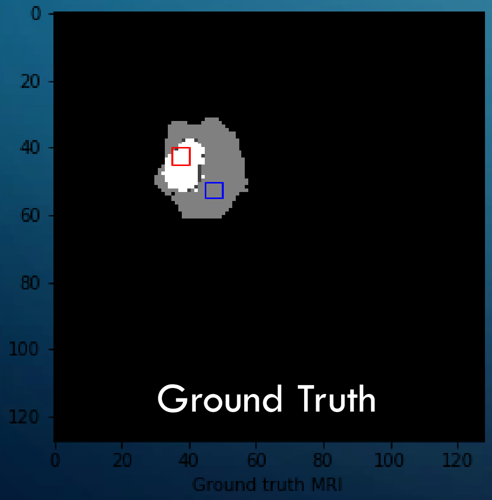


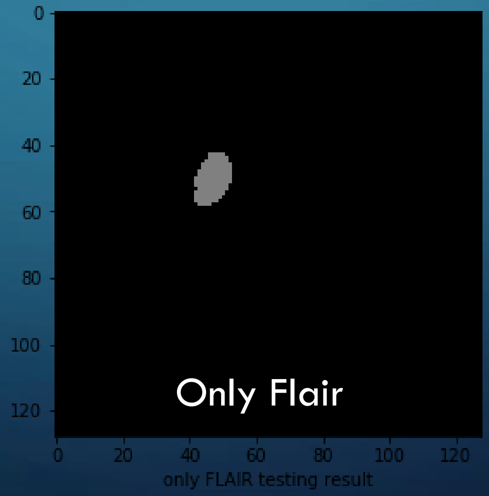
3D-Unet + Flair + T1CE

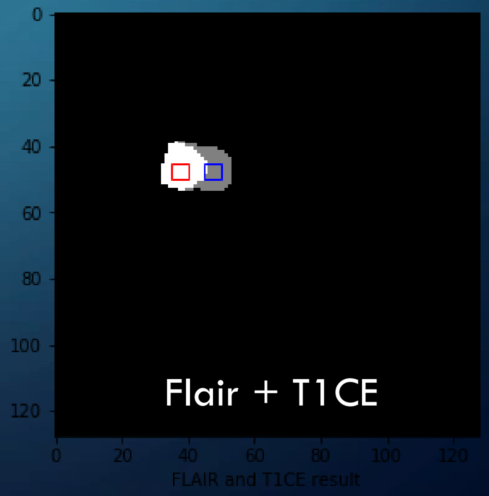
EXPERIMENTAL RESULTS

- **Qualitative example segmentation:**









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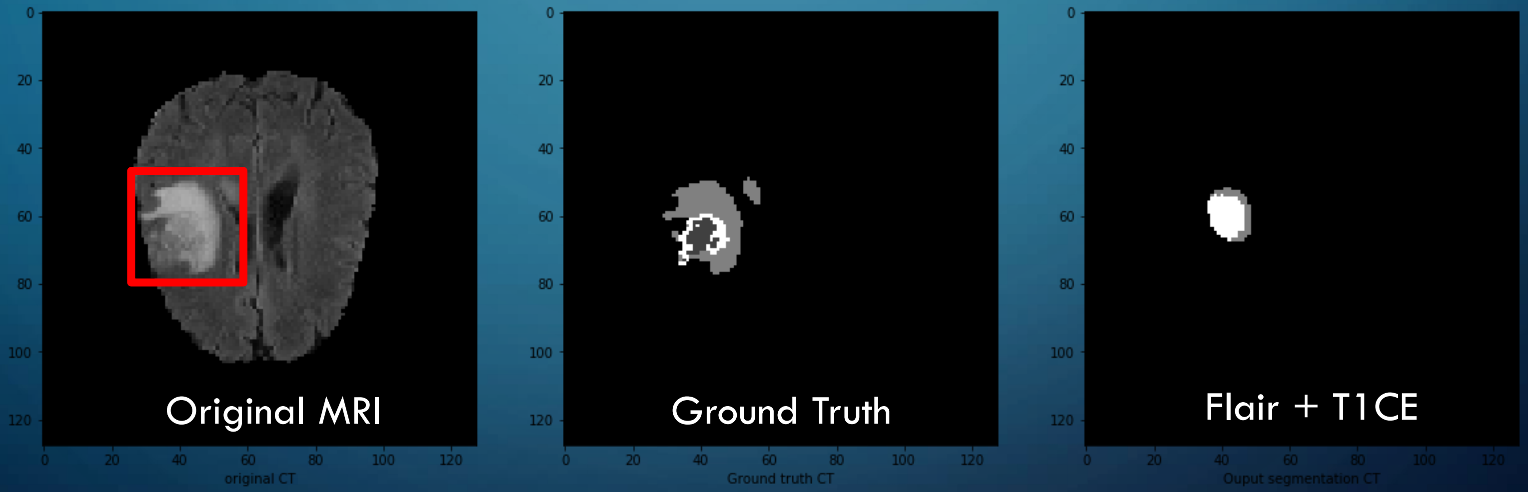

CONCLUSIONS & FUTURE WORK

- We demonstrated the effectiveness of 3D-Unet on BraTS 2019 challenge.
- Used two different types of data, including FLAIR and T1CE to train our model.
- In the training procedure, we utilized the Weighted-Mse loss function to solve the label imbalance problem.
- We might consider to combine multiple types of data together for ensemble training to enhance modalities and improve the performance of tumor segmentation.

REFERENCE

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5. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS), IEEETransactions on Medical Imaging 34(10), 1993-2024 (2015)

THANK YOU