Tumor Segmentation on Multi-Modal Brain MRI

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neuromatch academy

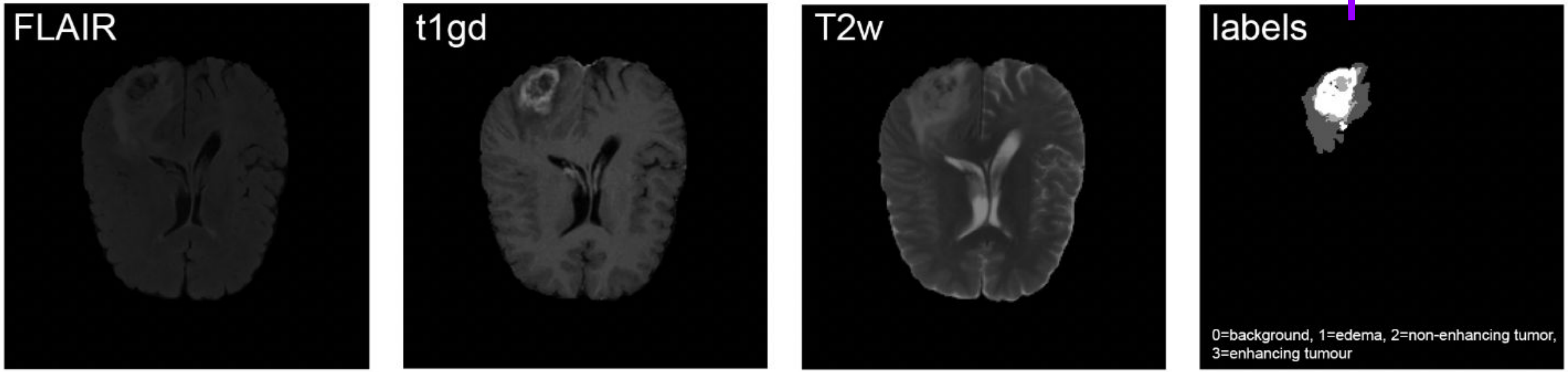
✨ Introduction ✨

- **Medical image segmentation** (e.g., tumors, lesions) is **difficult**.
- **Traditional method:** manual segmentation → time consuming, requires expertise.
- **DL**: learn from segmented data from manual method + apply to new data

✨ Data ✨

- [The Medical Segmentation Decathlon] (Antonelli et al., 2022)
- Multimodal MRI data (FLAIR, T1w, T1gd, T2w)
- 4D volumes (484 people with labeled tumors)
  - ***(240 x 240 x 155)*** x 4 (modalities)
- Source → BRATS 2016 and 2017 datasets.

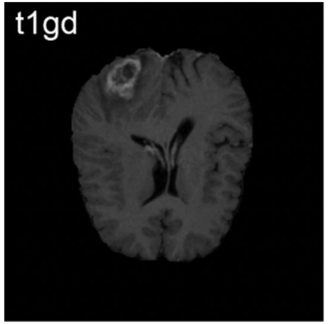
```
labels:
0:    "background"
1:    "edema"
2:    "non-enhancing tumor"
3:    "enhancing tumour"
```



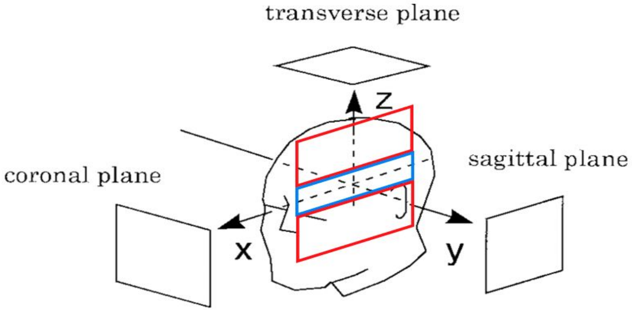
✨ Data - Preprocessing Steps ✨

1. ***Split 484:*** a) Train (72%, N=348); b) Validation (18%, N=87); c) Test (10%, N=49).

2. ***Crop out blank edge pixels to reduce x & y dimensions:*** 240x240 → 192x192.



3. ***Select 14 slices above(+) and below(-) the middle z-slice:*** *z = 155 → 29 (middle z +/-14).*



4. ***Exclude 1 modality:*** No to T1w since T1Gd provides superior information.

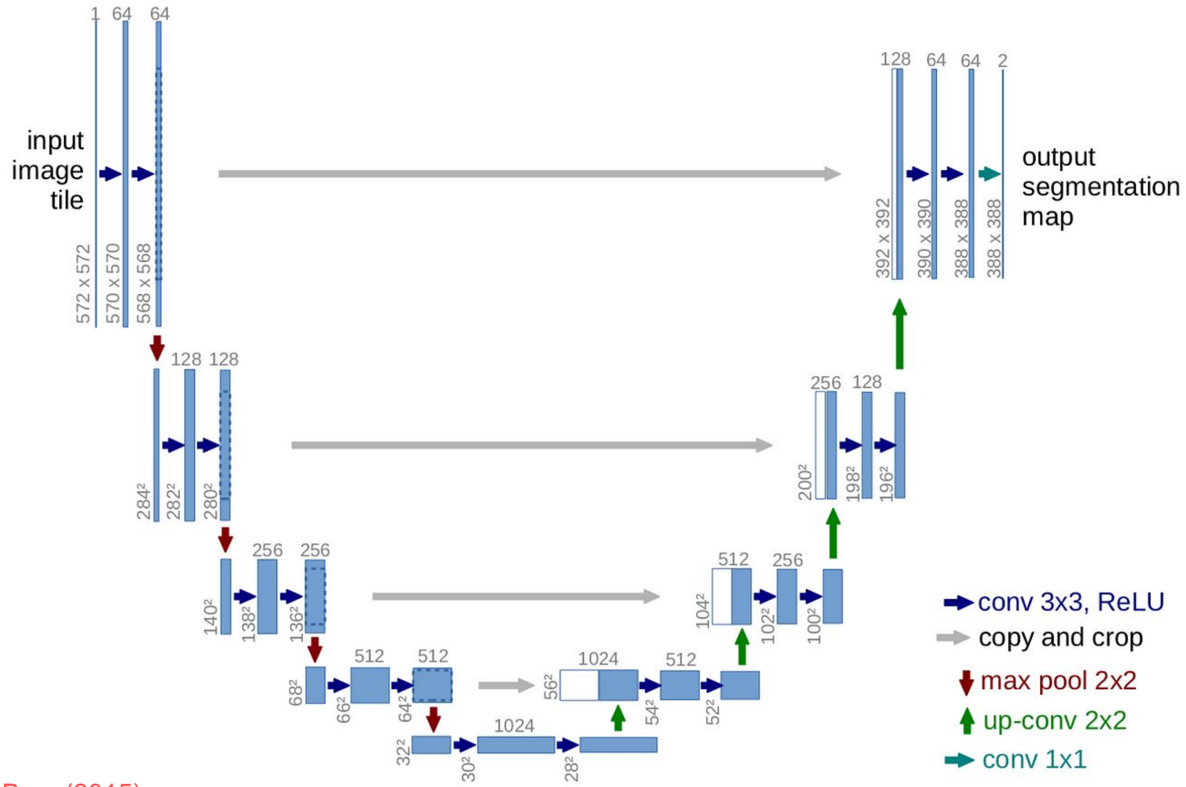
🧠 **192 x 192 x 29 x 3** 🧠

5. ***Normalize:*** grayscale in different intensity levels → Using MinMaxScaler

6. ***Binarize:***

```
0:    "background"             → 0
1:    "edema"                  ┐
2:    "non-enhancing tumor"    ├ 1
3:    "enhancing tumour"       ┘
```

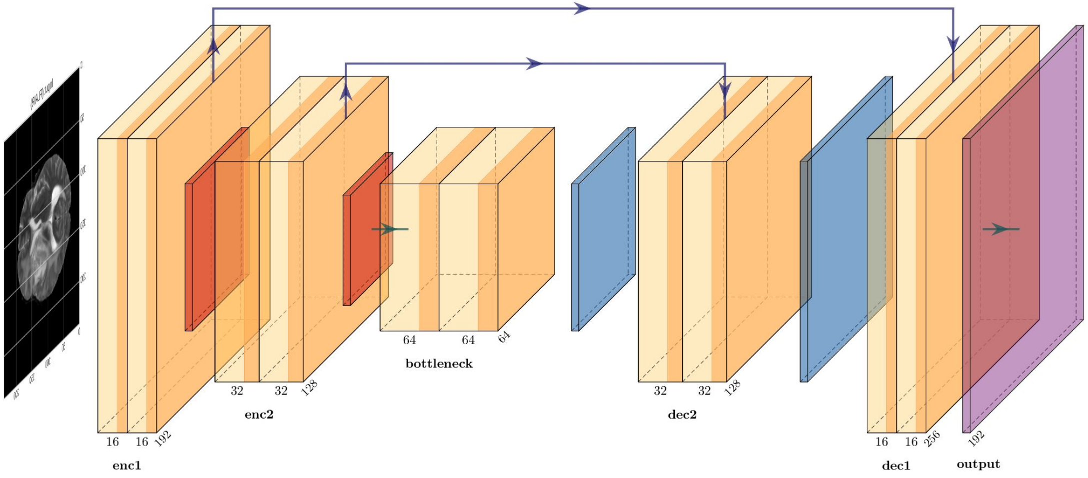
✨ The Model: UNet ✨



Ronneberger, Fischer, & Brox (2015)

Example of UNet only. **Does not reflect final implementation.**

✨ Finding the Most Effective Loss Function (1/2)



Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 16, 192, 192]	448
BatchNorm2d-2	[-1, 16, 192, 192]	32
ReLU-3	[-1, 16, 192, 192]	0
MaxPool2d-4	[-1, 16, 96, 96]	0
Conv2d-5	[-1, 32, 96, 96]	4,640
BatchNorm2d-6	[-1, 32, 96, 96]	64
ReLU-7	[-1, 32, 96, 96]	0
MaxPool2d-8	[-1, 32, 48, 48]	0
Conv2d-9	[-1, 64, 48, 48]	18,496
BatchNorm2d-10	[-1, 64, 48, 48]	128
ReLU-11	[-1, 64, 48, 48]	0
ConvTranspose2d-12	[-1, 32, 96, 96]	8,224
Conv2d-13	[-1, 32, 96, 96]	18,464
BatchNorm2d-14	[-1, 32, 96, 96]	64
ReLU-15	[-1, 32, 96, 96]	0
ConvTranspose2d-16	[-1, 16, 192, 192]	2,064
Conv2d-17	[-1, 16, 192, 192]	4,624
BatchNorm2d-18	[-1, 16, 192, 192]	32
ReLU-19	[-1, 16, 192, 192]	0
Conv2d-20	[-1, 1, 192, 192]	17

For faster compute time:

- Run on a simpler U-Net (2 Encoders, 1 Bottleneck, 2 Decoders, Features: [16, 32, 64], Trainable params: 57,297)
- Subsetting Train and Validation sets (each with 500 2D images)

✨ Finding the Most Effective Loss Function (2/2) ✨

Testing the following:

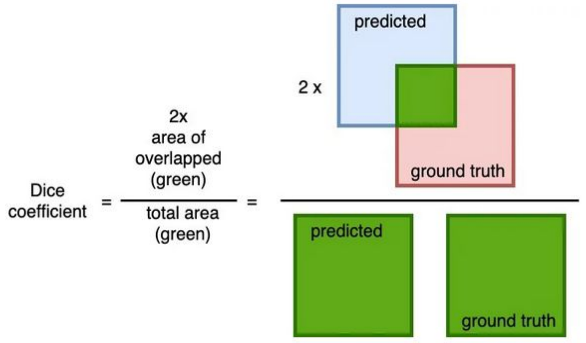
- BCE:

$$BCE = -\frac{1}{N}\sum_{i=0}^{N} y_i \cdot log(\hat{y}_i) + (1 - y_i) \cdot log(1 - \hat{y}_i)$$

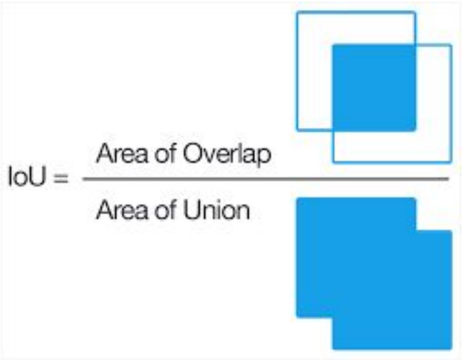
- Focal Loss:

$$FocalLoss = -\sum_{i=1}^{i=n}(i - p_i)^{\gamma} log_b(p_i)$$

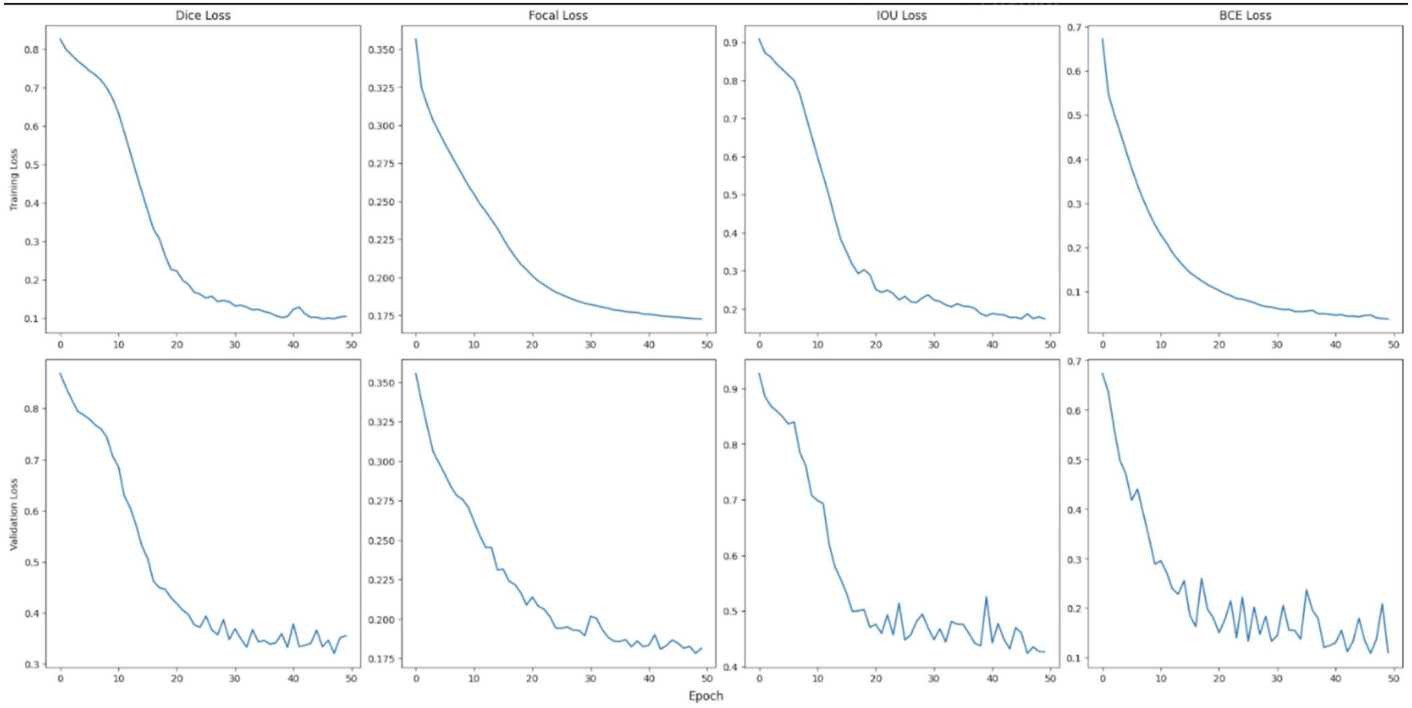
- Dice Loss:



- IOU Loss:



✨ Loss Curves Comparison for Training and Validation Data ✨



Stability in validation loss is crucial.

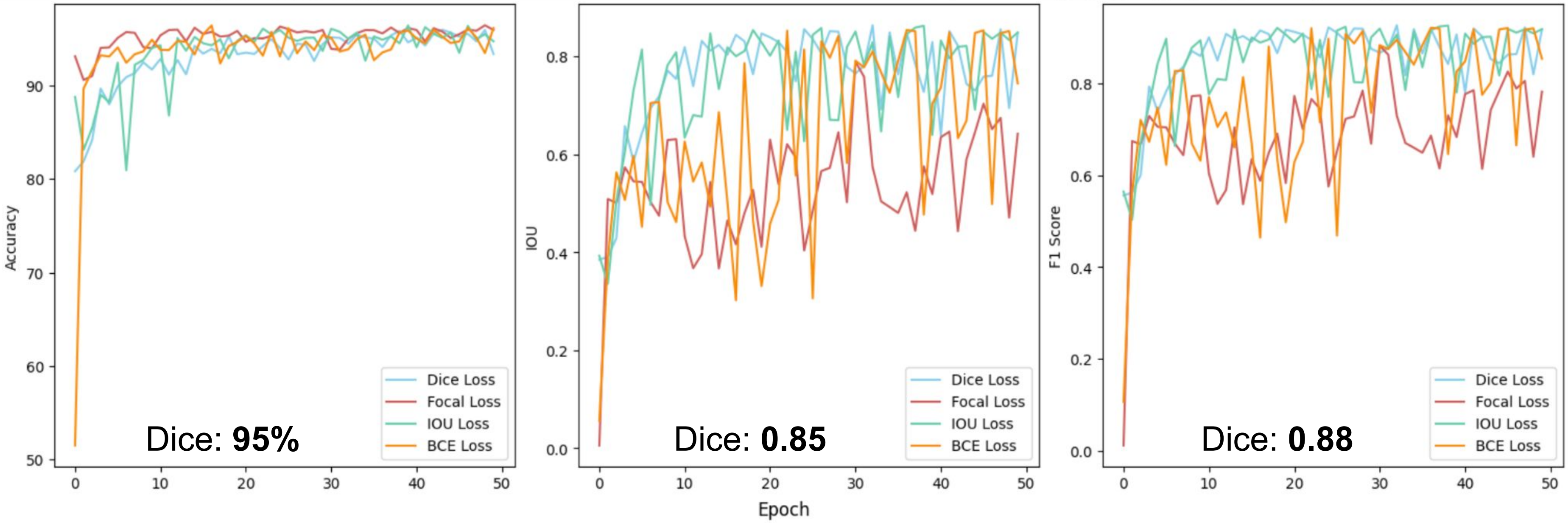
decrease in loss function

↓

training is stable

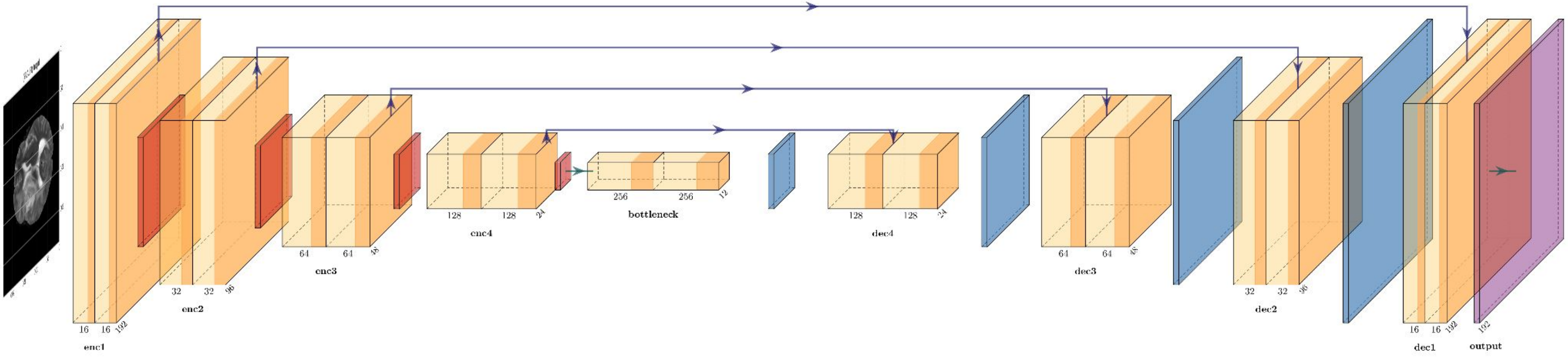
✨ Performance Metrics Comparison Across Loss Functions ✨

Metrics for **evaluating** the effectiveness of the segmentation model: **Dice** is superior.



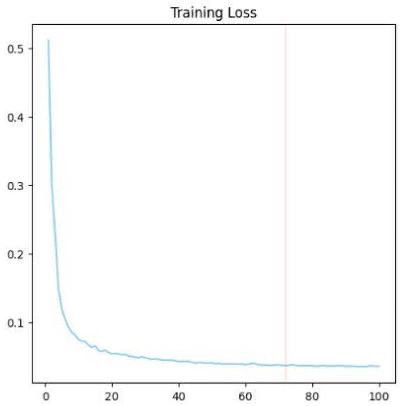
✨ Final Model ✨

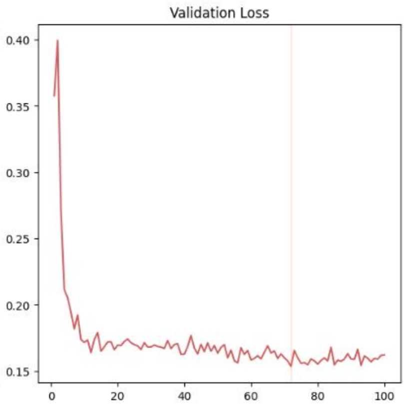
- `4 Encoders, 1 Bottleneck, 4 Decoders`
- `Features/layer: [16, 32, 64, 128, 256]`
- `Trainable params: 1,941,105`



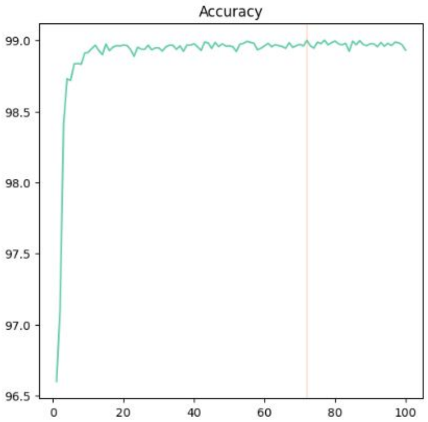
✨ Results ✨

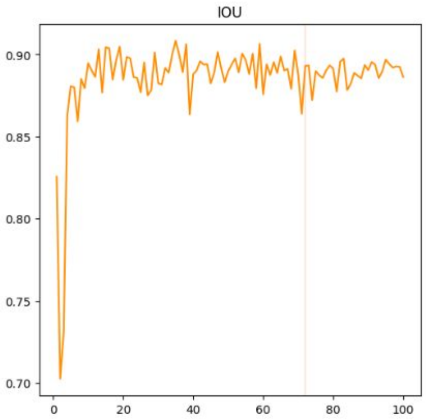
- Model performance on the ***Test Set:***
  - **Test Loss: 0.1521**
  - **Test Accuracy: 99.19%**
  - **Test IoU: 0.7670**
  - **Test F1: 0.8479**

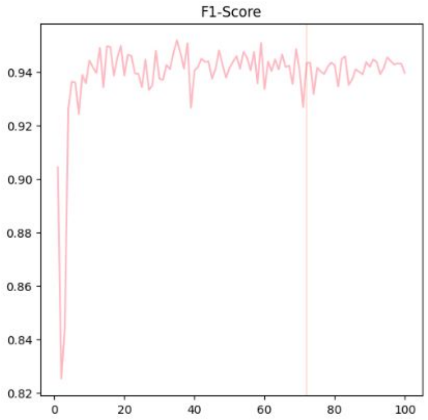




Graphs portray model performance on the ***Validation Set***





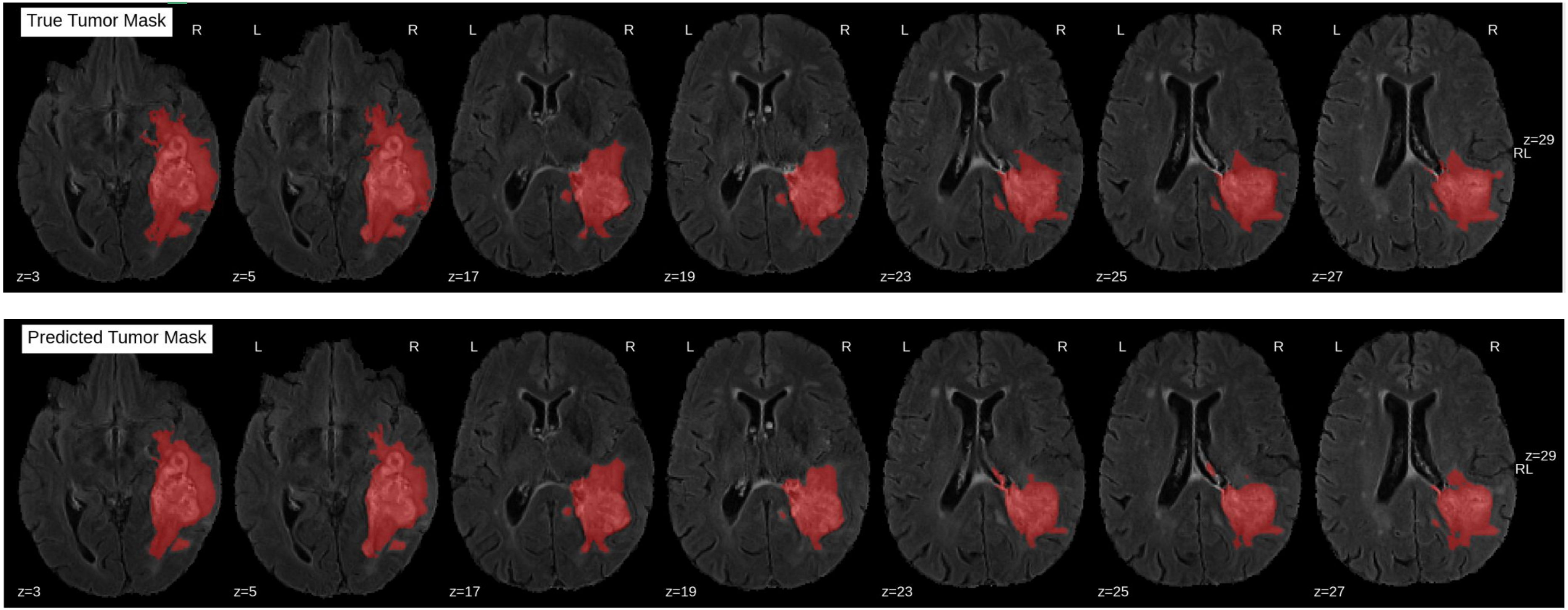


Vertical red line represents best performance on **validation** set.

Model Performance on 1 person from the Test set

Tumor mask overlaid on FLAIR

ID: BRATS_068



Model Performance on a different person from the Test set

Tumor mask overlaid on T2w

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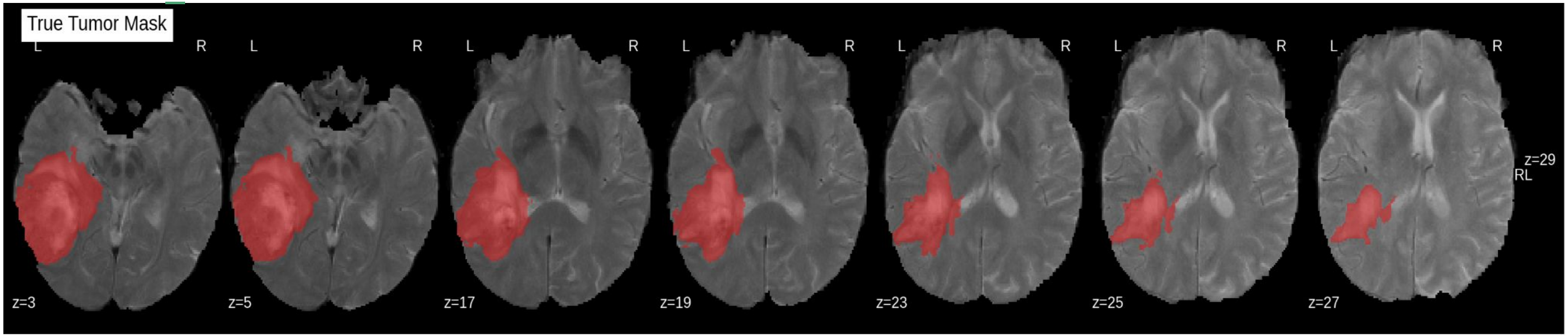

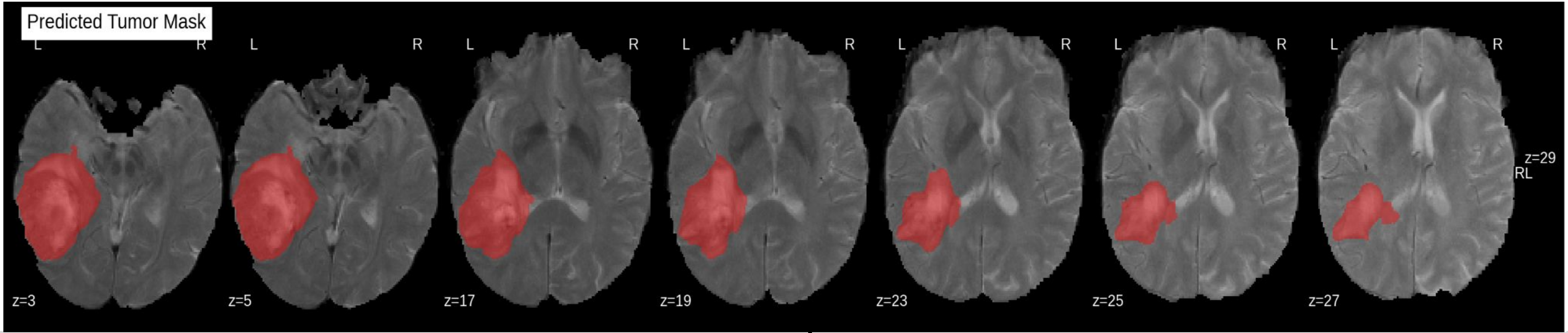

✨ Conclusion ✨

- **The U-Net model is *effective* in tumor segmentation**.

- **Future work:**
    - Use a **more complex model** (e.g., 3D U-Net).
    - Use **more data** (whole-brain + additional MRI modalities).
    - Segmenting **multi-labeled tumors** to increase medical usefulness.