Multimodal Medical Imaging Optimization Lab
Department of Biomedical Engineering
National Taiwan University

Medical Image Analysis *DBME5030*

Term Project Report

Brain Tumor Segmentation from MRI images using Patch-Based Attention U-Net for Data-Efficient Learning

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Introduction

- **Problem Statement**

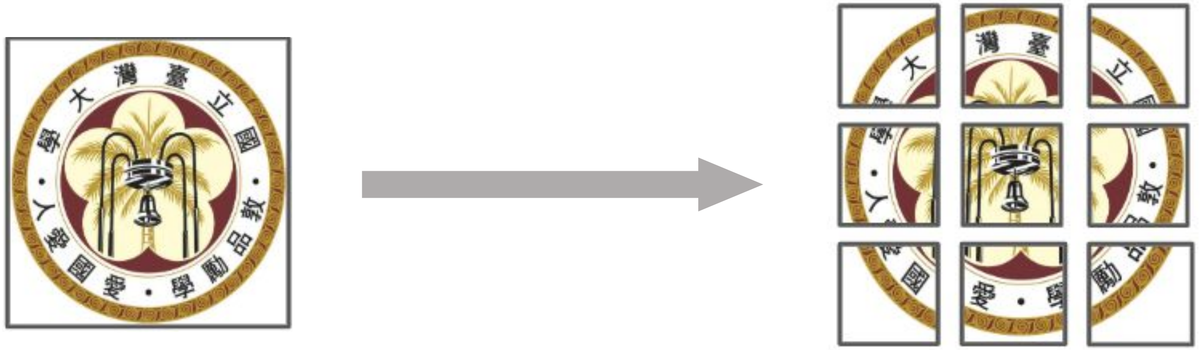
Brain tumor segmentation and survival prediction in glioma, using multimodal MRI scans with Deep Learning Based Methods and an ensemble model comprising of three different convolutional neural network architectures.

❖ **Accurate Segmentation of Brain Tumor:**

- ➢ Early diagnosis
- ➢ Treatment planning
- ➢ Survival rate prediction
- ➢ Reduces workload and subjectivity in radiologist interpretation

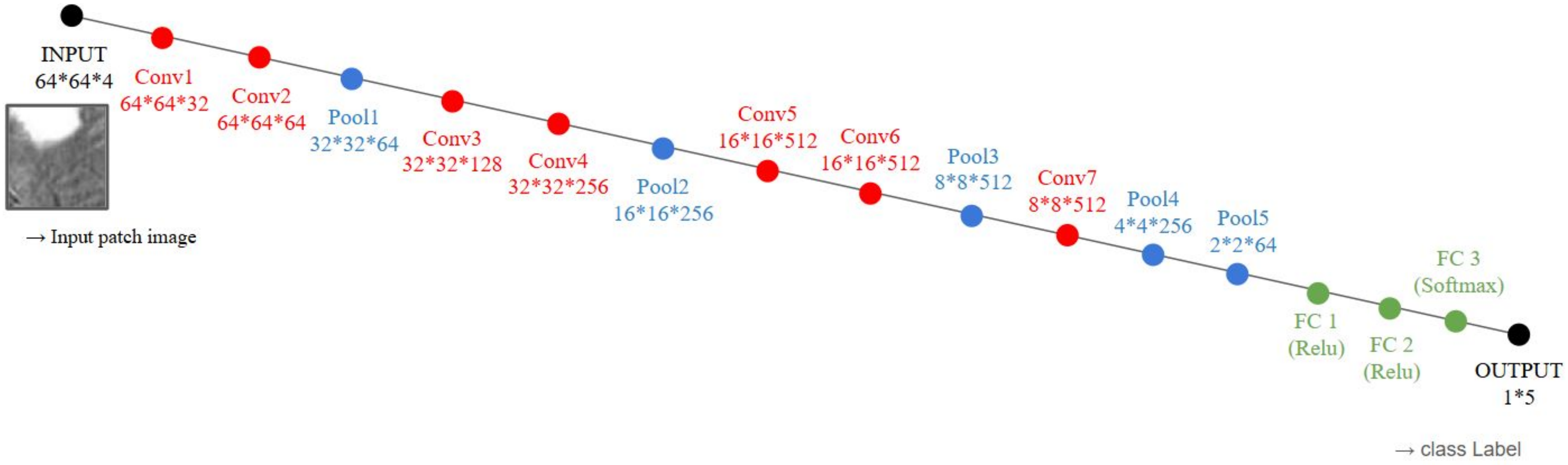
Previous Results from HW1

- Patch-Based Convolutional Neural Network (PBCNN) :
  - Train models using “patches” of the original image.
- Big Data Analysis Approach:
  - Data Cleansing, Data Transformation & Enrichment Patch Standardization



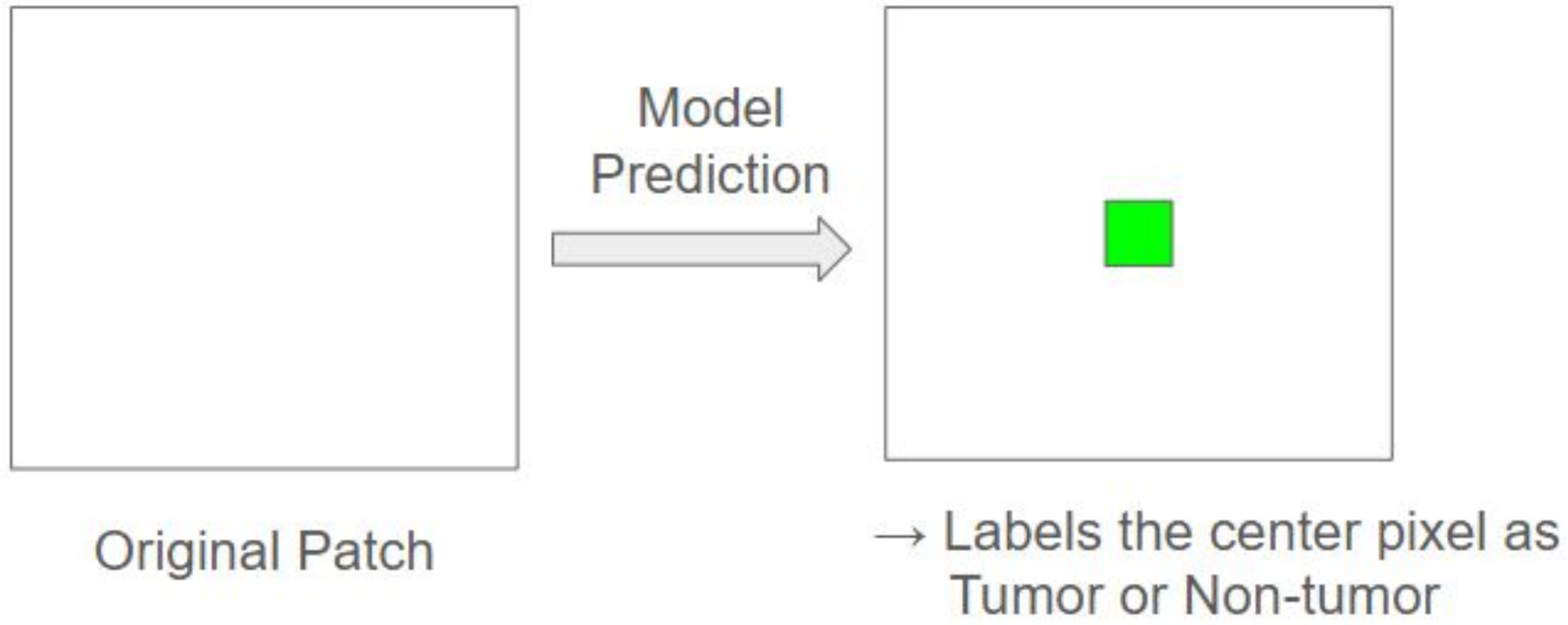
Previous Results from HW1

- PBCNN Model Architecture:



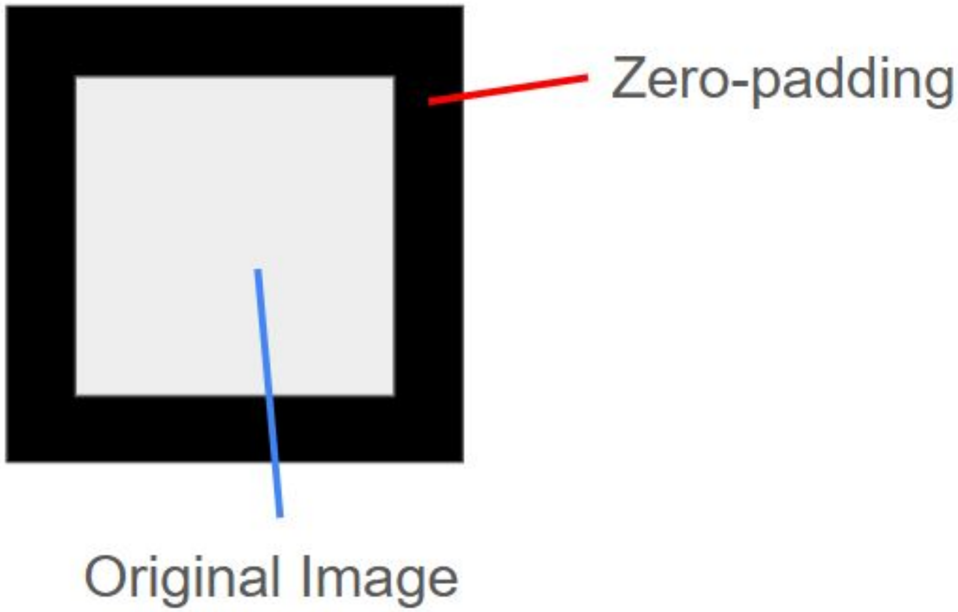
Previous Results from HW1

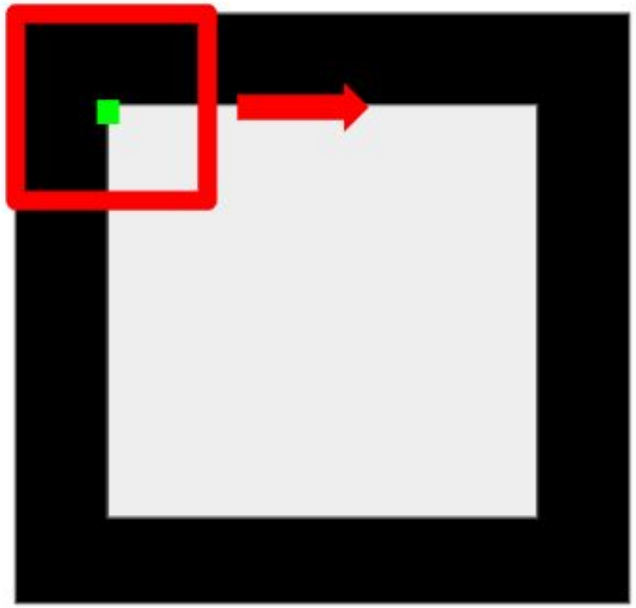
- Mask Generation:



Previous Results from HW1

- Mask Generation:





→ Sliding Window Technique:
(Repeat until all original pixels has been the center pixel once)

→ TOO SLOW!!!

Previous Results from HW1

- PBCNN implementation on BraTS 2020:

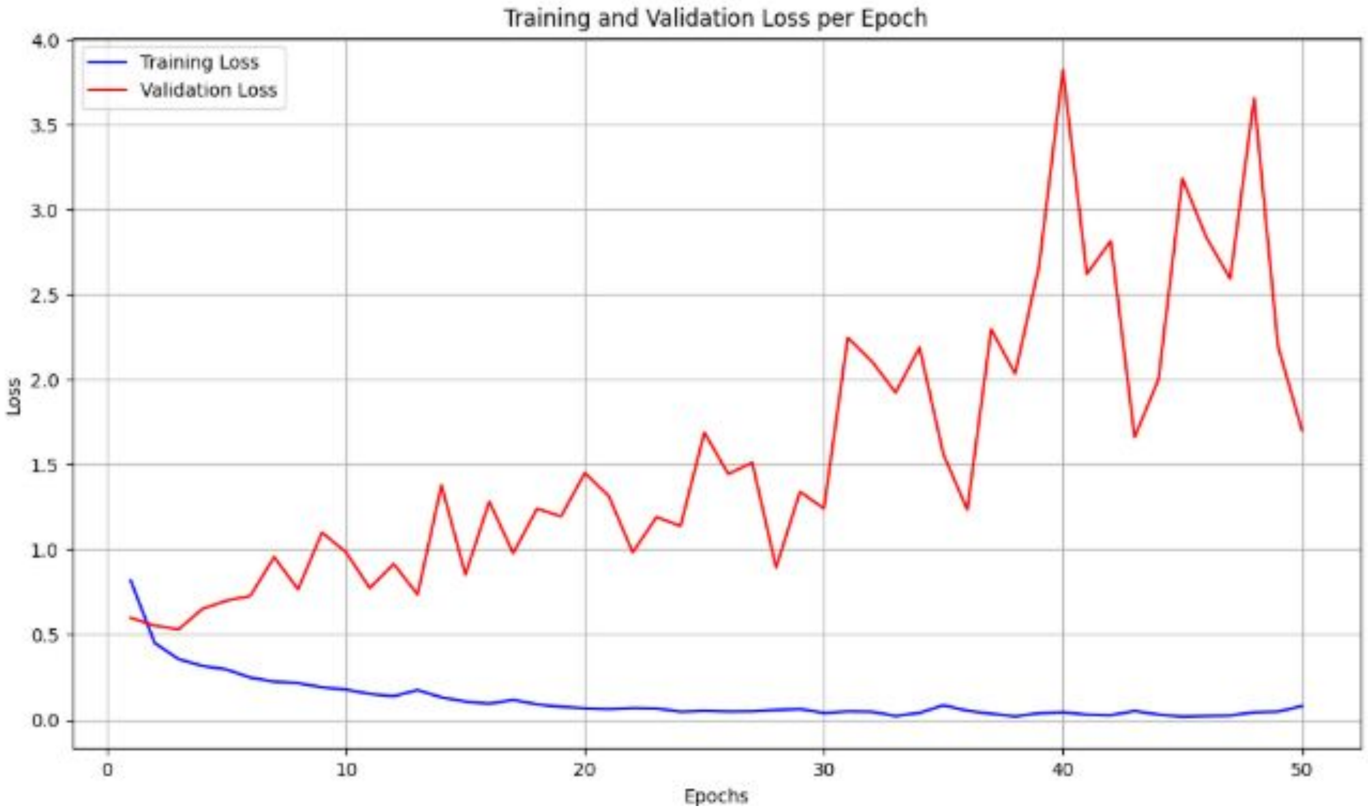
❖ Dataset: 60 patients from MICCAI_BraTS2020_TrainingData

	Training set	Validation set	Test set
Total Patient number	40	10	10

❖ Model: Propose PBCNN, epoch=50, learning rate =0.001, Adam Optimizer

Previous Results from HW1

- PBCNN implementation on BraTS 2020:



Overfitted

→ Class imbalance

→ learns well in training

→ poor generalization

Previous Results from HW1

- Pros and Cons:

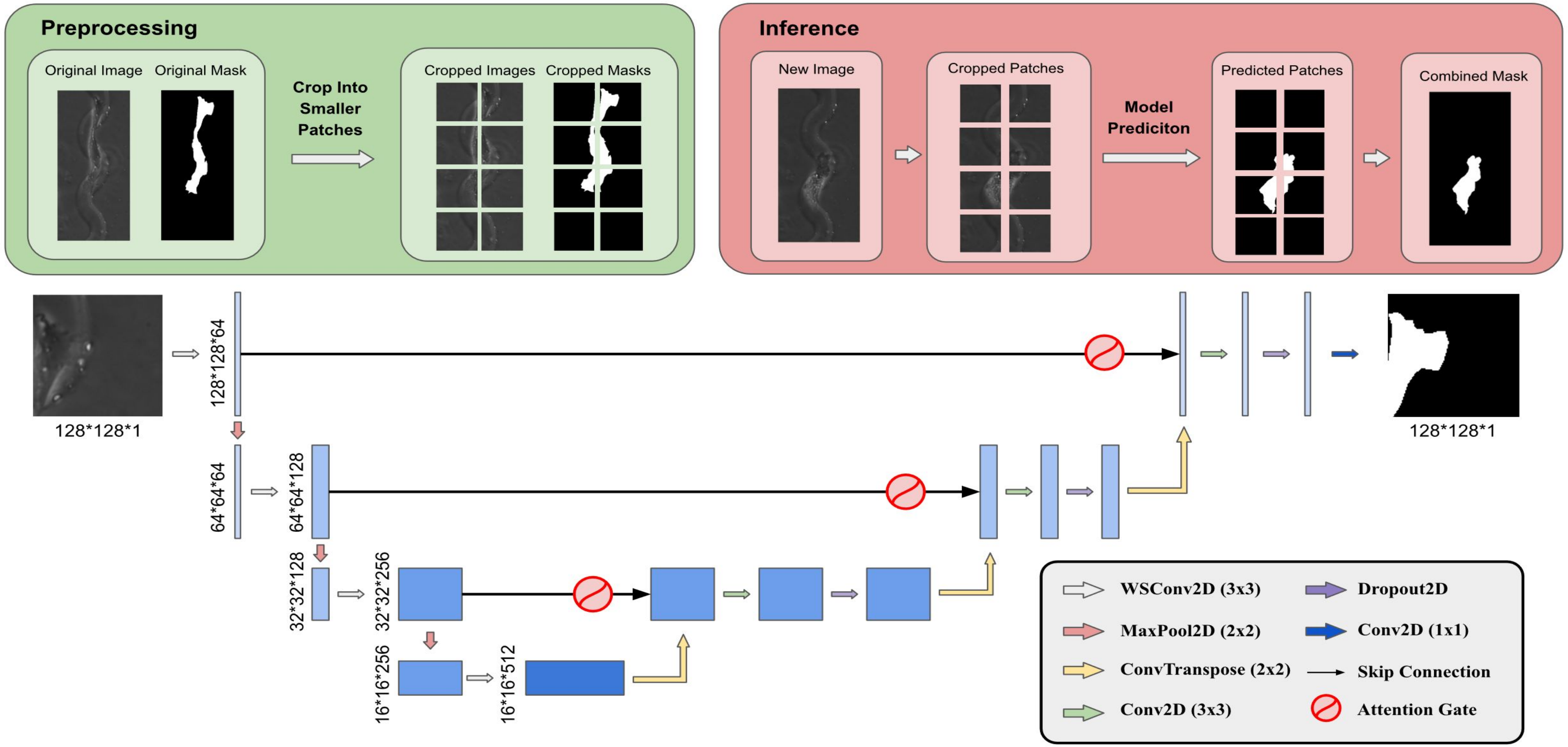
PROS	CONS
• Local Detail Capture (PBCNN Advantage) • Efficiency & Low computational cost • Combines **data quality control** and **model efficiency** • Big Data Pipeline (More Uniform Input (Patches))	• Loses global context • Susceptible to class imbalance ◦ Requires patch selection • Susceptible to training data quantity and quality • Slow segmentation mask generation speed

Project Goals

- Retain “Pixel-wise” segmentation (finer details) from Patch-Based method
- Less susceptible to class imbalance
- Fully utilize the cropped dataset without selecting patches

Materials and Methods

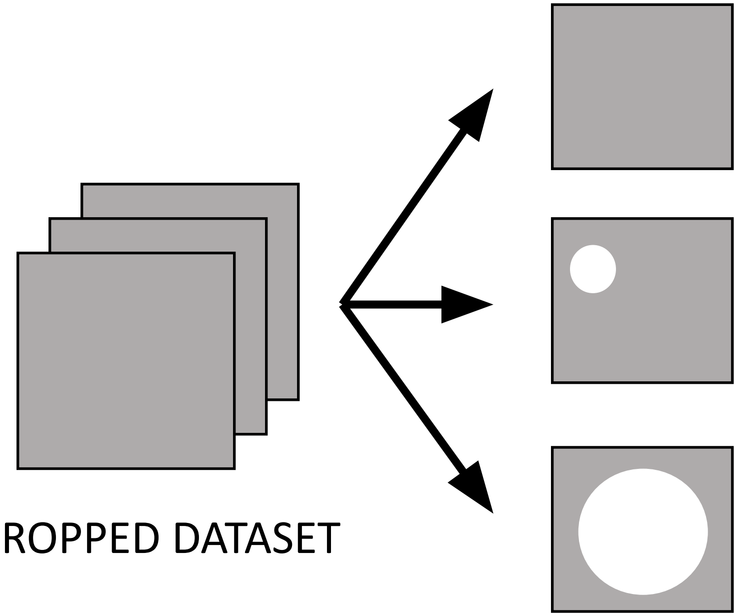
- Patch-Based Attention U-Net model architecture



Materials and Methods

- Patch-Based Attention U-Net: Dynamic Loss function Selection

    Switch loss function based on predicted mask



CROPPED DATASET

Background Patches → Binary Cross Entropy Loss (BCE loss)

Enhance True Negatives

Small ROI Patches → BCE Loss + Tversky Loss

Enhance True Negatives + penalize false positives

Large ROI Patches → Tversky Loss + Focal Tversky loss

Penalize False Positives & False Negatives

[1] Chen, K.-L., Lin, Y.-N., Chao, P. G., & Chen, K. T. (2025). *A Low-Resource Training Strategy for Cell Segmentation using Patch-Based Attention U-Net*. OpenReview. https://openreview.net/forum?id=tbjpQbcIxW

Materials and Methods

- Patch-Based Attention U-Net
  - ✔ Able to train a model using minimal Dataset
  - ✔ Proposed a dynamic loss function selection method to fully utilize cropped dataset while stabilize training without the need to select training data.
  - ✔ Adaptable to dataset morphology (for diverse brain tumor morphology)

Materials and Methods

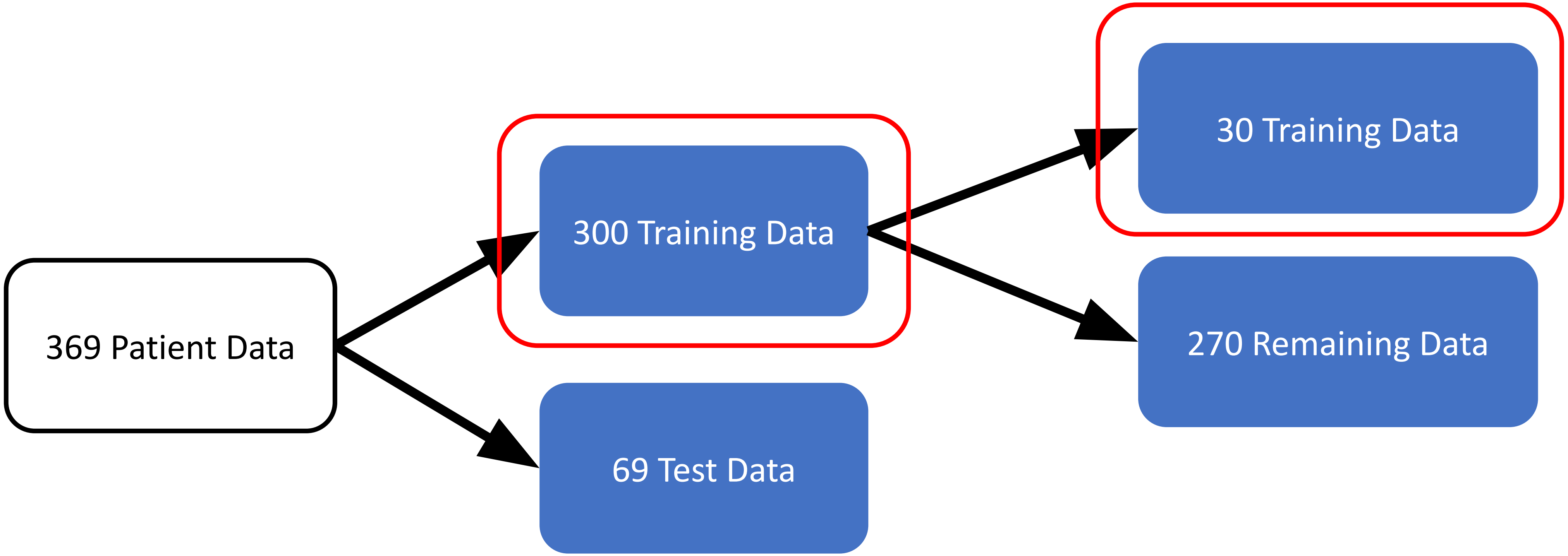
- BraTS dataset:
  - 369 patients
  - t1, t1ce, t2, FLAIR

- Preprocessing Pipeline:

Slice and stack all modalities to 256*256*4 → Z-score normalization → Crop into 128*128*4 with 64 overlap pixels

$$\boxed{z = \frac{x - \mu}{\sigma}}$$

Materials and Methods



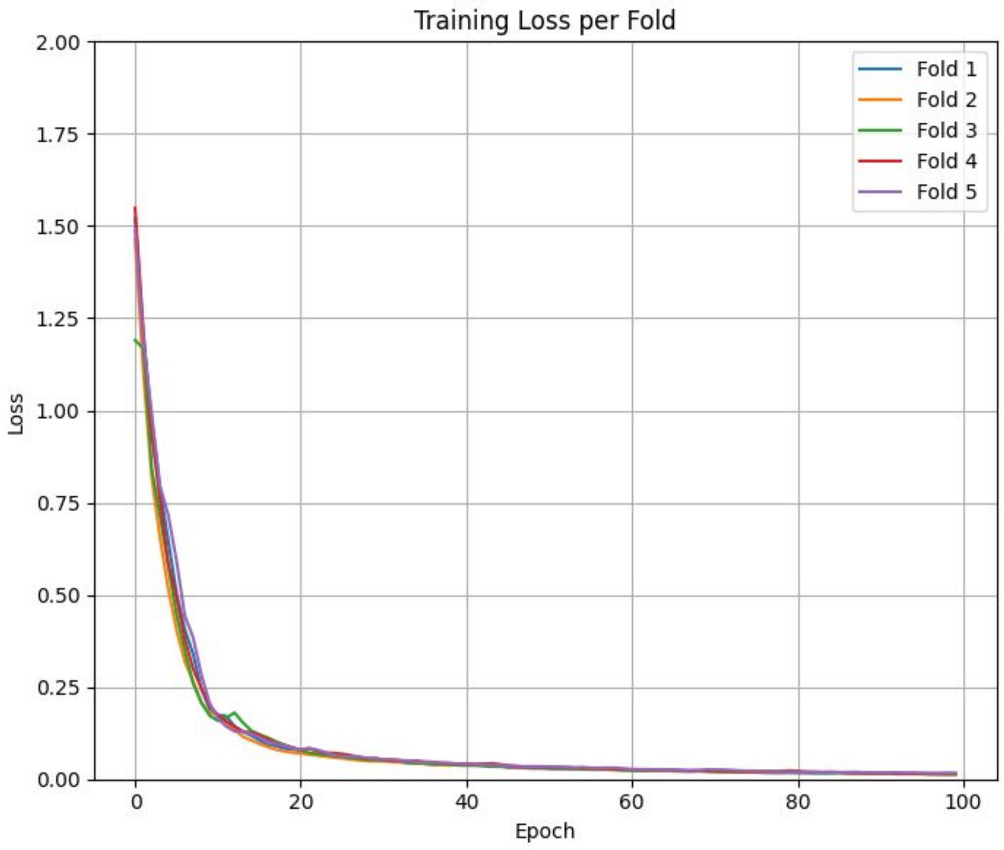
- Train brain tumor segmentation models based using normal training data (300 patients) v.s. low training data (30 patients)
- Compare model performances of two scenarios Patch-based Attention U-Net v.s. U-Net v.s. nnU-Net

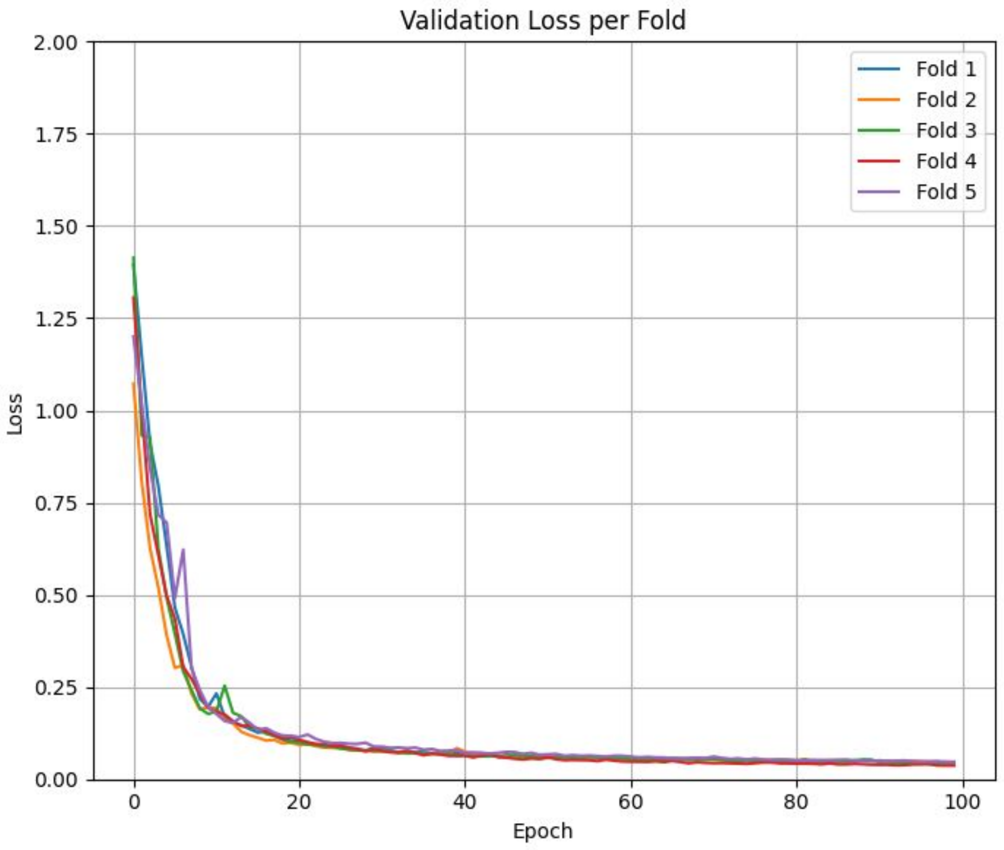
Materials and Methods

- Training Settings:
  - ✔ 5 layer for every model
  - ✔ batch size = 64 , learning rate = 0.0001,
  - ✔ 5-fold cross validation
  - ✔ Optimizer = Adam optimizer
  - ✔ Loss function = Dynamic loss function

Results

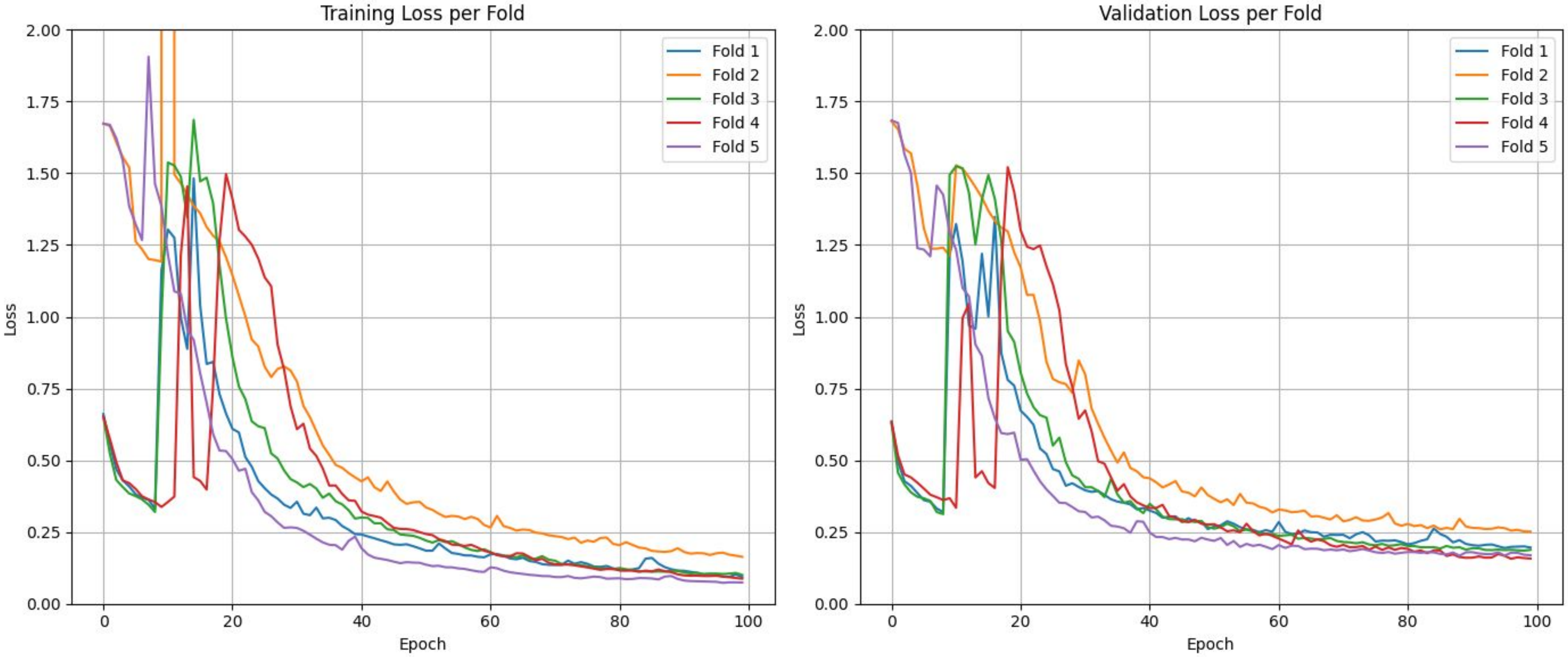
- Patch-Based Attention U-Net loss curve on normal (300) training dataset





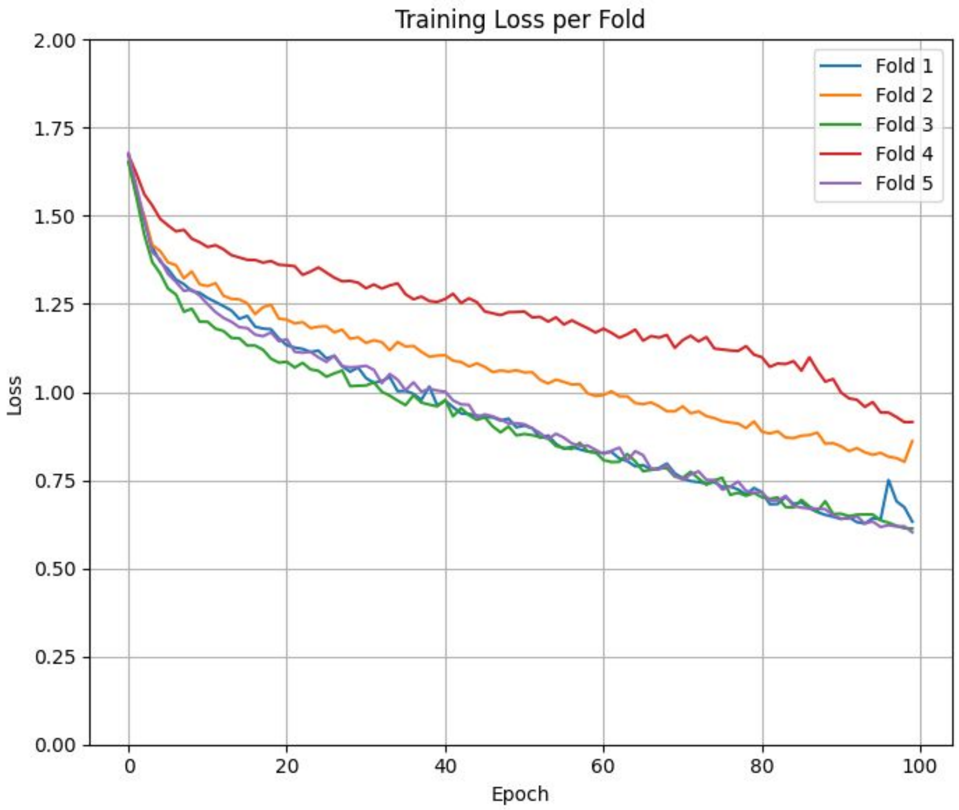
Results

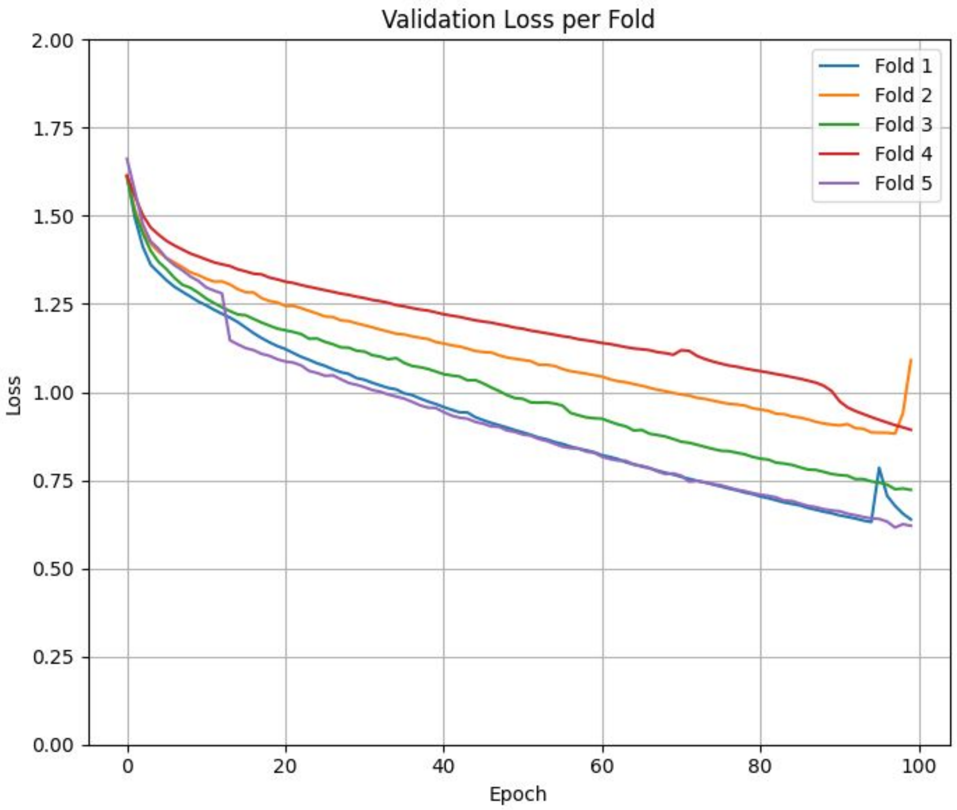
- U-Net loss curve on normal (300) training dataset



Results

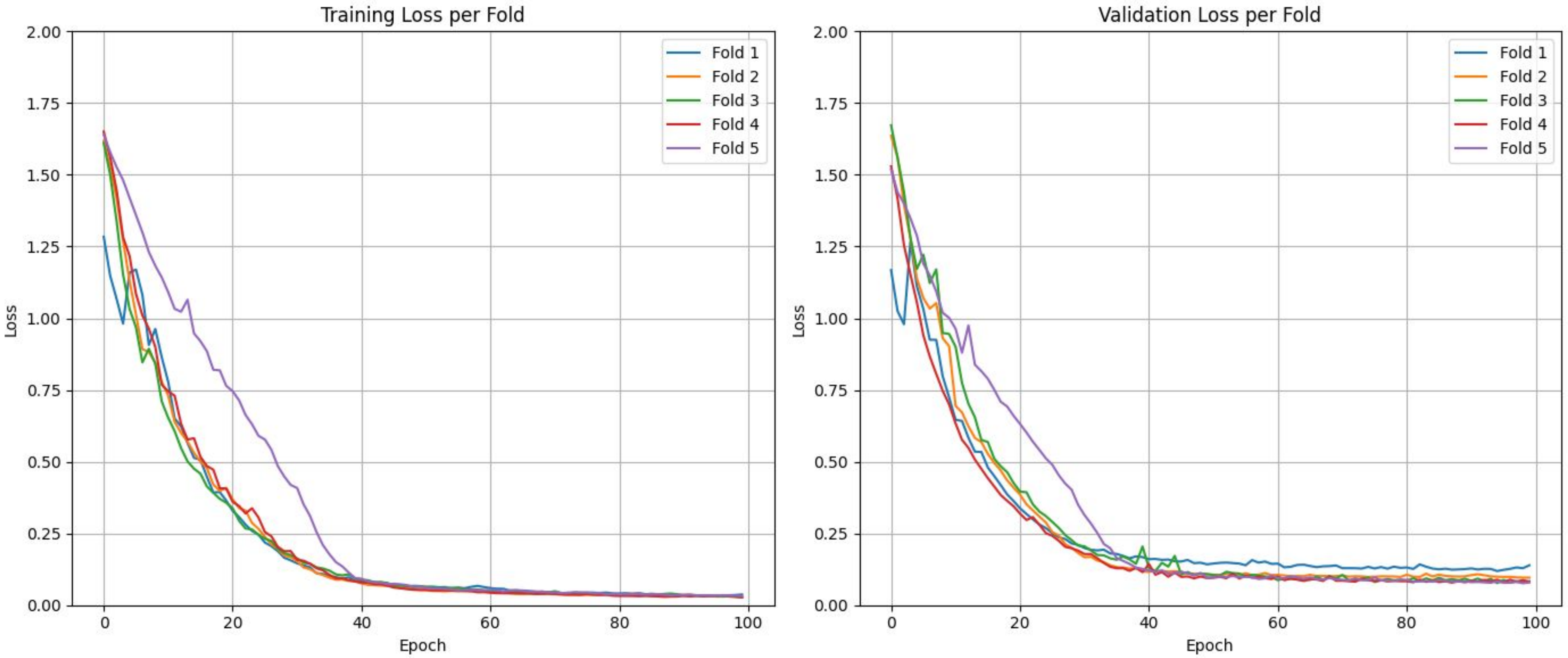
- nnU-Net loss curve on normal (300) training dataset





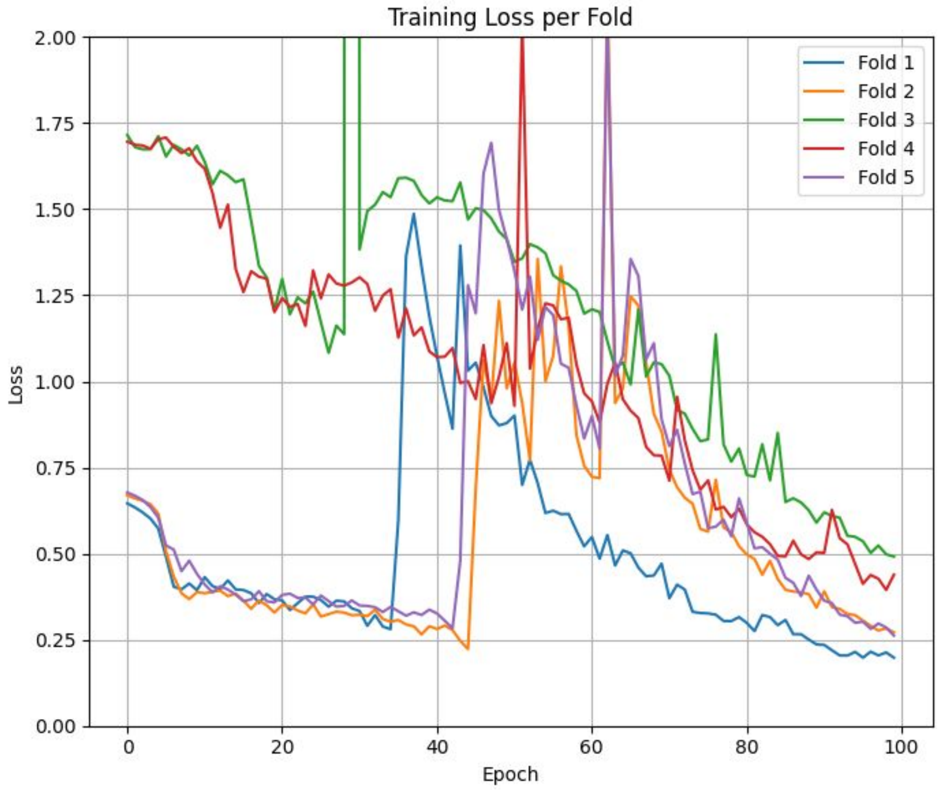
Results

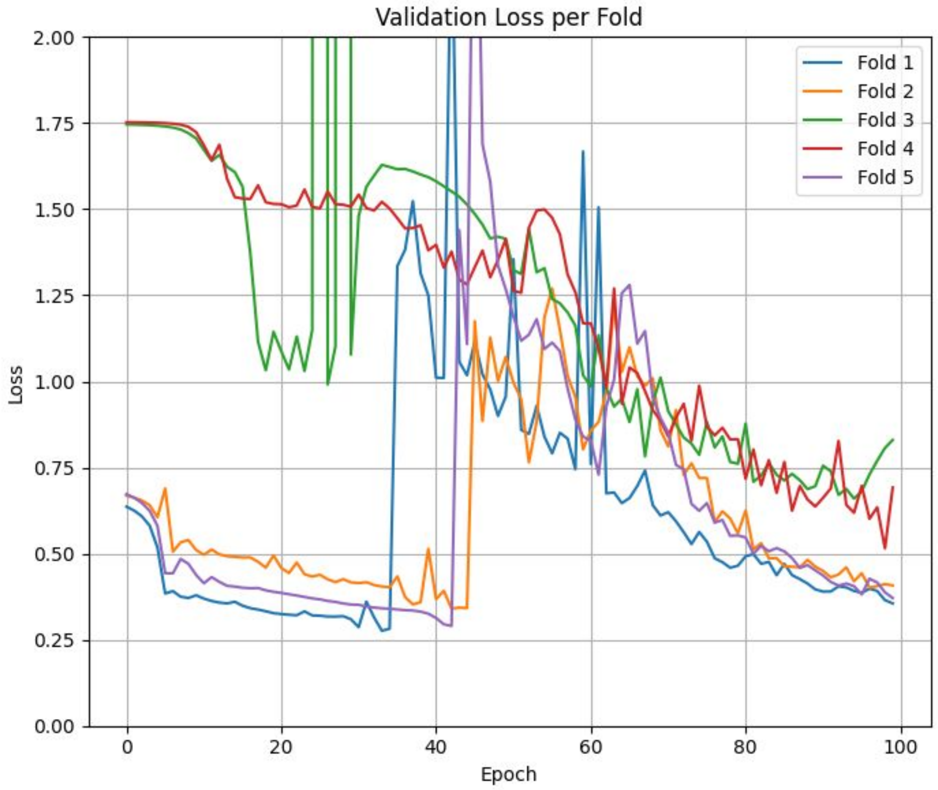
- Patch-based Attention U-Net loss curve on Low (30) training dataset



Results

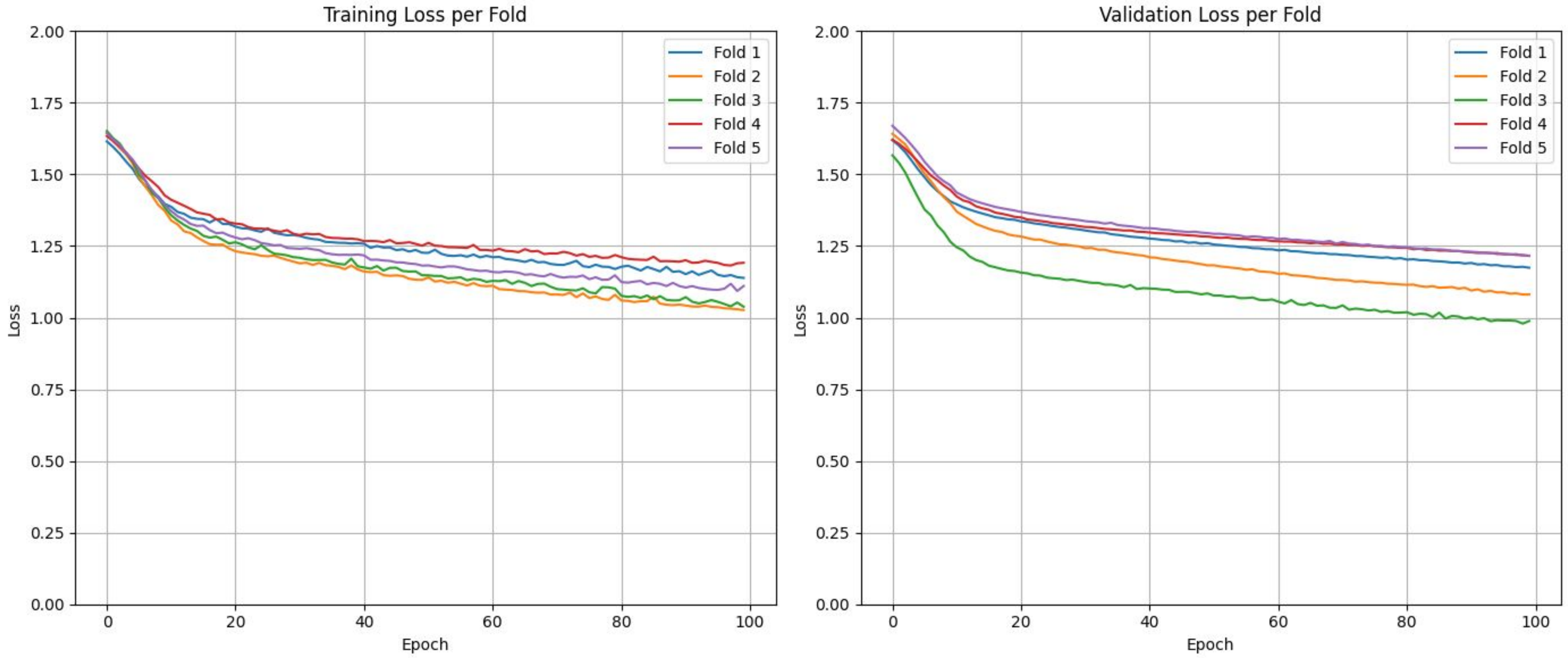
- U-Net loss curve on Low (30) training dataset





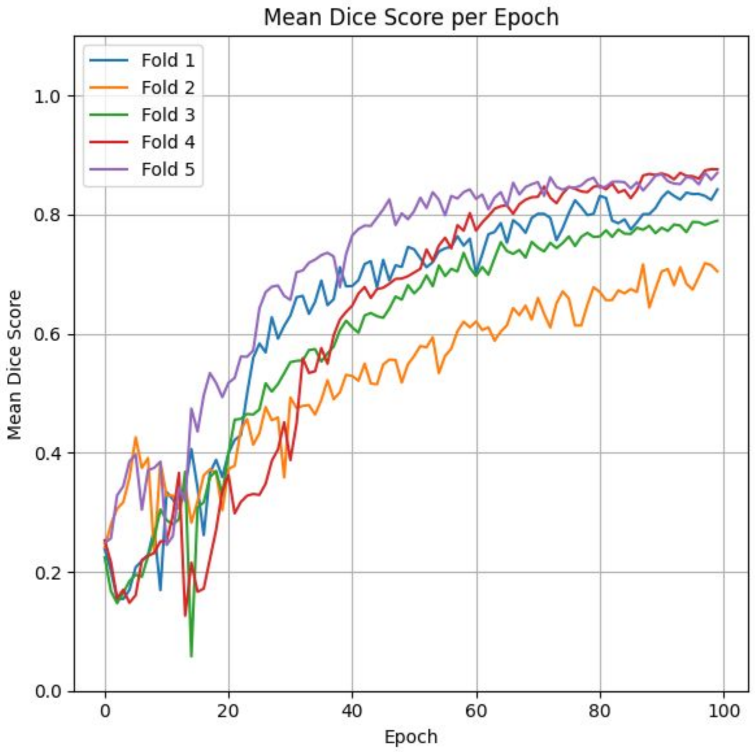
Results

- nnU-Net loss curve on Low (30) training dataset

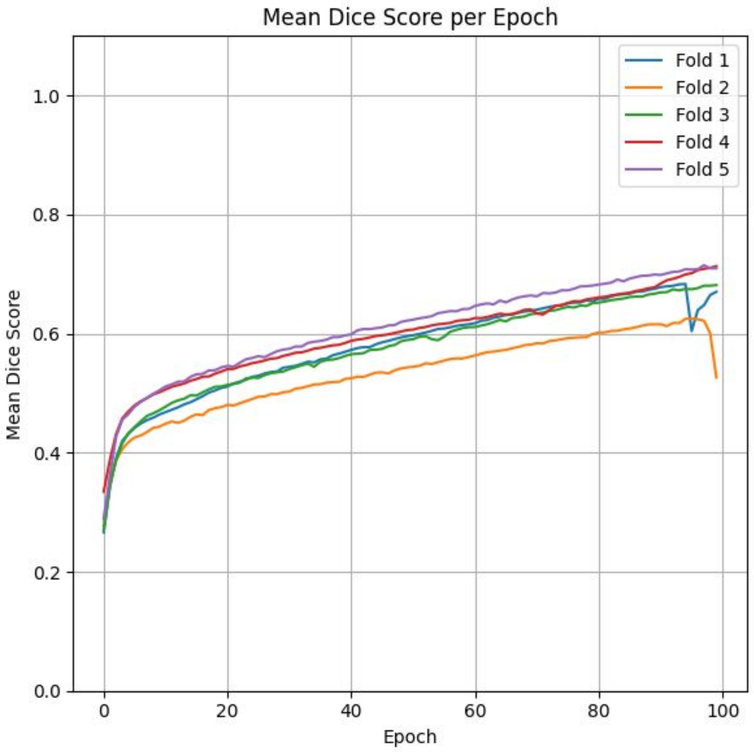


Results

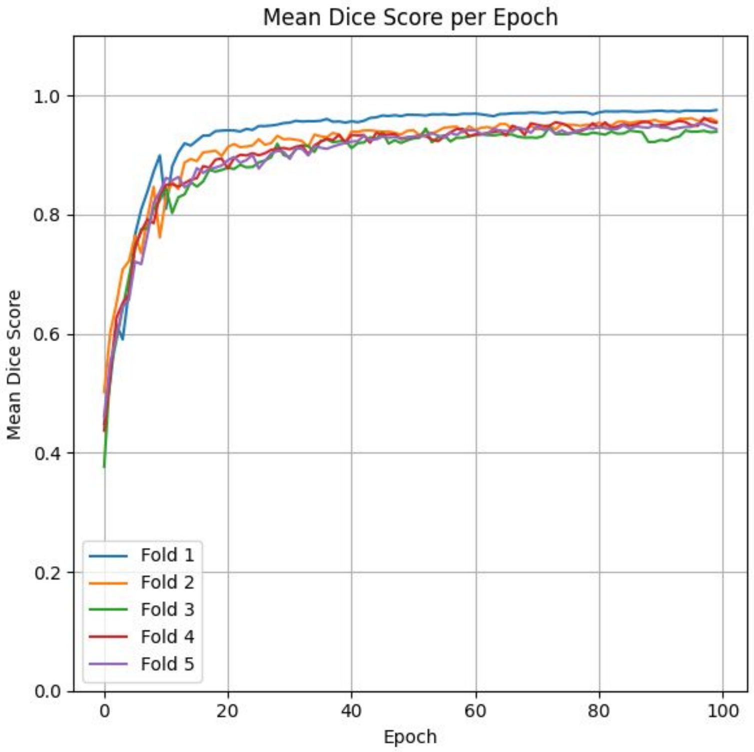
- Mean Dice score on normal (300) training dataset



U-Net



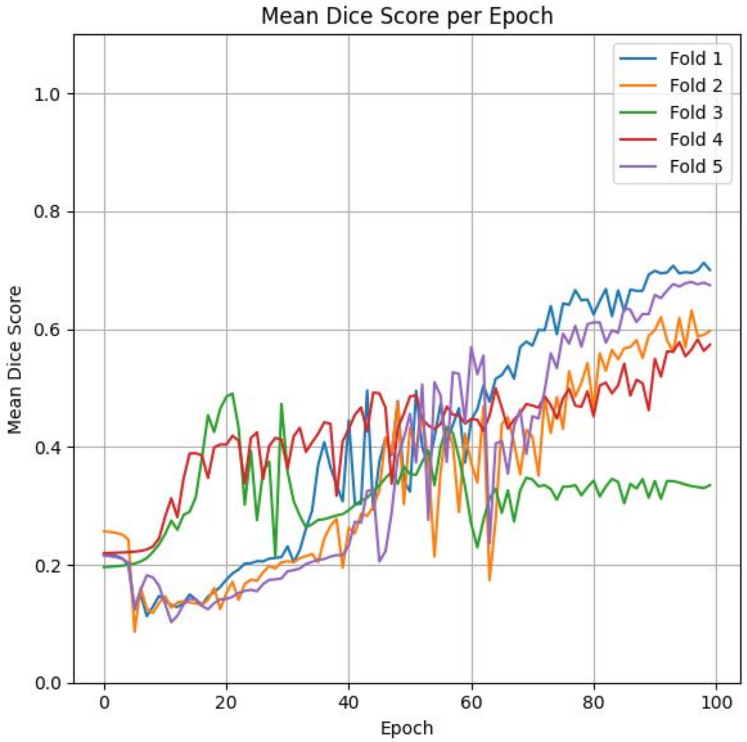
nnU-Net



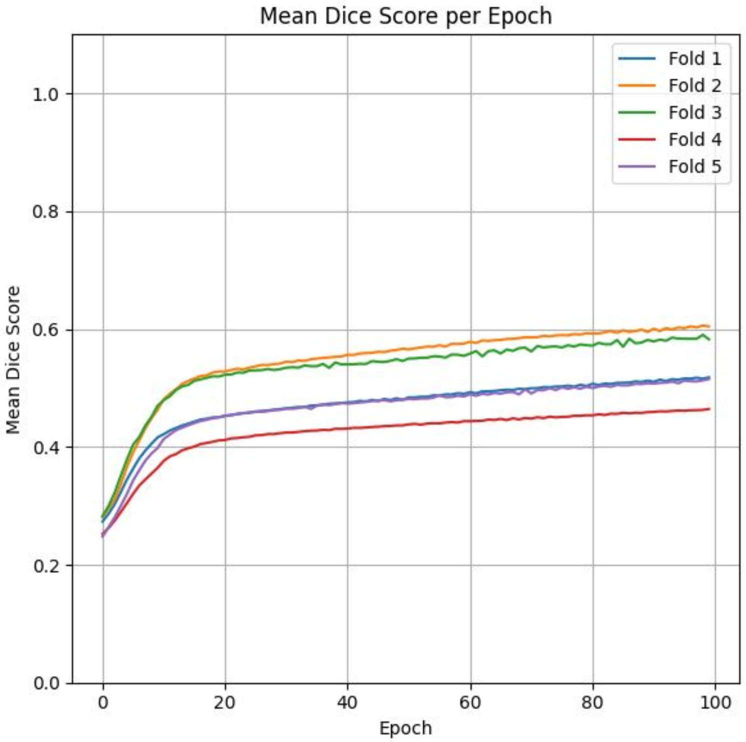
Patch-Based Attention U-Net

Results

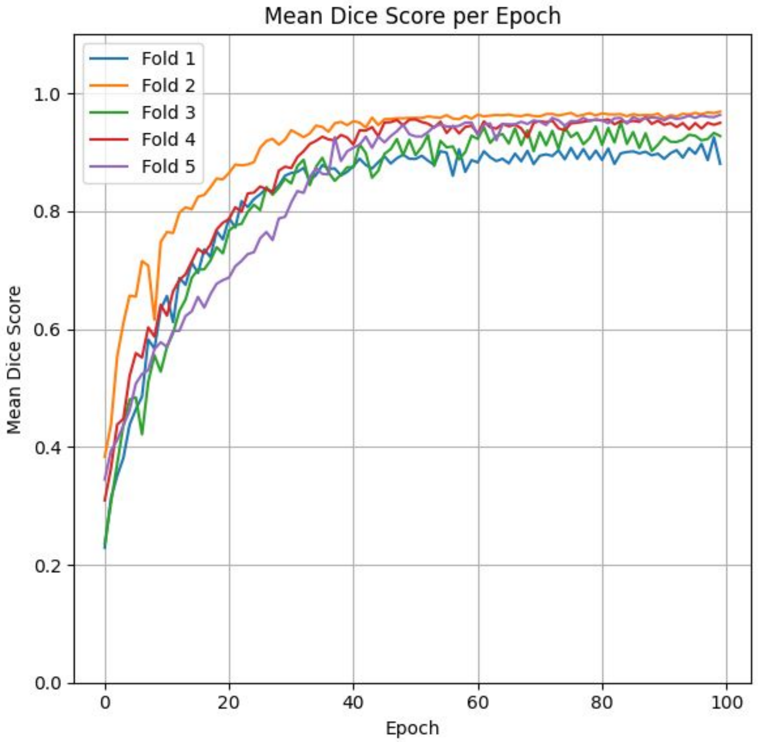
- Mean Dice score on low (30) training dataset



U-Net



nnU-Net



Patch-Based Attention U-Net

Results

- Mean Dice score on test Dataset using normal (300) training data

	Mean Dice Score on test dataset
U-Net	0.8383
nnU-Net	0.6968
Patch-Based Attention U-Net	0.8754

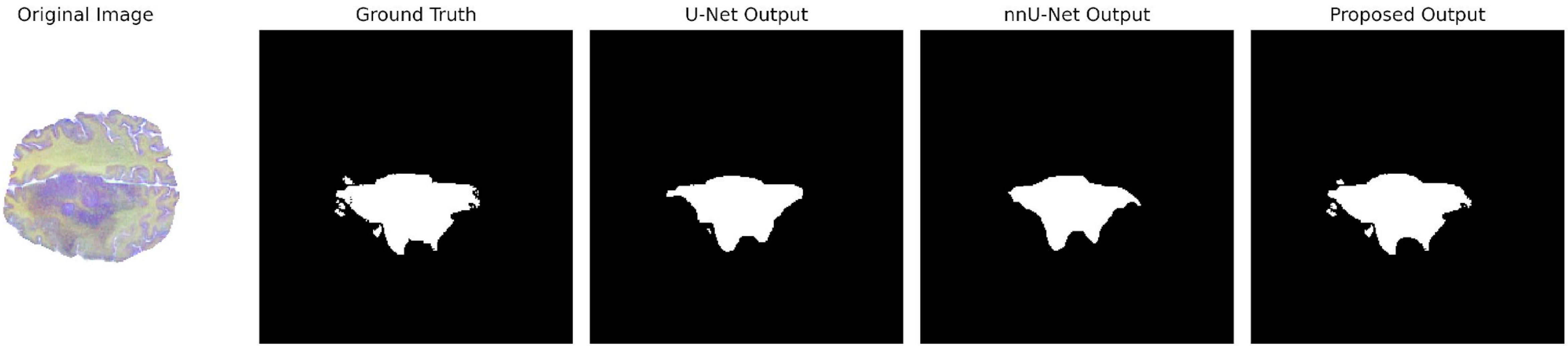
Results

- Mean Dice score on test Dataset using Low (30) training data

	Mean Dice Score on test dataset	Mean Dice Score on remaining Dataset
U-Net	0.5650	0.4871
nnU-Net	0.5369	0.4589
Patch-Based Attention U-Net	0.7560	0.7270

Results

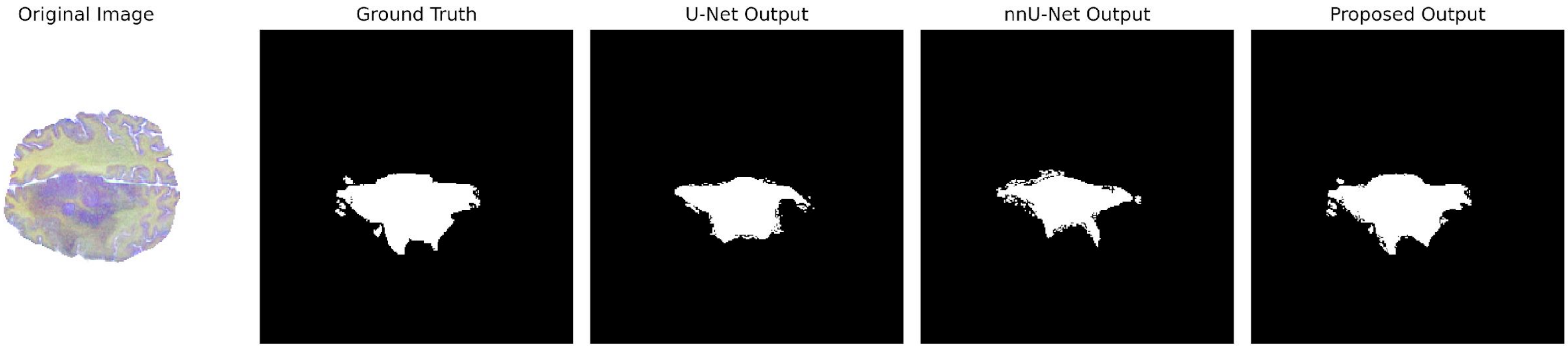
- Segmentation Output comparison using normal (300) training dataset



- Patch-Based Attention U-Net segments finer details of the tumor

Results

- Segmentation Output comparison using low (30) training dataset



- Patch-Based Attention U-Net's is more accurate when using limited training data

Conclusion

- U-Net structures achieve faster mask generation than Convolutional Neural Networks
- Patch-Based Attention U-Net achieves more accurate segmentation outputs
- Patch-Based Attention U-Net can converge when using low training data
- Dynamic loss function selection can mitigate class imbalance issues

Future works

- Explore mamba-based or transformer-based light weight models for better segmentation outputs using low training data
- Test model performance across BraTS challenge in other year $(2012 \sim 2025)$
- Repeat experiment using different random seeds to ensure robustness of the method
- Explore multiclass segmentation for whole tumor (WT), Tumor core (TC), Enhanced tumor (ET) to provide extra information

Thank you for Listening!