Imperial College London

8 February 2023

Brain Tumor Segmentation (BraTS) Based on U-net

Computer Vision Project - Winter School 2023

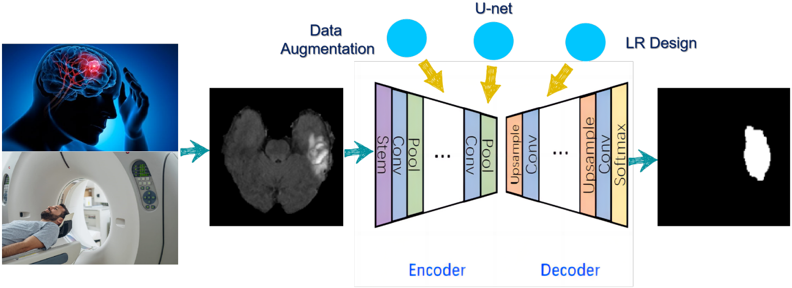
Group 2

1. 1 Introduction
2. 2 Materials and Methods
   - Data augmentation
   - Model Design based on U-net
   - Loss Function Design
   - Learning Rate Design
3. 3 Results

Teamwork for CV project

- **Zhen Huang**: Speaker, coding, report writing
- **Jingyi Chai**: Report writing, coding, PPT
- **Le Su**: Report writing, coding

1 Introduction



2 Materials and Methods

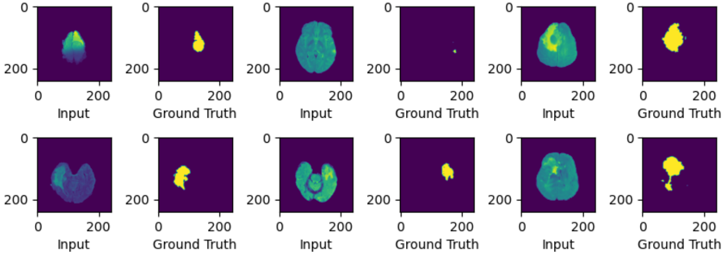


Figure 1: Example Images in the Dataset.

- Using all the *YES* and 50 % *NO* as the data set
- 90 % of the data (3921 images) as the **training set**
- the remaining 10 % (434 images) as the **validation set**

2.1 Data Augmentation

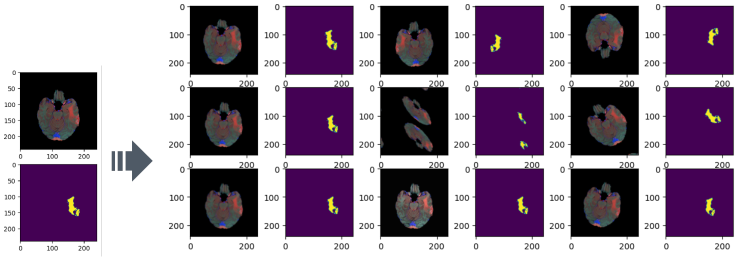


Figure 2: Illustration of Data Augmentation.

- Using the **Albumentations**[1] to apply random data augmentation methods
- Crop / Rotate / Filp / Blur / Sharpen / Distortion

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2.2 Model based on U-net

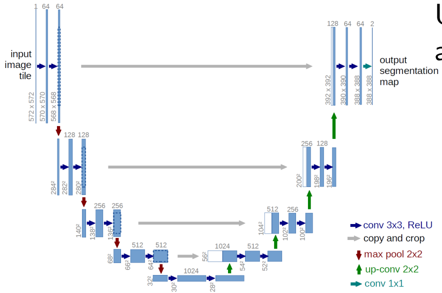


Figure 3: U-net Architecture[2]

U-shaped structure: **contracting path** and **expansive path**.

- The contracting path consists of 4 blocks, each block uses 2 effective convolutions and 1 Max Pooling downsampling.
- The expansive path has a similar structure but different sizes of Feature Map.

2.3 Loss Function Design

$$\mathrm{l}((\mathrm{x},\mathrm{y}),\theta) = -DiceScore\left(y_{true}, y_{pred}\right) + 0.1 \times \frac{\sum_{i=1}^{n}\left(y_{true} - y_{pred}\right)^2}{n}$$

Penalty term

An MSE (Mean Square Error) penalty term can prevent overfitting, improve the generalization ability of the model, and make our optimization scheme stable and fast.

Regular Term	Dice Score	IoU	Loss
✓	0.9223	0.8565	-0.9221
✗	0.9149	0.8442	-0.9149

Table 1: Results with and without regularization on the Val-set

2.4 Learning Rate Design

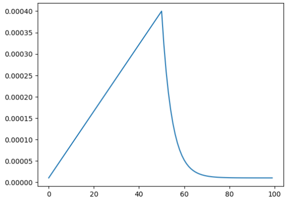


Figure 4: Graph of Exponential Annealing.

Warm-up

Choosing the Warm-up can make the learning rate smaller in the first few epochs or some steps of the training so that the model can gradually stabilize.

2.4 Learning Rate Design

Cosine Annealing

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min})\left(1 + \cos\left(\frac{T_{\text{cur}}}{T_{\max}}\pi\right)\right)$$

where $\eta_{\min}$ and $\eta_{\max}$ represent ranges for the learning rate, with $\eta_{\max}$ being set to the initial LR; T_{cur} represents the number of epochs that were run since the last restart.

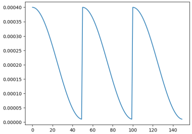


Figure 5: Graph of Cosine Annealing.

2.4 Learning Rate Design

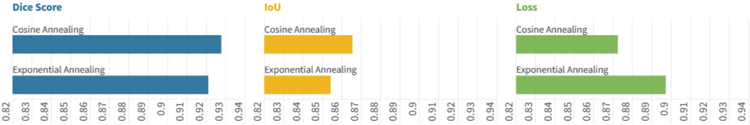
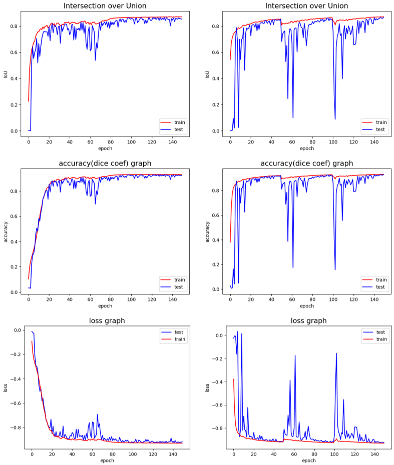


Figure 6: Comparison of Cosine Annealing and Exponential Annealing.

2.4 Learning Rate Design



- The Exponential LR strategy makes the convergence fast and the oscillations small. Dice score 0.9210 and IoU 0.8543.
- The Cosine Annealing method steps out of the local optimum gives better results. Dice score 0.9308 and IoU 0.8710.

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3 Results

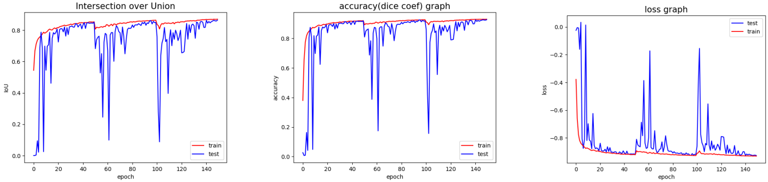

Figure 7: The IoU, DiceScore, and Loss Curve in Training with Cosine Annealing.

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3 Results

Set	Dice Score	IoU	Loss
Train-set	0.9308	0.8710	-0.9306
Val-set	0.9277	0.8656	-0.9275

Table 2: Model performance on Train-set and Val-set

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Test Results

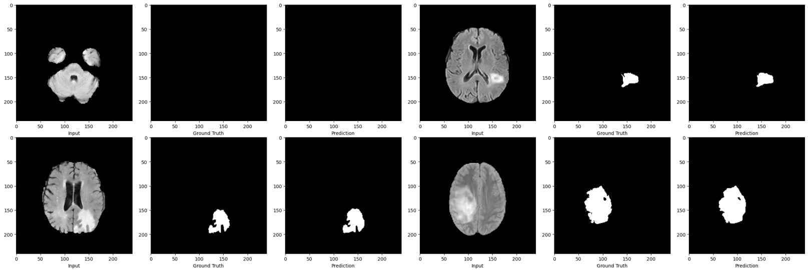

Figure 8: Model performance on predicting using validation data.

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Thanks for listening !

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