BRAIN TUMOR SEGMENTATION

Gli Scienziati

Federico Cesare Cattò

Master’s student in Data Science.
Bachelor's in Statistic.

Francesco Beretta

Master's student in Data Science.
Bachelor's in Statistic.

Chiara Pelizza

Master's student in Data Science.
Bachelor's in Statistic.

AI for Brain Tumor Segmentation: Enhancing Clinical Precision

- Gliomas are aggressive brain tumors affecting the central nervous system.
- MRI is the key imaging tool for diagnosis and treatment planning.
- Accurate segmentation of tumor subregions is essential:
  I) **ET** – Enhancing Tumor
  II) **WT** – Whole Tumor
  III) **TC** – Tumor Core
- Manual segmentation is time-consuming, subjective, and requires expert radiologists.

A Complex Task in Clinical Practice

Manual Limitations

Labour-intensive and prone to variability.

Critical Impact

Crucial for diagnosis and therapy planning.

Tumour Complexity

Variability in size, shape, and location.

Workload Burden

Increasing demands on clinical staff.

Tumor Segmentation in MRI with AI

Deep Learning

Pixel-level image analysis

Pattern Recognition

AI identifies complex patterns

Segmentation

Automated region detection

Objective Measurement

Consistent, quantifiable output

Project Pipeline

Data Exploration

1. Studied MRI modalities and tumor masks.

Preprocessing

2. Standardized data for model training.

Model Training

3. Trained a U-Net on 2D slices with Dice Loss to optimize segmentation accuracy.

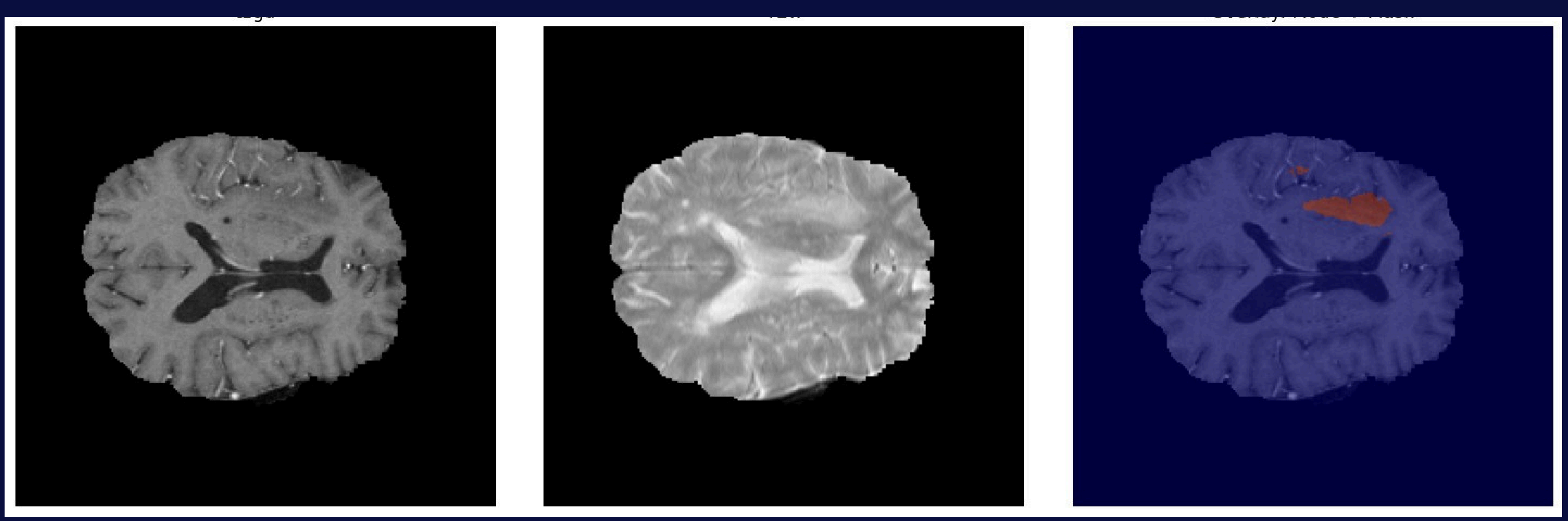
Evaluation and Testing

4. Tested on unseen data using Dice Score and visual checks.

Data Exploration: BraTS Dataset

Dataset Overview

- ✓ 484 labeled training cases
- ✓ Provides anonymised, expert-annotated MRI scans
- ✓ 300 unlabeled test cases
- ✓ Global benchmark for AI tumor segmentation



Data Exploration: BraTS Dataset

MRI Modalities

- FLAIR: Highlights edema and abnormal fluid
- T1w: Structural anatomical imaging
- T1gd: Contrast-enhanced tumor regions
- T2w: Accentuates fluid and tissue differences

Segmentation Labels

- Label 1: Non-enhancing Tumor Core
- Label 2: Peritumoral Edema
- Label 4: Enhancing Tumor

Key Challenges

- High-resolution 3D images: 240 × 240 × 155, 4 channels
- Severe **class imbalance**: Background ≈ 99%

Preprocessing

Extract Tumor Slices

Select slices with tumor presence, ensuring patient tracking to enable accurate separation of training and validation datasets (Data Leakage Problem).

Recode Masks

Recode the segmentation masks from their original labels (0, 1, 2, 4) to a simplified scale (0, 1, 2, 3) for model compatibility.

Normalize Per Modality

Apply z-score normalization to each MRI modality to standardize the data and improve consistency.

Cropping

Removing the outer regions of an image to focus on the region of interest, reducing irrelevant background and emphasizing important features.

Preprocessing

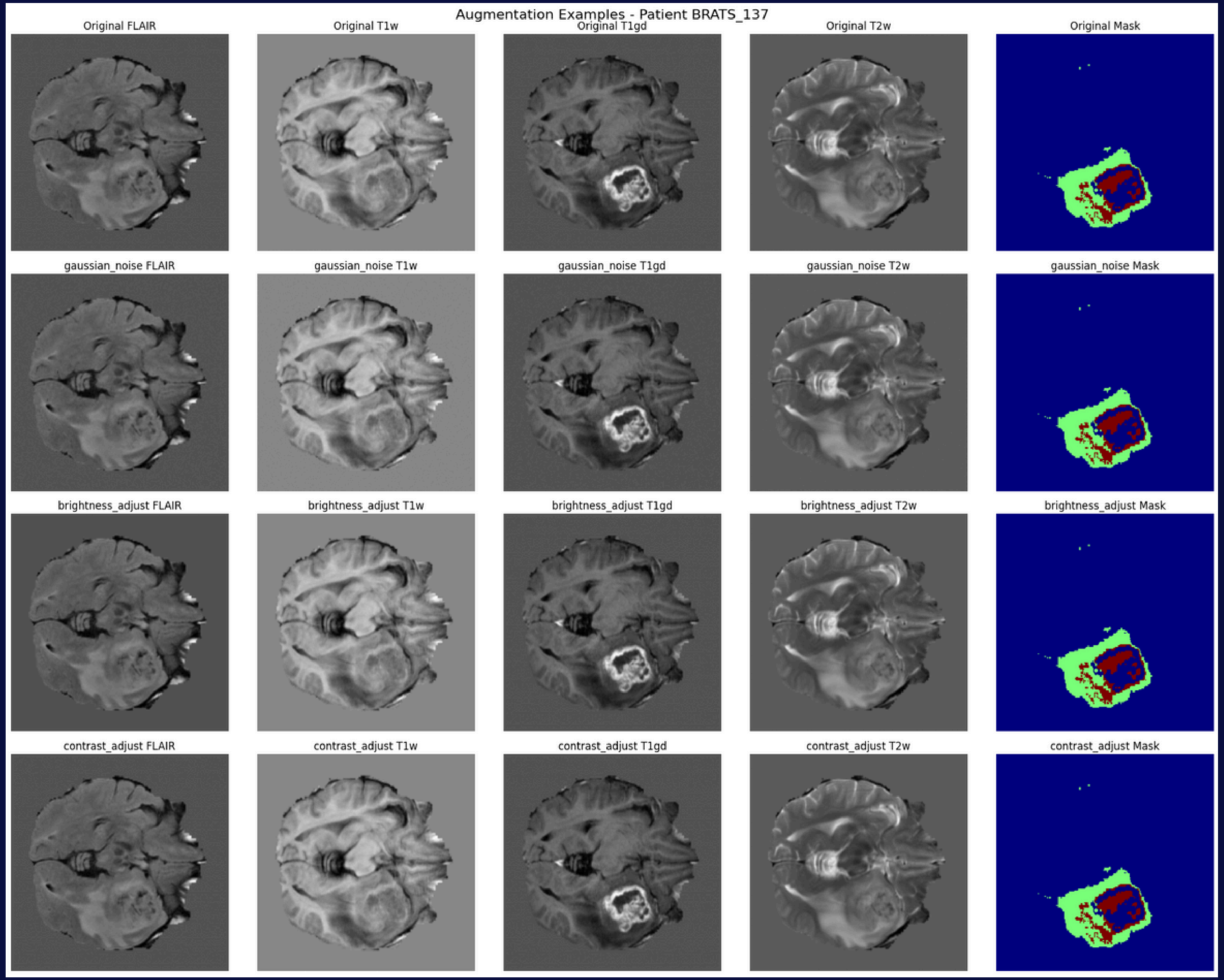
Data Augmentation

Applied to counter severe class imbalance (small tumors)

Two techniques explored:

- **Rotations**: spatial transformations to increase variability
- **Color & Noise alterations**: non-spatial changes to simulate acquisition differences

Final Choice: only non-spatial augmentations as geometric changes are unrealistic



Model Training: The 2D U-Net Model

Proven deep learning model for medical image segmentation

Encoder-Decoder structure with characteristic "U" shape

Encoder

Extracts features, reduces spatial resolution

Decoder

Reconstructs segmentation mask, restores details

Skip Connections

Preserve spatial information for precise tumor contours

U-Net 2D Architecture

1 Input

- ✓ Image size: 240 x 240
- ✓ Channels: 4 (FLAIR, T1w, T1gd, T2w)
- ✓ Output Classes: 4 (Background + Tumor Regions)

2 Encoder Path

- ✓ 4 Blocks:
  - 2 × Conv2D (3×3) + BatchNorm + ReLU
  - MaxPooling (2×2)
- ✓ Filters progression: 64 → 128 → 256 → 512

3 Bottleneck

- ✓ 2× Conv2D with 1024 filters

4 Decoder Path

- ✓ 4 Blocks:
  - Conv2DTranspose (2×2, stride 2)
  - Skip Connection (concatenate features)
  - 2 × Conv2D + BatchNorm + ReLU
- ✓ Filters progression: 512 → 256 → 128 → 64

5 Output Layer

- ✓ Conv2D (1×1) with softmax activation
- ✓ Pixel-wise classification into 4 classes

Evaluation: Dice Metrics

Dice Score

- Harmonic mean of Precision and Recall
- Penalizes false positives (common in imbalanced data)
- Higher Dice → better overlap
- Standard metric for image segmentation accuracy

Dice Loss

- Derived from Dice Score
- Measures overlap between prediction and ground truth
- Lower Dice Loss → better segmentation
- Minimized during training to optimize performance

$$\mathrm{Dice}_{multi}(Y,T) = \frac{1}{C}\sum_{c=1}^{C}\frac{2\sum_i Y_{i,c}T_{i,c}+\varepsilon}{\sum_i Y_{i,c}+\sum_i T_{i,c}+\varepsilon}$$

$$\mathrm{DiceLoss} = 1-\frac{1}{C}\sum_{c=1}^{C}\frac{2\sum_i Y_{i,c}T_{i,c}+\epsilon}{\sum_i Y_{i,c}+\sum_i T_{i,c}+\epsilon}$$

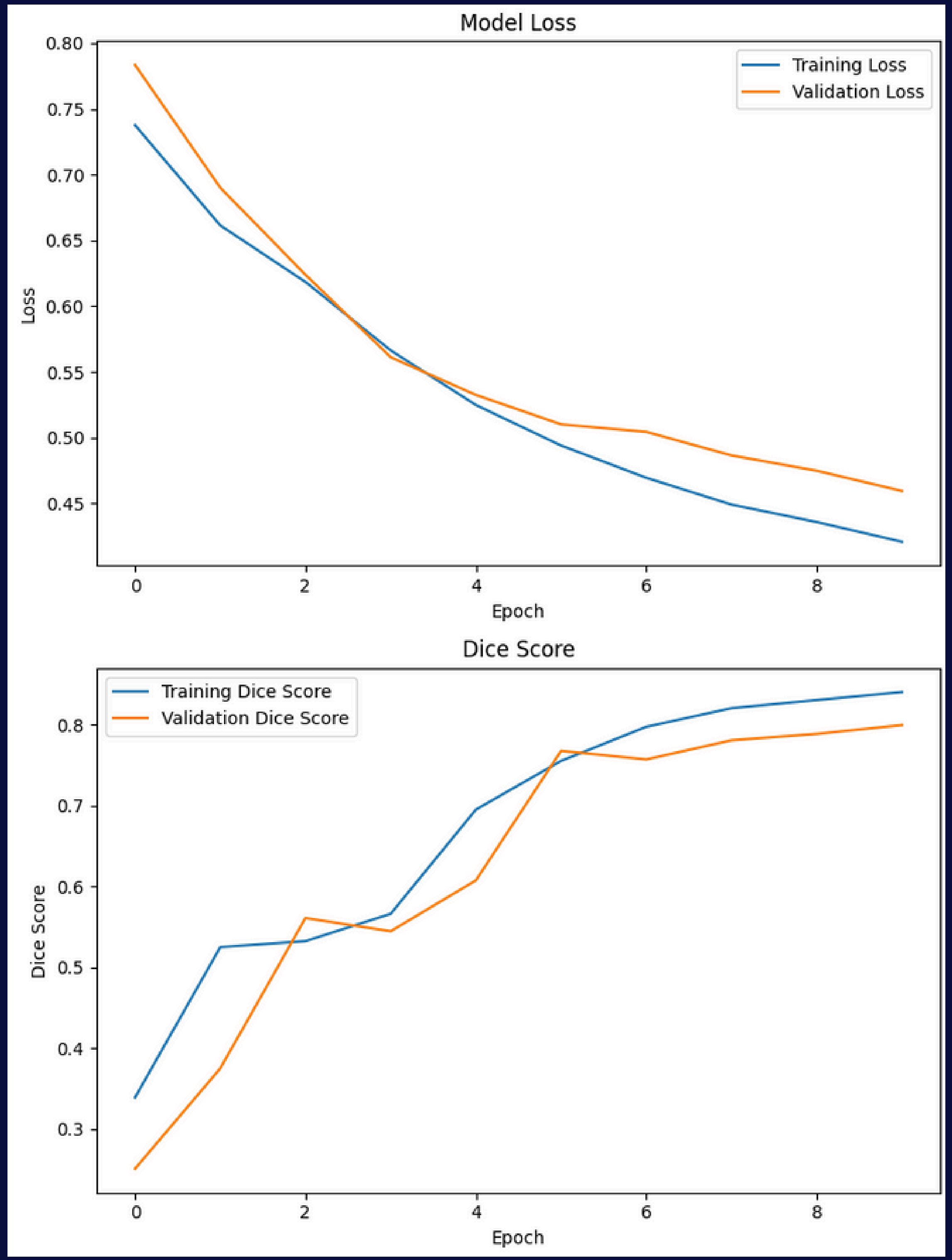
$Y_{i,c}$ model's predicted value for pixel i in class c

$T_{i,c}$ ground truth value for pixel i in class c

U-Net Experimentation & Results

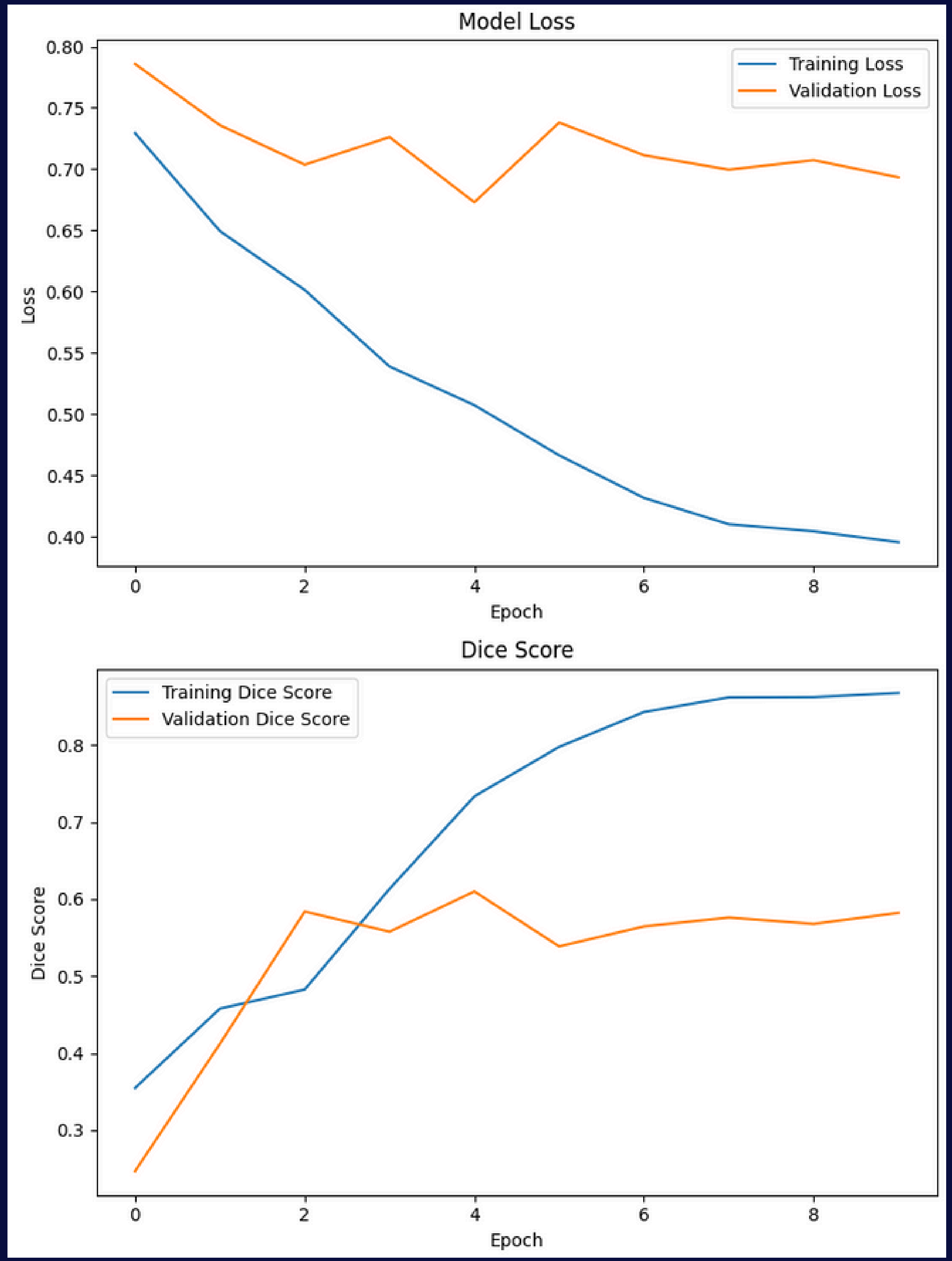
Attempt 1

Data
Leakage
Problem



Attempt 2

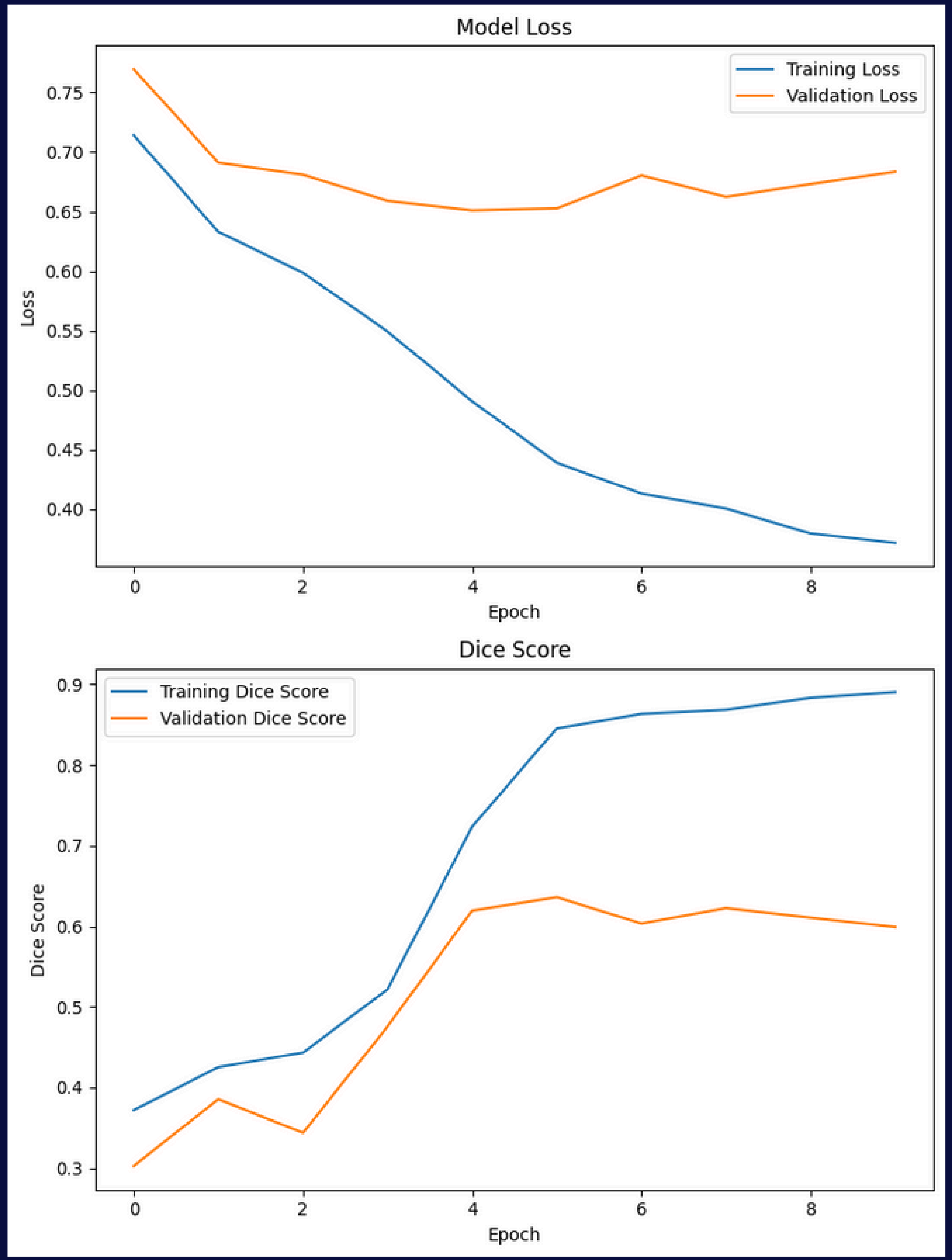
Data
Leakage
Solved



U-Net Experimentation & Results

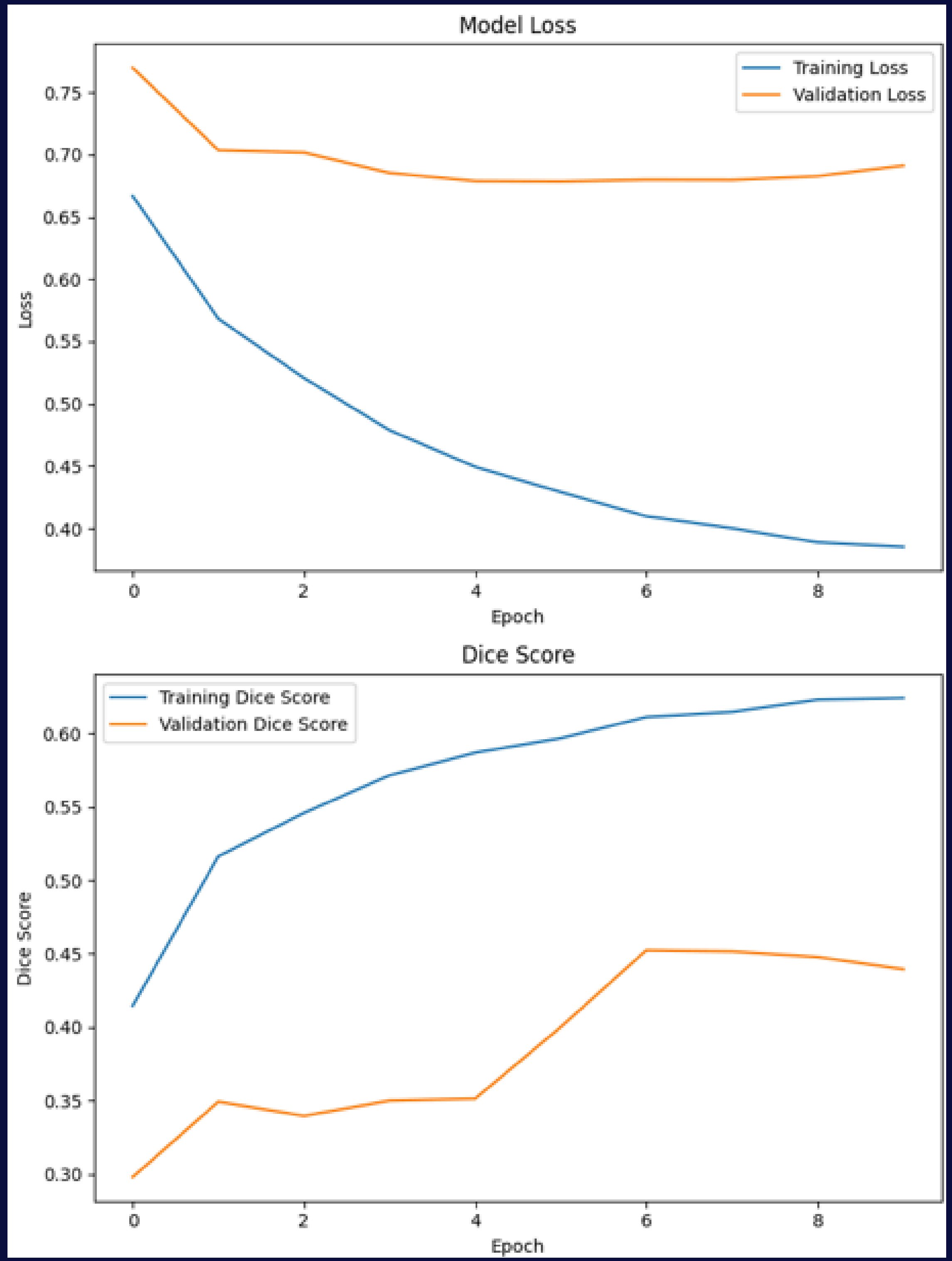
Attempt 3

Normalization for each modality



Attempt 4

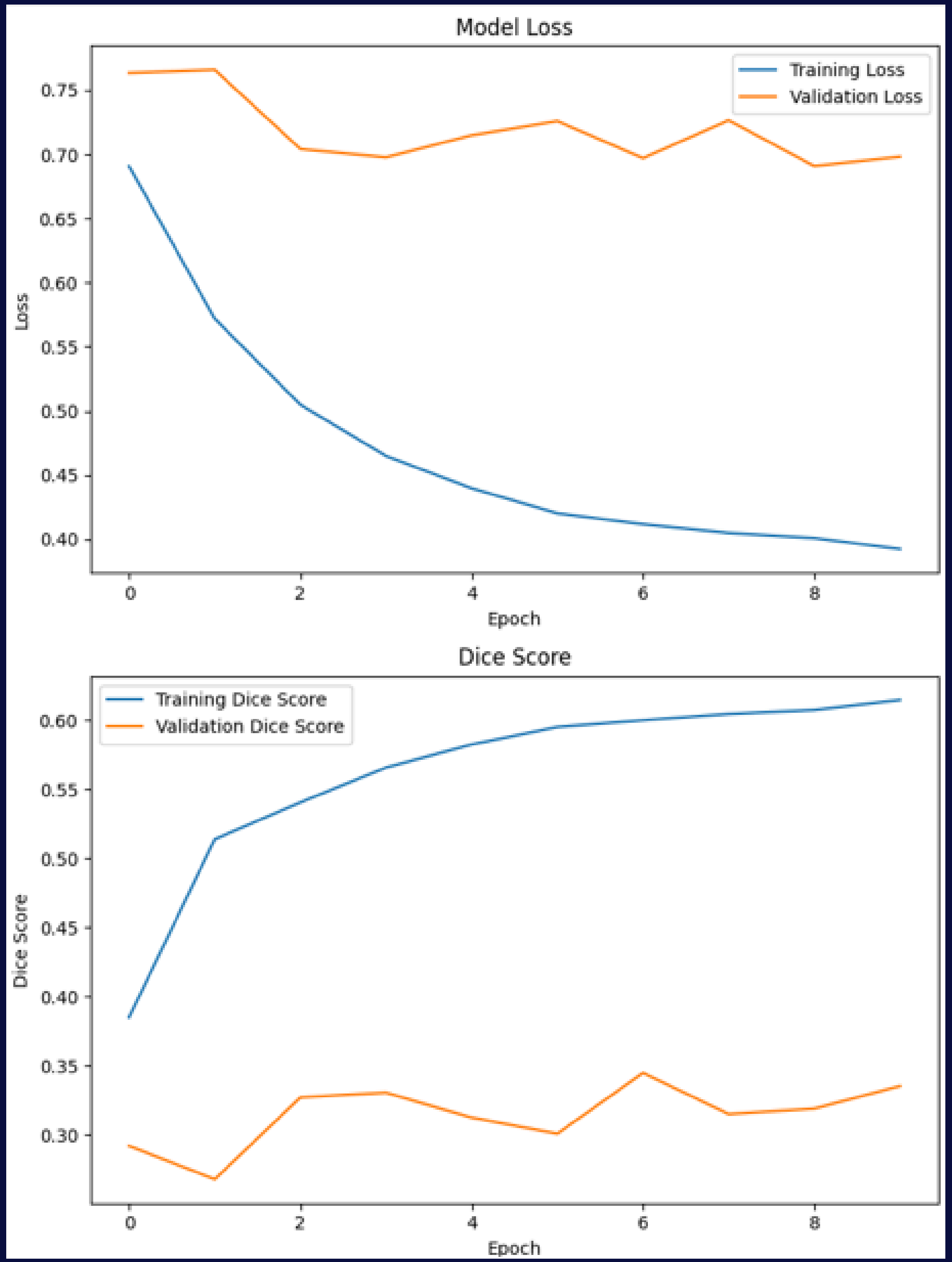
Cropping



U-Net Experimentation & Results

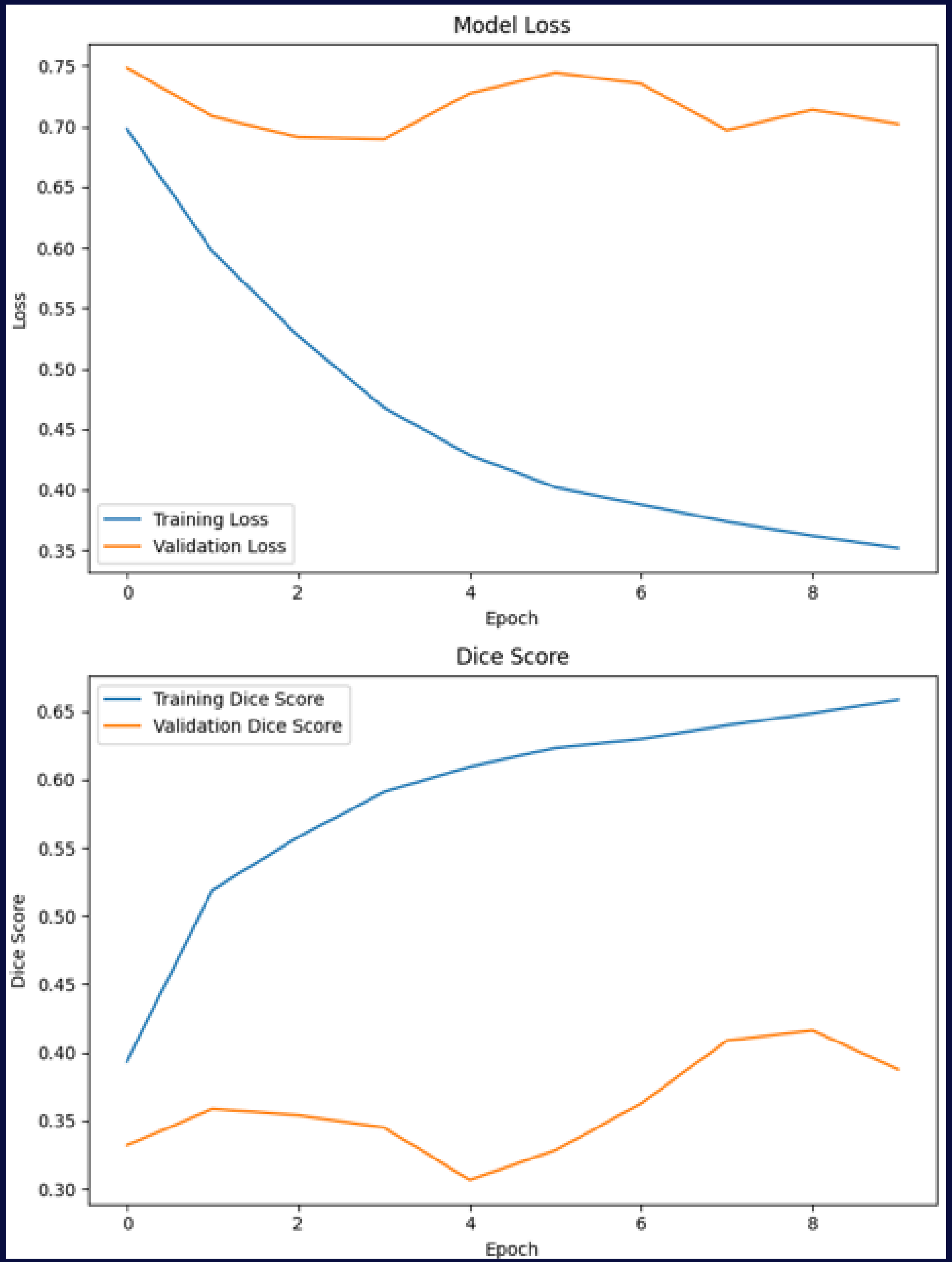
Attempt 5

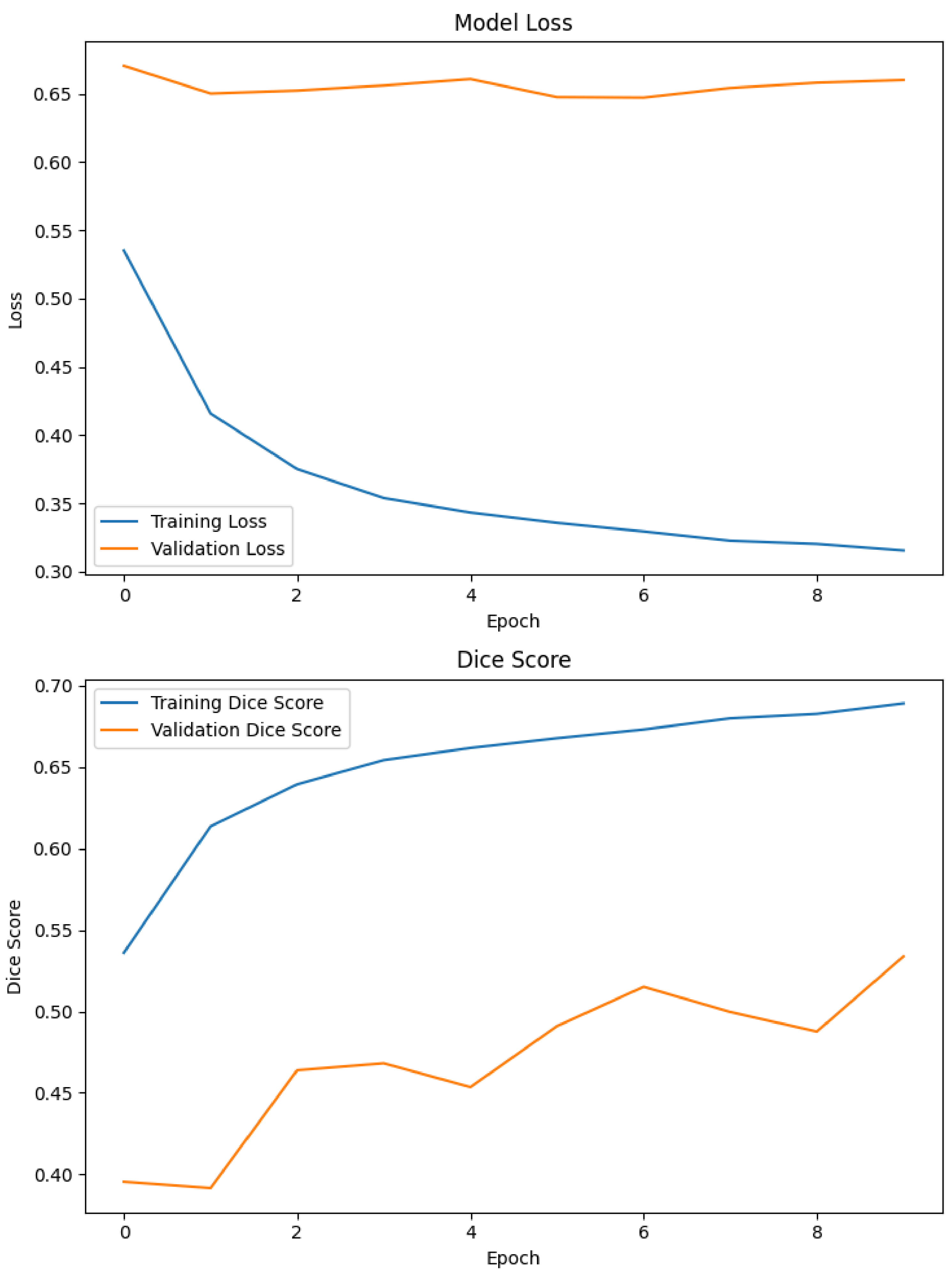
Data Augmentation (Rotations)



Attempt 6

Data Augmentation (Noise)





Combined Results

Selected all different processing methods, combined to search optimal performance:

- ✓ Modality-wise normalization
- ✓ Targeted noise-based augmentation for minority classes
- ✓ Cropping

0.53

Dice Score

Overlap with true tumour regions

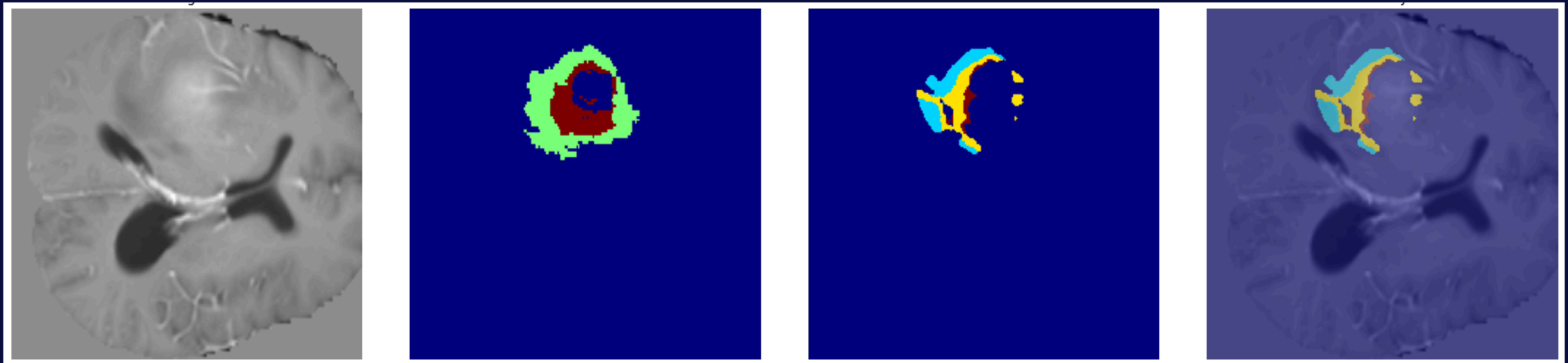
0.66

Dice Loss

Mismatch between predicted and true tumour regions

Visualising the Segmentation

Example of a T1gd MRI scan with ground truth and model prediction.



Original Scan

Raw T1gd MRI image

Ground Truth

Expert-annotated tumour regions.

Prediction

AI-predicted tumour boundaries

Overlay

Original Scan and Prediction overlap

The overlay shows quite good tumor region detection, with slight differences highlighting areas for improvement.

Additional Experimental Models

UNetAttention2D

Adds Attention Gates on skip connections.

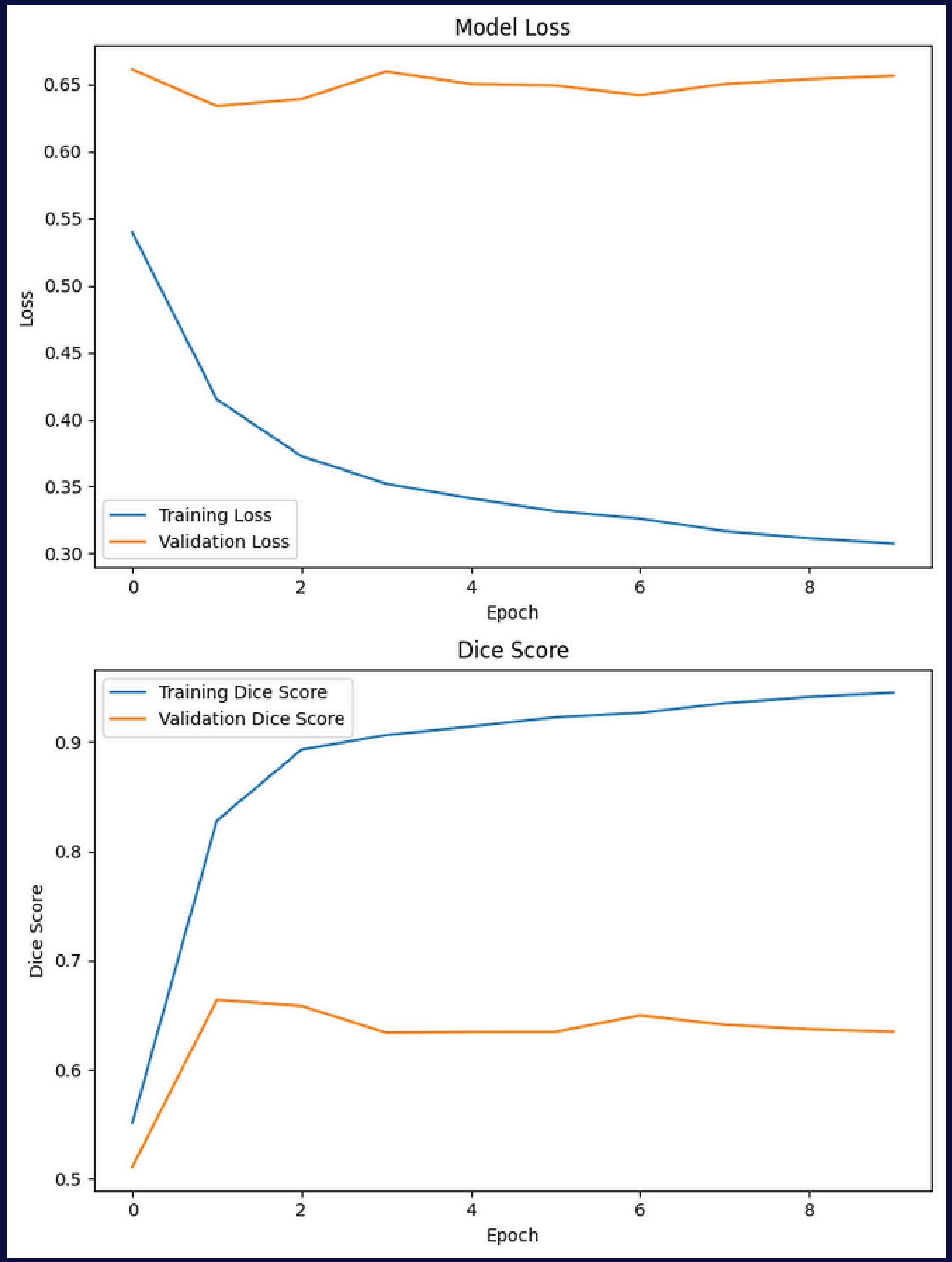
Uses decoder signals to weight encoder features, focusing on relevant information.

0.64

Dice Score

0.65

Dice Loss



Additional Experimental Models

UNetResidual2D

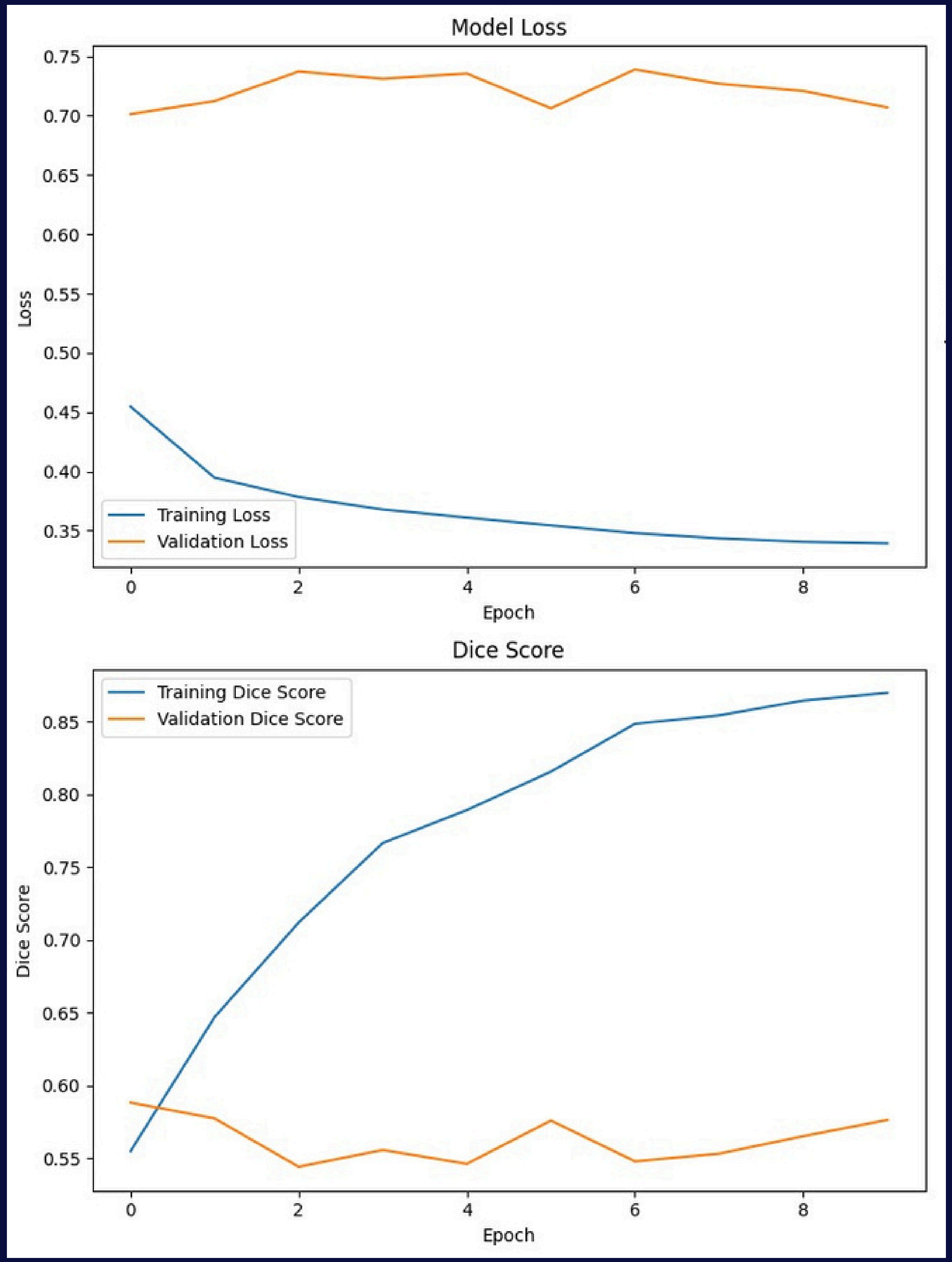
- Introduces Residual Connections for improved gradient flow and applies dropout for better regularization.
- Useful to reduce overfitting, especially with limited data.

0.58

Dice Score

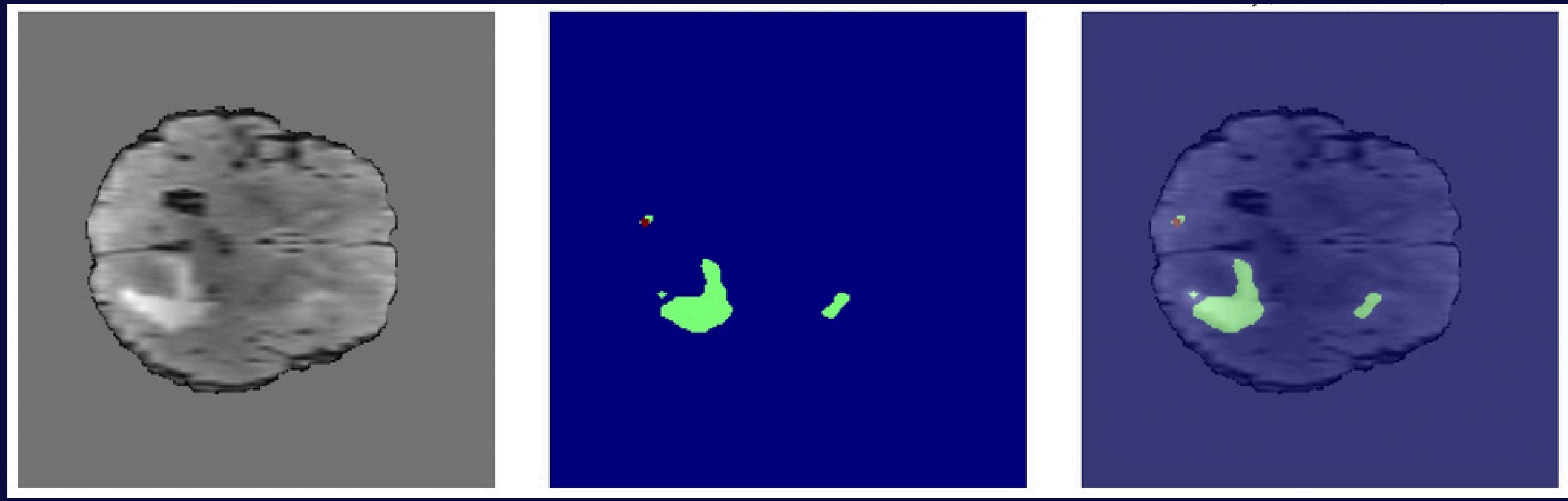
0.70

Dice Loss

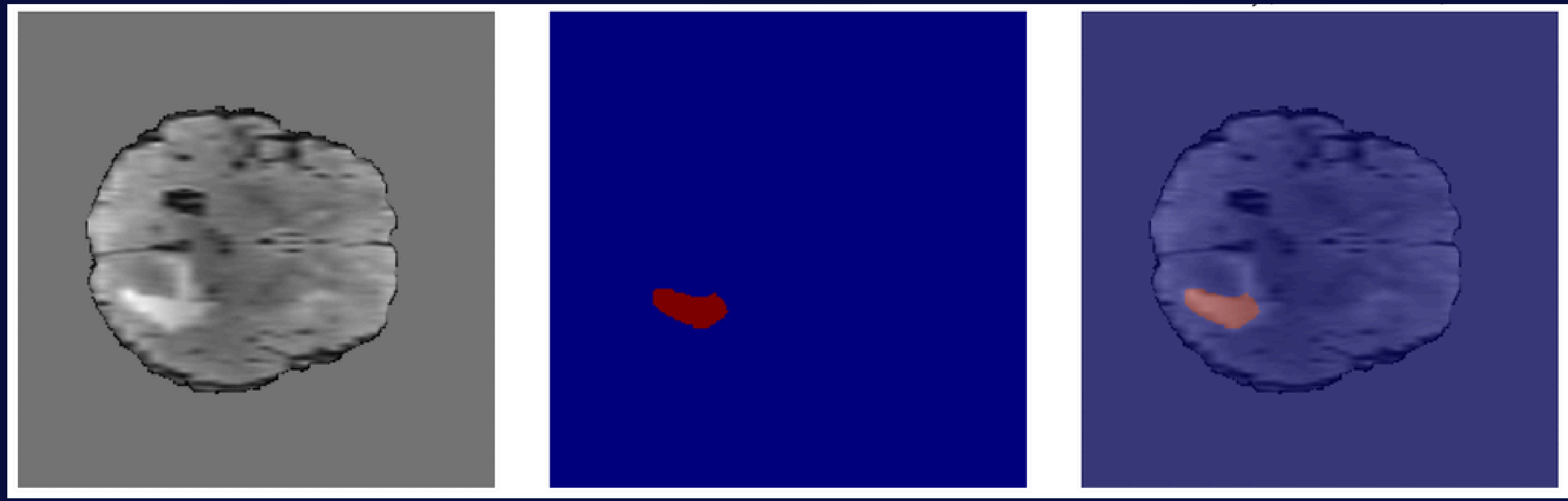


Testing : Visualising Model Segmentation Results

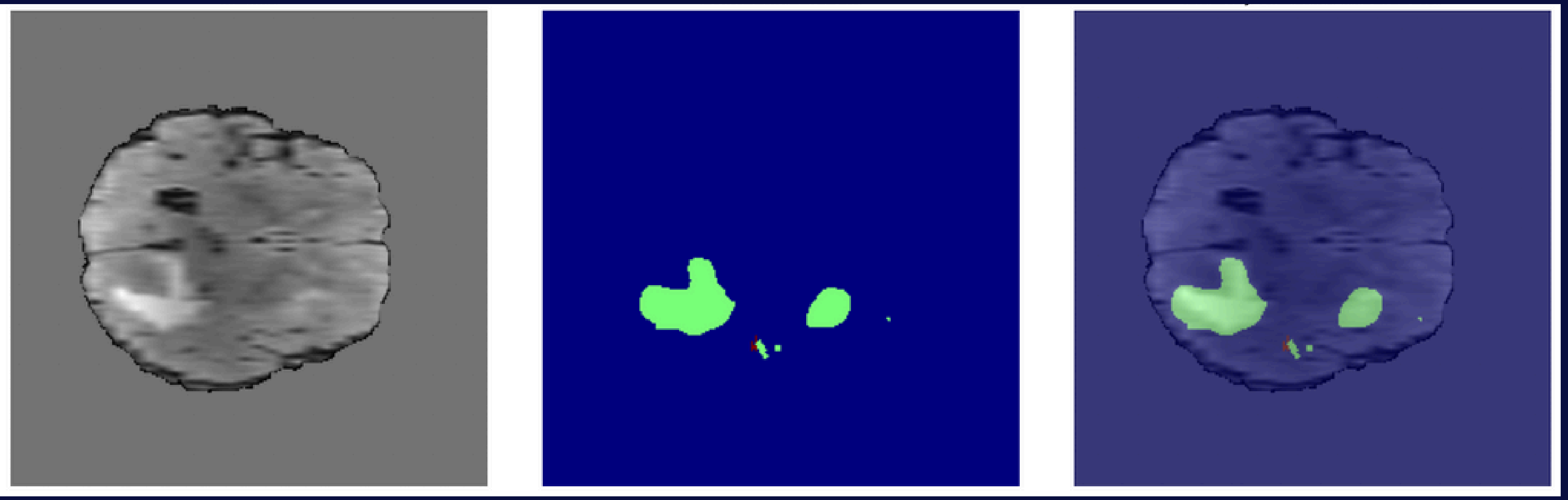
Combined Model



Residual Combined Model



Attention Combined Model



Conclusions

Ineffective Preprocessing

Modality-wise normalization, cropping and non-spatial augmentation not improved segmentation accuracy

Model Comparison

Among the three models tested, the Attention U-Net achieved the best performance

Clinical Impact & Future Directions

Clinical Impact

- ✓ Reduces time and variability in manual tumor segmentation
- ✓ Provides consistent, objective support for radiologists
- ✓ Enhances accuracy in diagnosis and treatment planning

Future Directions

- ✓ Explore 3D architectures for richer spatial understanding
- ✓ Apply advanced augmentation and class balancing techniques
- ✓ Validate on external clinical datasets to ensure robustness

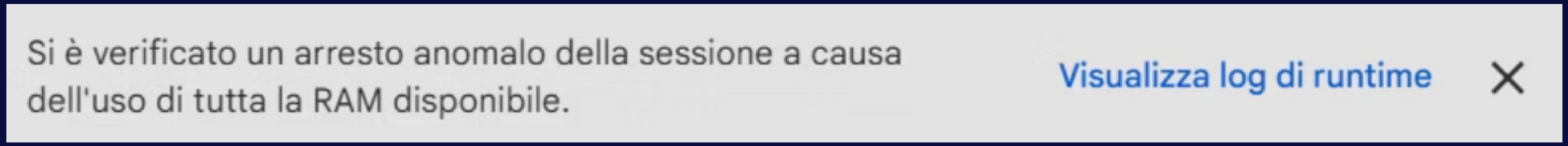
Project Limitations

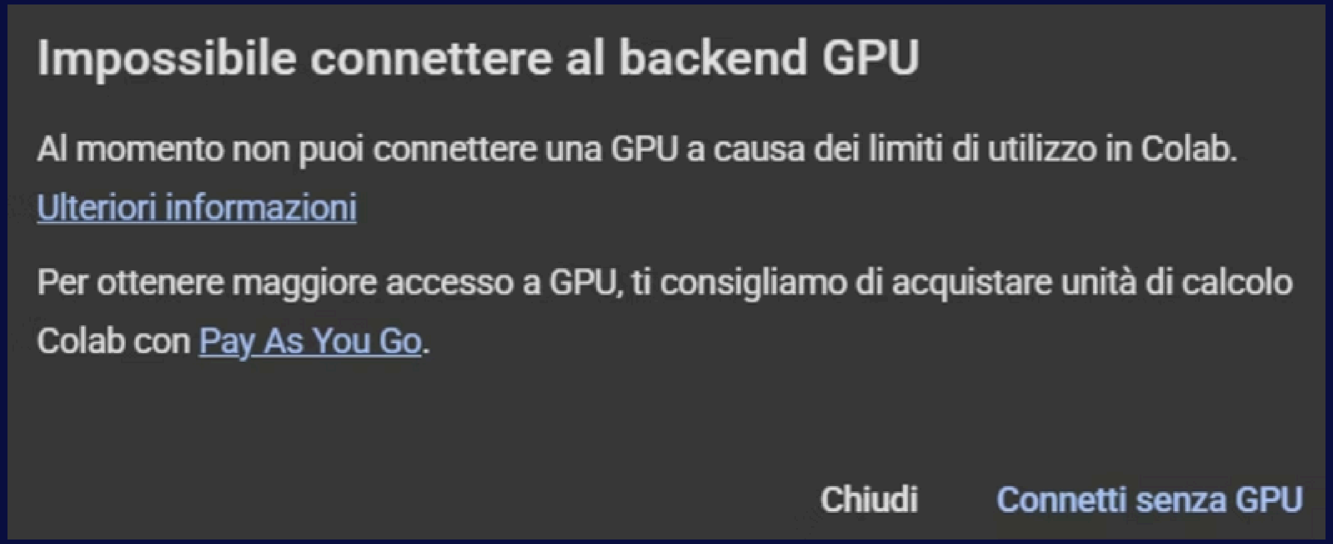
Unable to train the model on large datasets or full 3D images

Computational limitations (insufficient RAM and GPU)

Limited model performance and reduced hyperparameter tuning due to long training times

Lack of practical experience with medical imaging





Thank You For The Attention