Medical Imaging and Applications (EE-XXX)

Project Report

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Submitted to:

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Title: Brain Tumor Segmentation in MRI images.

Objective

The primary objective of this project is to develop and train deep learning models for **accurate and automated segmentation of brain tumors** in multimodal Magnetic Resonance Imaging (MRI) scans from the BraTS 2020 dataset. Specifically, the goal is to:

1. **Segment Tumor Sub-regions**: Accurately delineate three tumor sub-regions in MRI scans:
    - **Necrotic and non-enhancing tumor core (NCR/NET, Label 1)**.
    - **Peritumoral edema (ED, Label 2)**.
    - **GD-enhancing tumor (ET, Label 3)**.
    - Exclude non-tumor regions (background, Label 0).
2. **Leverage Multimodal MRI Data**: Utilize the most informative MRI modalities (T1ce and T2-FLAIR) to capture complementary information about brain anatomy and tumor characteristics, improving segmentation performance.
3. **Optimize Model Performance**: Implement and compare advanced convolutional neural network (CNN) architectures (U-Net, U-Net++, ResNet+U-Net, Attention ResNet+U-Net, and Attention with U-Net) to achieve high segmentation accuracy, particularly for small and clinically significant tumor regions.
4. **Evaluate Robustness**: Use a categorical cross-entropy loss and evaluation metrics (accuracy, IoU, Dice coefficient, sensitivity, precision, specificity, and class-specific Dice coefficients) to comprehensively assess model performance.

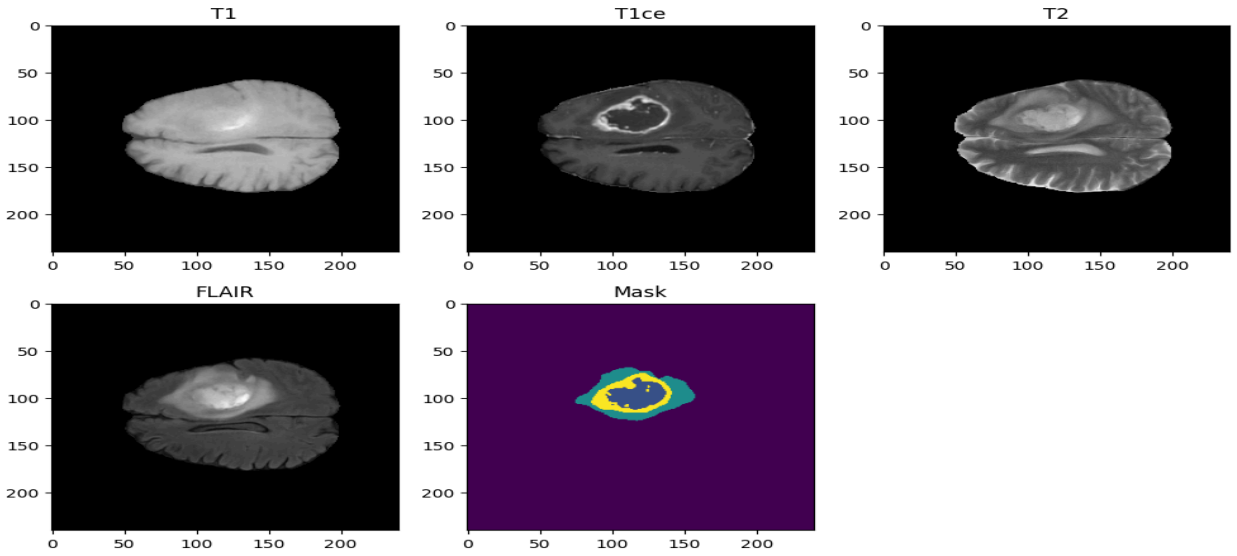
Overview

The Brain Tumor Segmentation project leverages the **BraTS 2020 dataset** to train deep learning models for segmenting brain tumors in multimodal MRI scans. The project involves preprocessing the data, selecting optimal modalities, designing and training CNN-based models, and evaluating performance with tailored metrics. Below is a detailed overview of the key components:

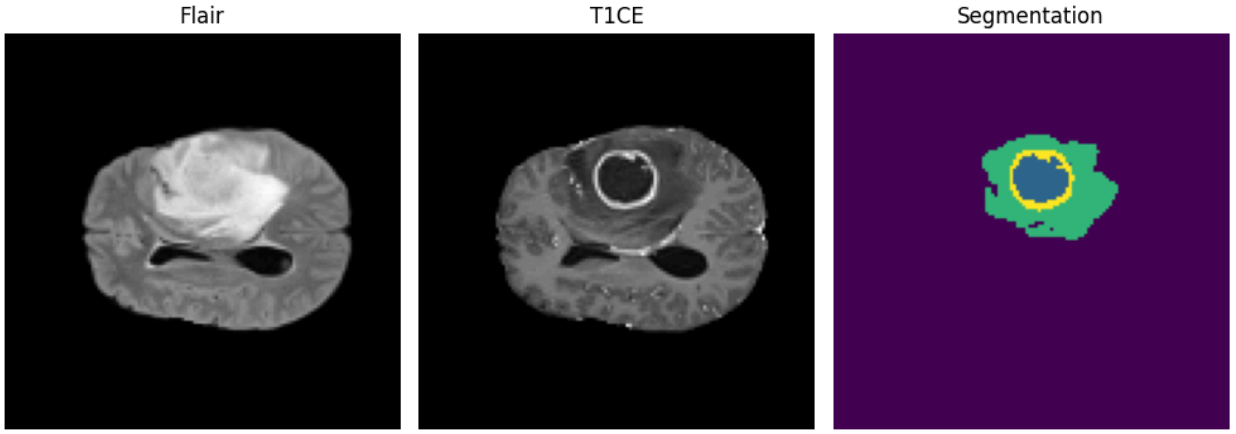
1. Dataset

- **BraTS 2020 Dataset**: A collection of **369** patients multimodal MRI scans from glioma patients, including four modalities per patient:
    - **T1 (Native)**: Highlights tissue structure.
    - **T1ce (Post-contrast T1-weighted)**: Enhances abnormalities with Gadolinium contrast.

- **T2 (T2-weighted)**: Emphasizes fluid content.
- **T2-FLAIR**: Suppresses fluid signals to highlight lesions, especially in white matter.
- Each modality has **155** slices.

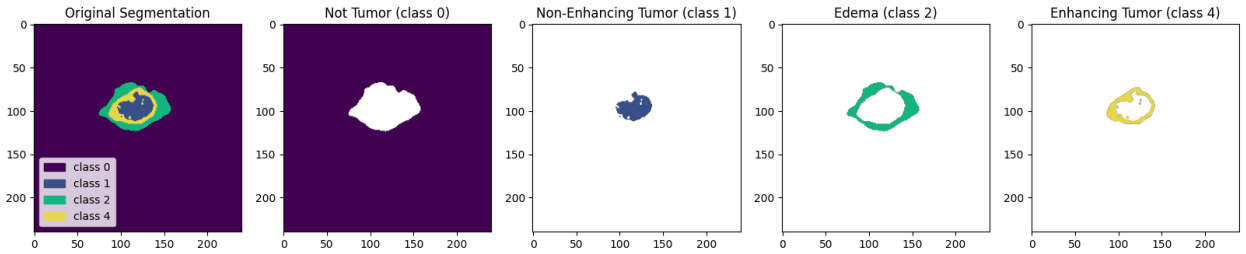


- **Selected Modalities**:
  - **T1ce** and **T2-FLAIR** are used for training, as they provide clearer and complementary information about tumor regions.
  - **T1** and **T2** are excluded to avoid redundancy and reduce noise from fluid signals that could hinder predictions.



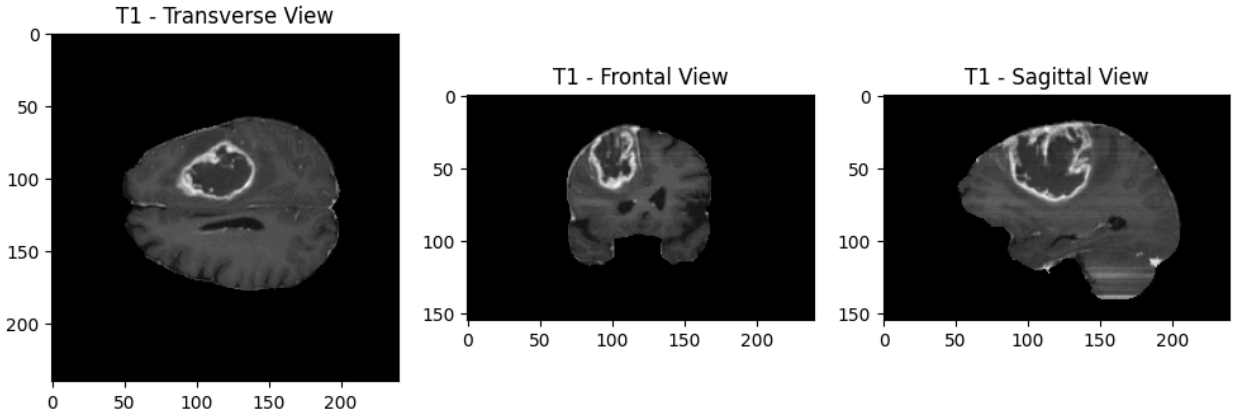
Annotations: Expert-annotated segmentation masks with four labels:

- **Label 0**: Not Tumor (background, overrepresented).
- **Label 1**: Necrotic and non-enhancing tumor core (NCR/NET).
- **Label 2**: Peritumoral edema (ED).
- **Label 4**: GD-enhancing tumor .

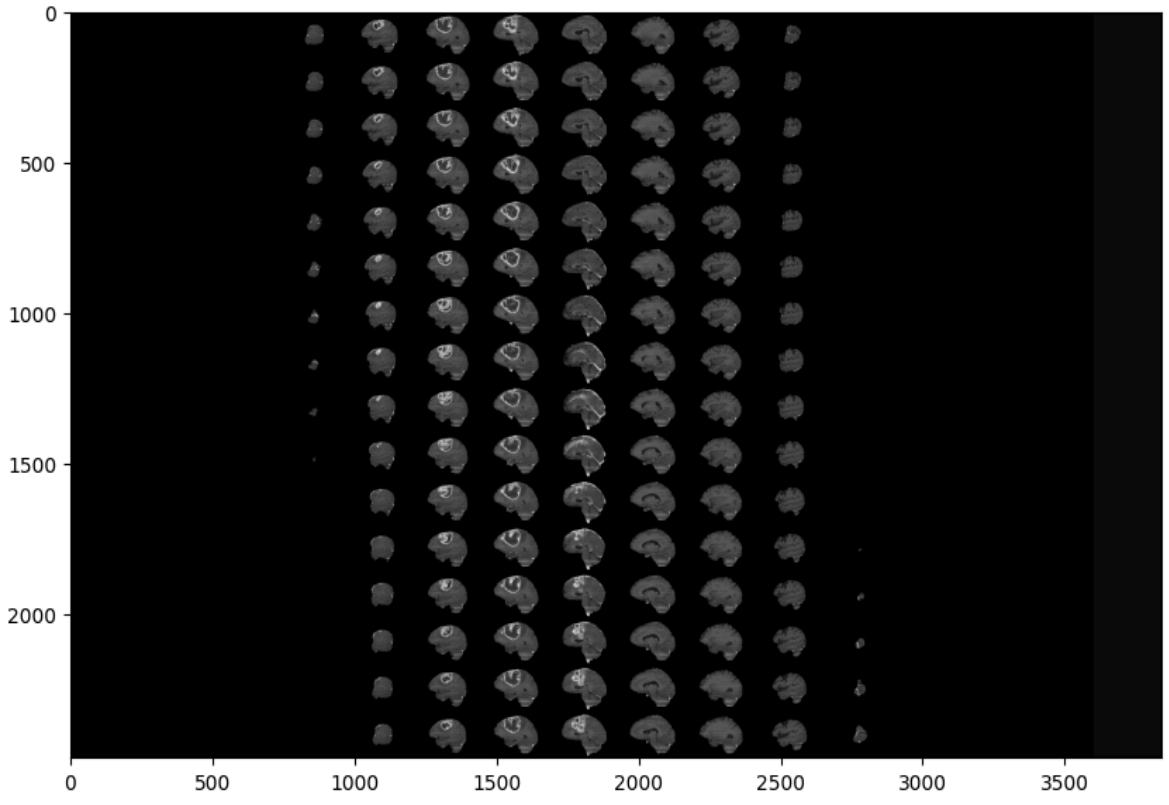


Data Structure:

- Each sample is a 3D volume (width, height, depth) composed of 2D slices along three planes: **axial**, **coronal**, and **sagittal**.



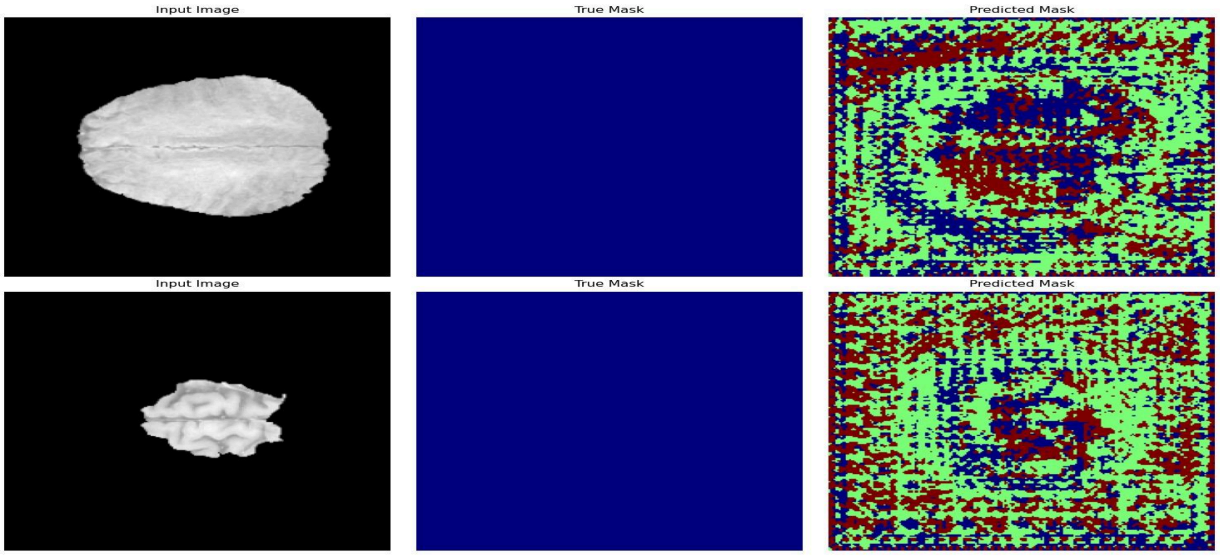
- Only informative slices are used to reduce training time and focus on tumor-containing regions.



2. Preprocessing

- **Median Filter**: Applied to reduce noise in MRI images while preserving edges.
- **Bias Field Correction**: Corrects intensity non-uniformities caused by magnetic field variations, improving image consistency.
- **Resampling**: Standardizes the spatial resolution across images for uniform input to the model.

Note: We preprocessed the data, but we got noisy images as output. so we continued the training with raw data. Here, the input image is a preprocessed image.



3. Models

The project evaluates multiple CNN architectures for segmentation, each designed to capture spatial and contextual features in MRI images:

- **U-Net**: A standard encoder-decoder architecture with skip connections, effective for medical image segmentation.
- **U-Net++**: An enhanced U-Net with nested skip connections to improve feature propagation and segmentation accuracy.
- **ResNet+U-Net**: Combines a ResNet backbone (for robust feature extraction) with a U-Net decoder, leveraging pretrained weights.
- **Attention ResNet+U-Net**: Integrates attention gates with ResNet+U-Net to focus on relevant regions, improving performance on small tumor areas.
- **Attention with U-Net**: Adds attention mechanisms to the standard U-Net to enhance focus on tumor sub-regions.

4. Loss Functions

- **Categorical Cross-Entropy**: Measures the difference between predicted probability distributions and one-hot encoded ground truth labels for each pixel, suitable for multi-class segmentation.
- **Dice Loss**: Focuses on the overlap between predicted and ground truth segmentations, addressing class imbalance by prioritizing small tumor regions.

5. Evaluation Metrics

A comprehensive set of metrics is used to evaluate model performance, particularly addressing the class imbalance in BraTS:

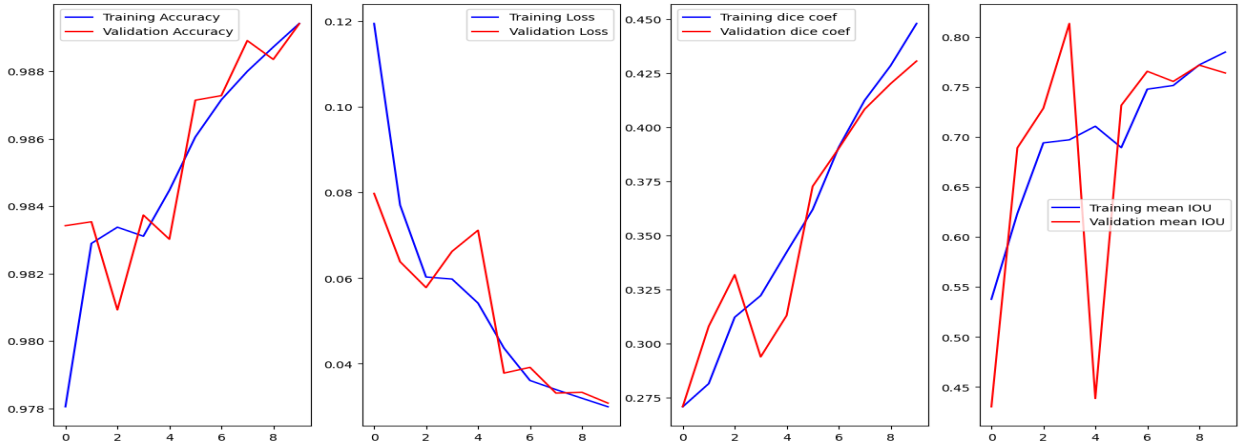
- **Accuracy**: Proportion of correctly classified pixels. Less reliable due to background class dominance.
- **Intersection over Union (IoU)**: Measures overlap between predicted and ground truth segmentations, averaged across classes.
- **Dice Coefficient**: Quantifies similarity between predicted and ground truth regions, sensitive to small tumor areas.
- **Sensitivity (Recall)**: Proportion of true positive pixels correctly identified, critical for detecting tumor regions.
- **Precision**: Proportion of predicted positive pixels that are correct, indicating prediction reliability.
- **Specificity**: Proportion of true negative pixels correctly identified, important for avoiding false positives.
- **Class-Specific Dice Coefficients**:
    - **dice_coef_necrotic**: Dice score for the necrotic core (Label 1).
    - **dice_coef_edema**: Dice score for peritumoral edema (Label 2).
    - **dice_coef_enhancing**: Dice score for the enhancing tumor (Label 3).

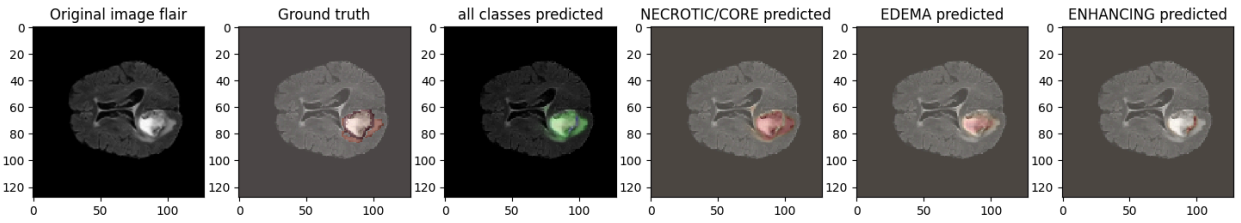
Training Configuration:

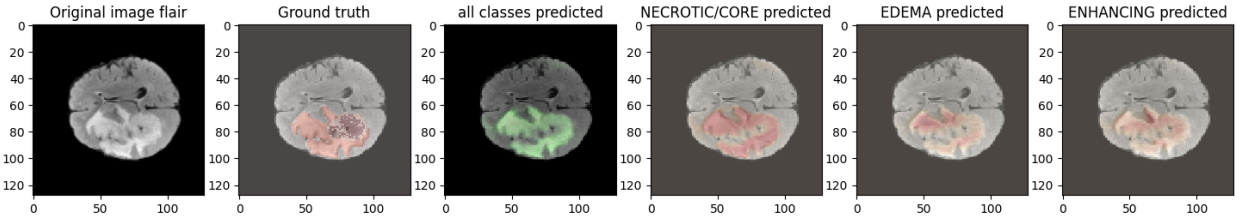
Parameters	**Values**
Epochs	10
Optimizer	Adam Optimizer
Loss	Categorical Cross Entropy
Learning rate	0.001

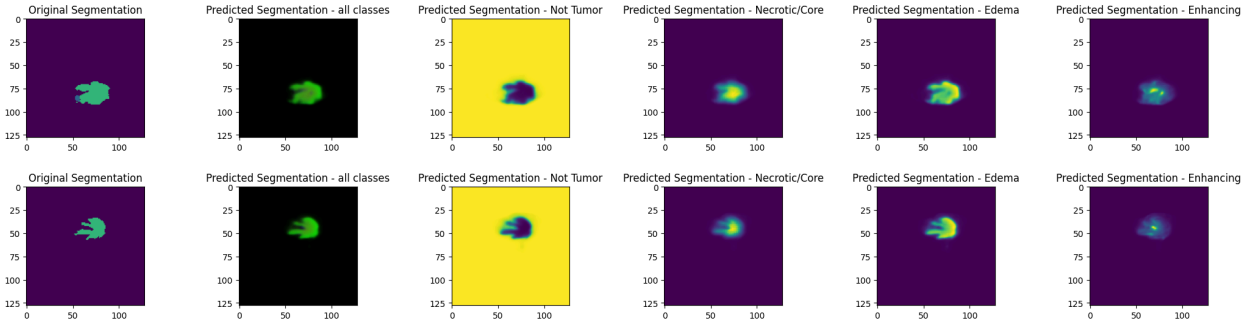
Results:

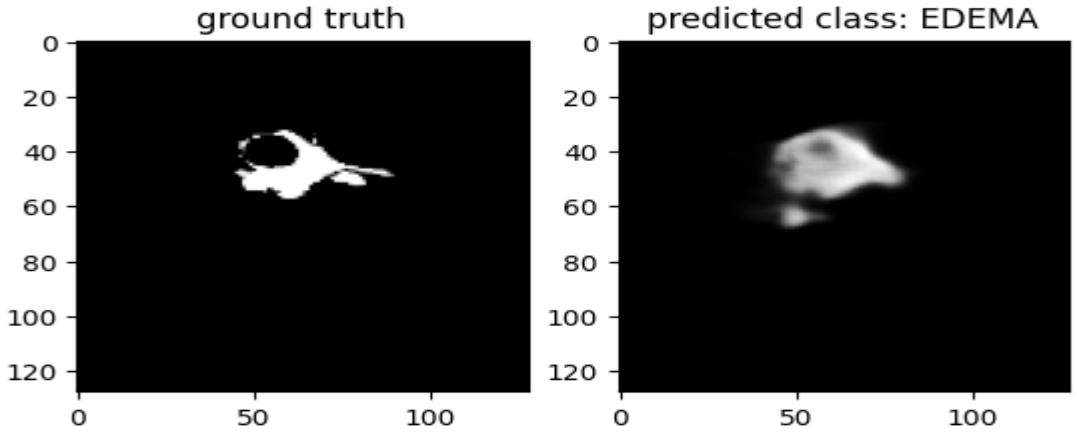
Model: Unet



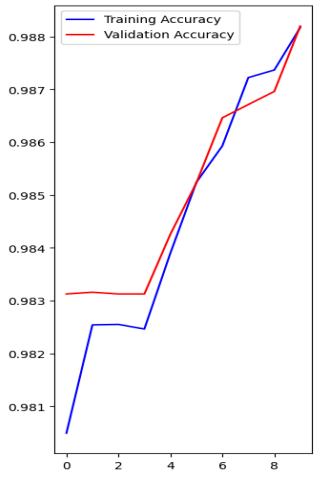


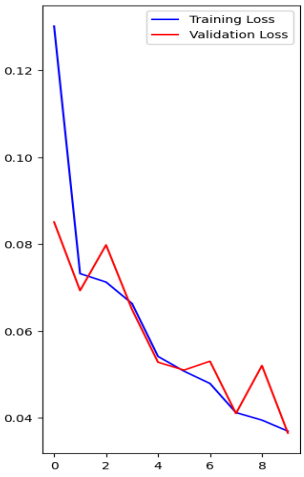


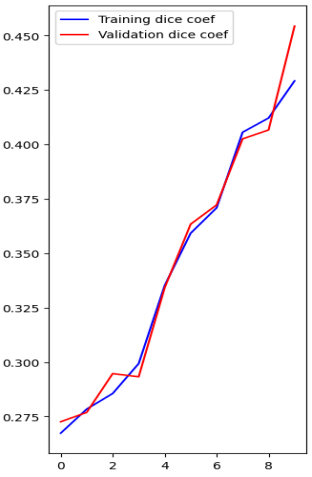


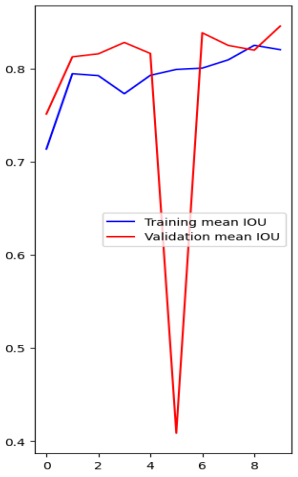


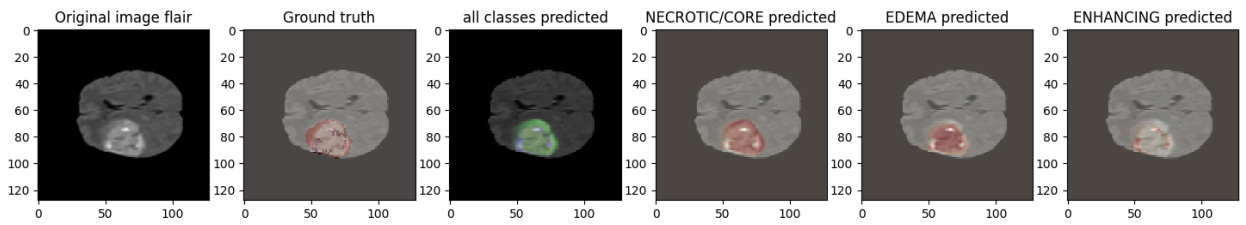
Model: Unet++

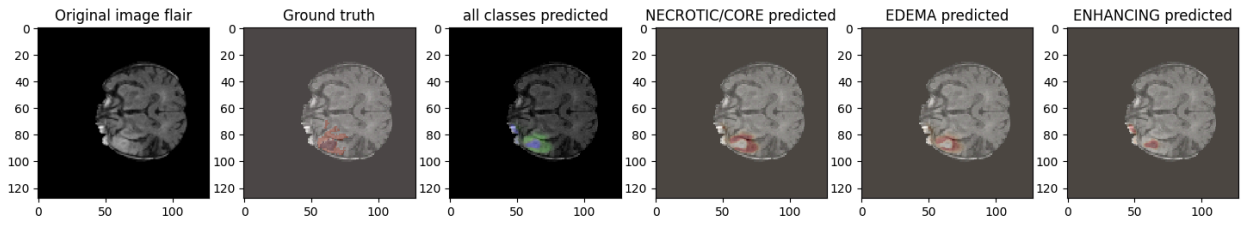

Training Accuracy
Validation Accuracy

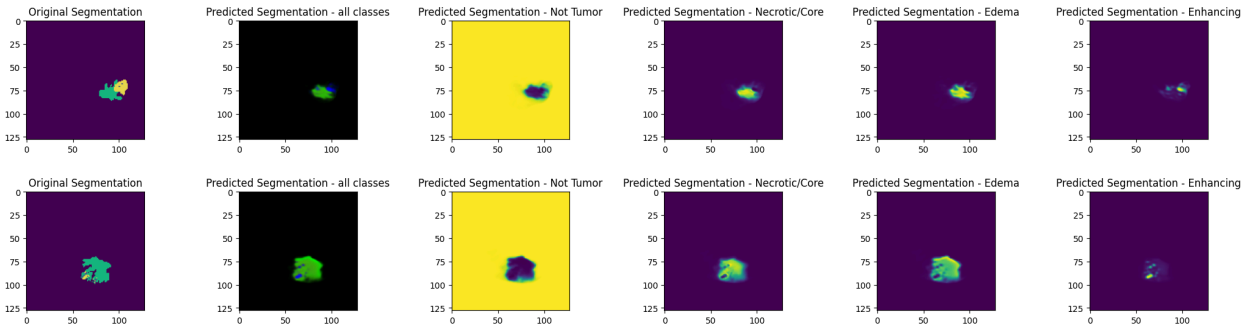

Training Loss
Validation Loss

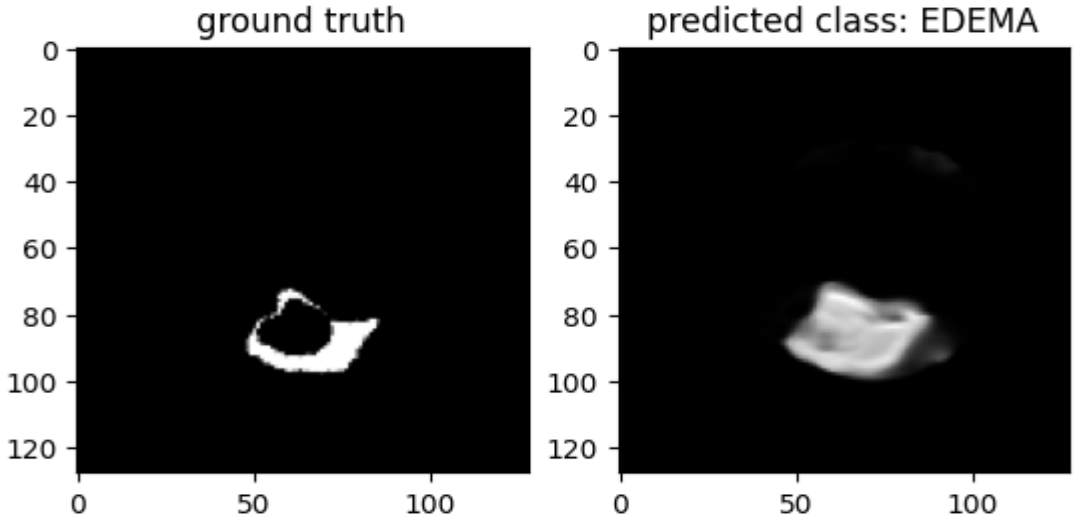

Training dice coef
Validation dice coef


Training mean IOU
Validation mean IOU

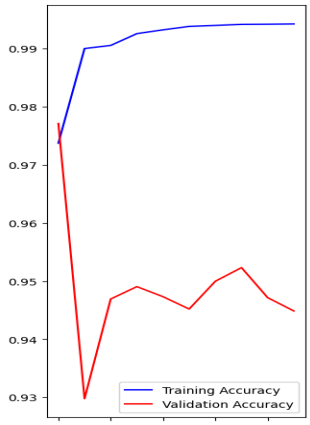

Original image flair
Ground truth
all classes predicted
NECROTIC/CORE predicted
EDEMA predicted
ENHANCING predicted

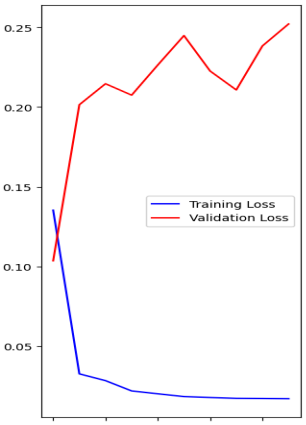

Original image flair
Ground truth
all classes predicted
NECROTIC/CORE predicted
EDEMA predicted
ENHANCING predicted

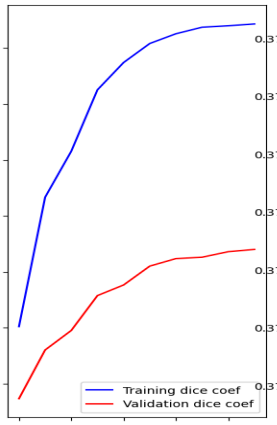

Original Segmentation
Predicted Segmentation - all classes
Predicted Segmentation - Not Tumor
Predicted Segmentation - Necrotic/Core
Predicted Segmentation - Edema
Predicted Segmentation - Enhancing
Original Segmentation
Predicted Segmentation - all classes
Predicted Segmentation - Not Tumor
Predicted Segmentation - Necrotic/Core
Predicted Segmentation - Edema
Predicted Segmentation - Enhancing

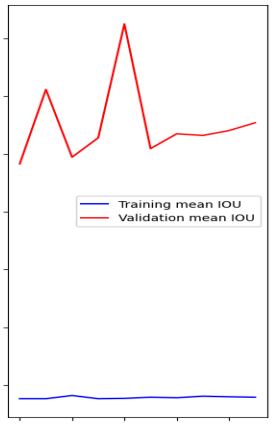

ground truth
predicted class: EDEMA

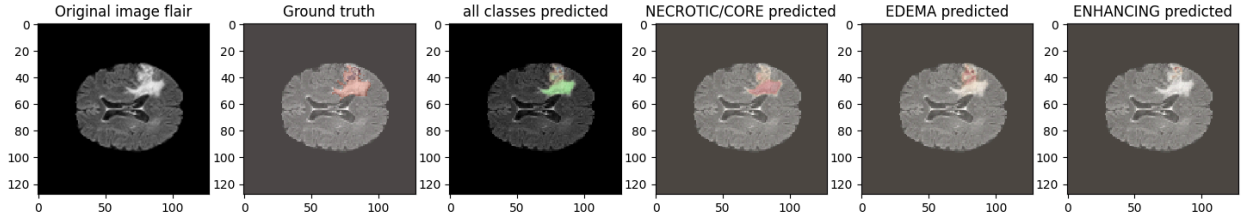
Model: Resnet+Unet

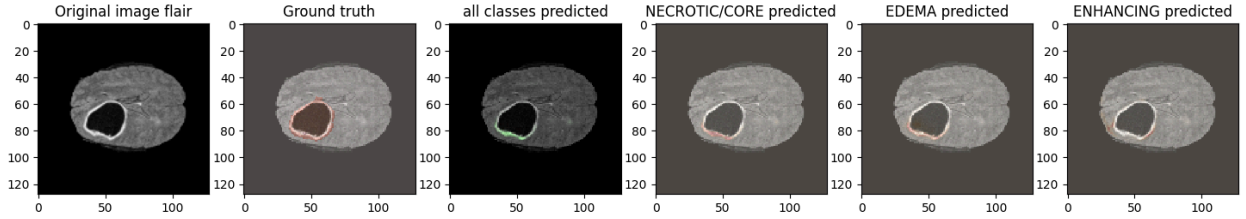


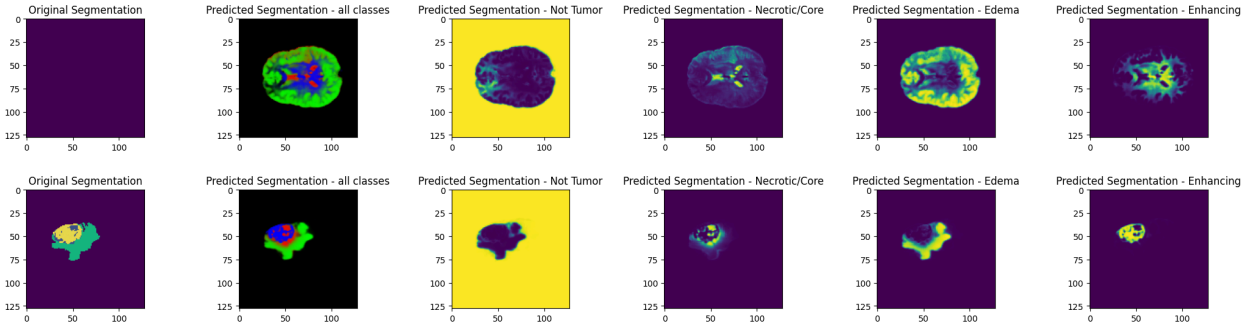


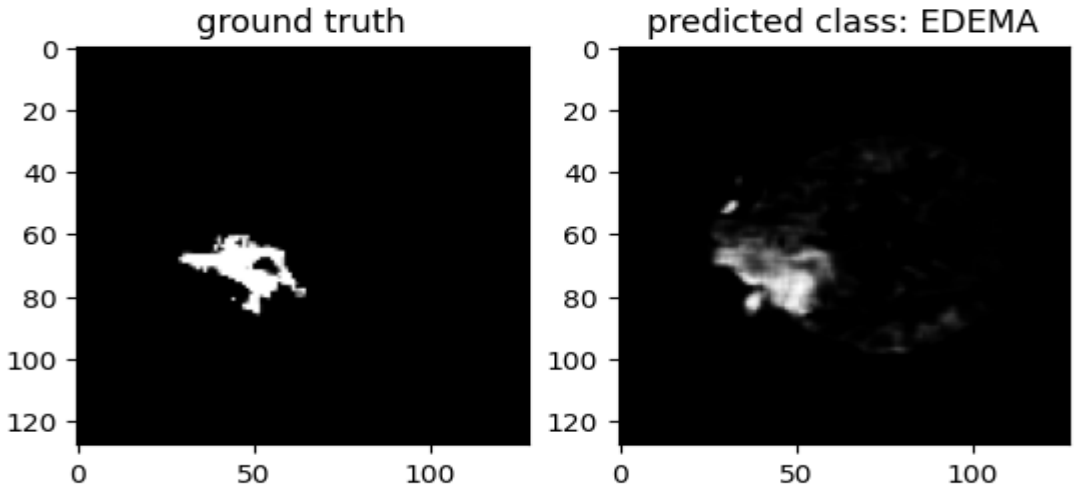




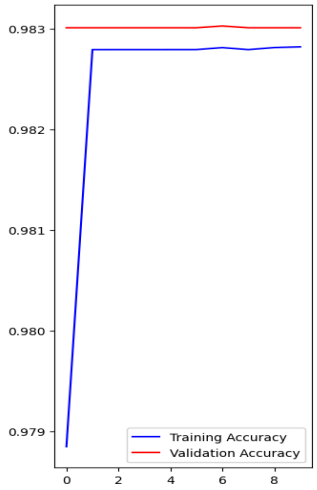


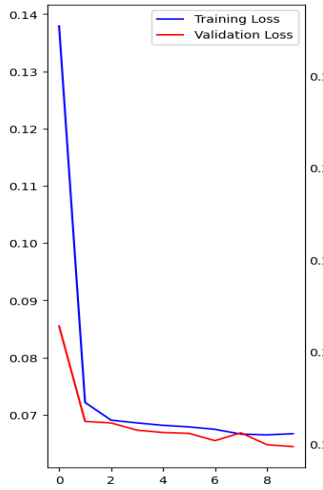


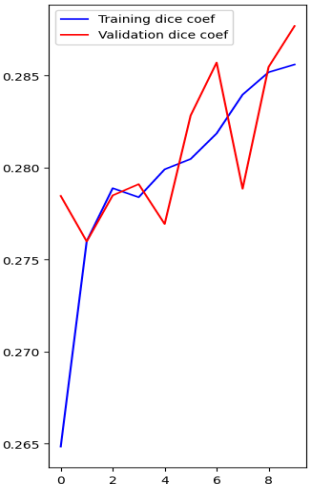


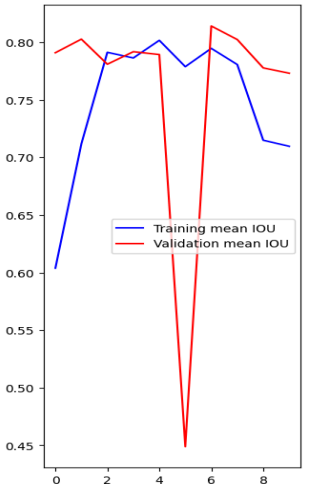


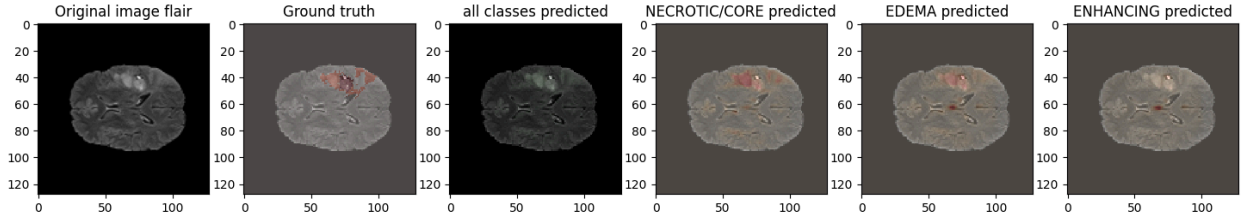
Model: Attention based Unet

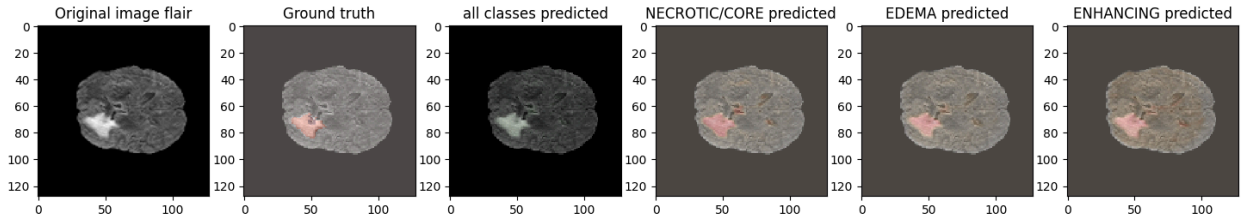


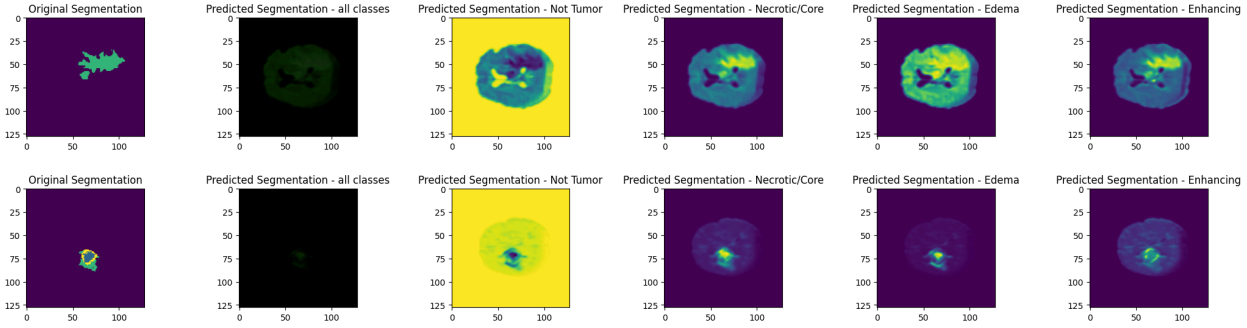


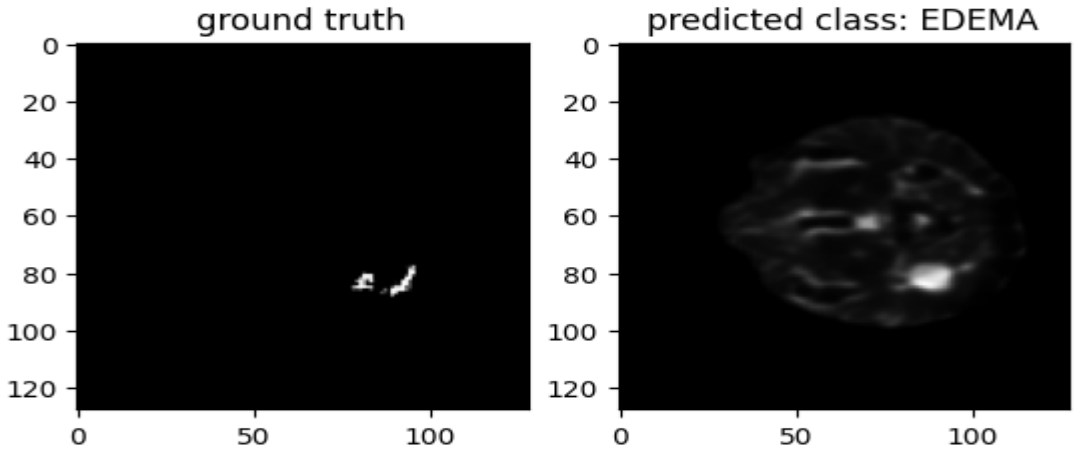




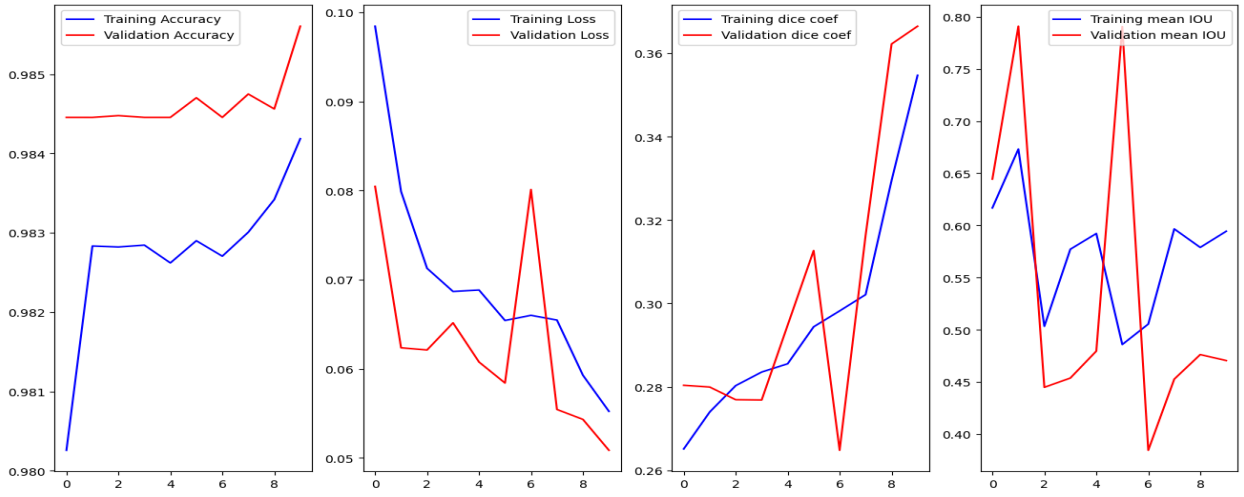


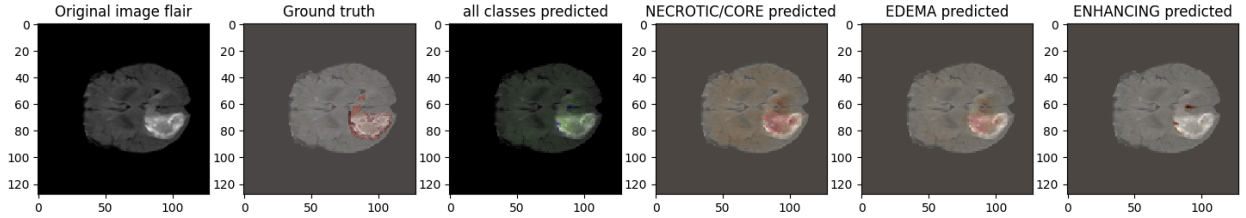


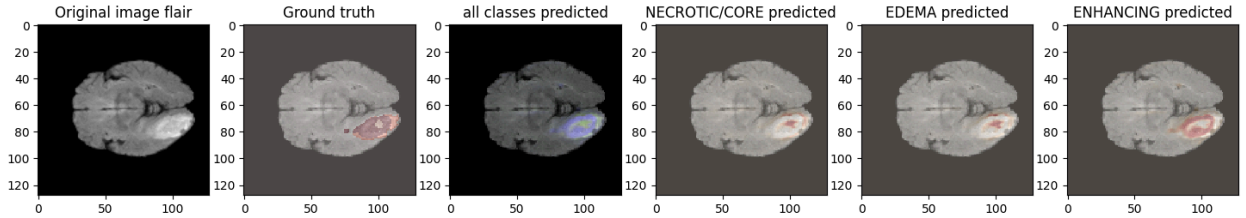


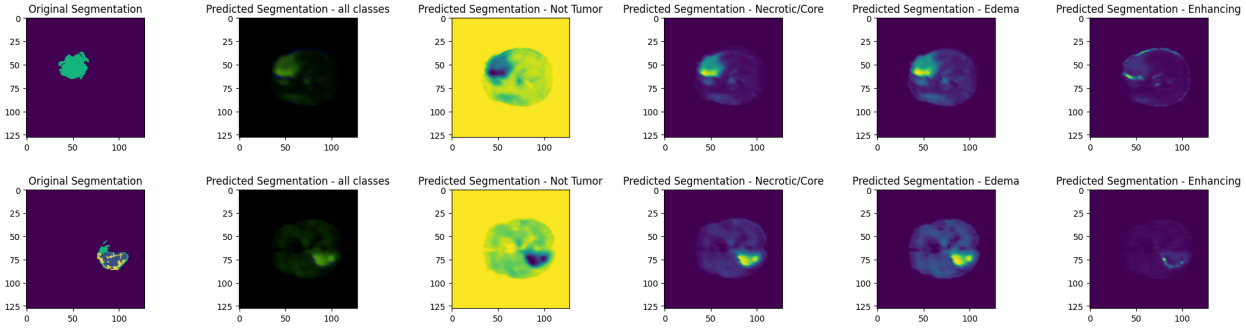


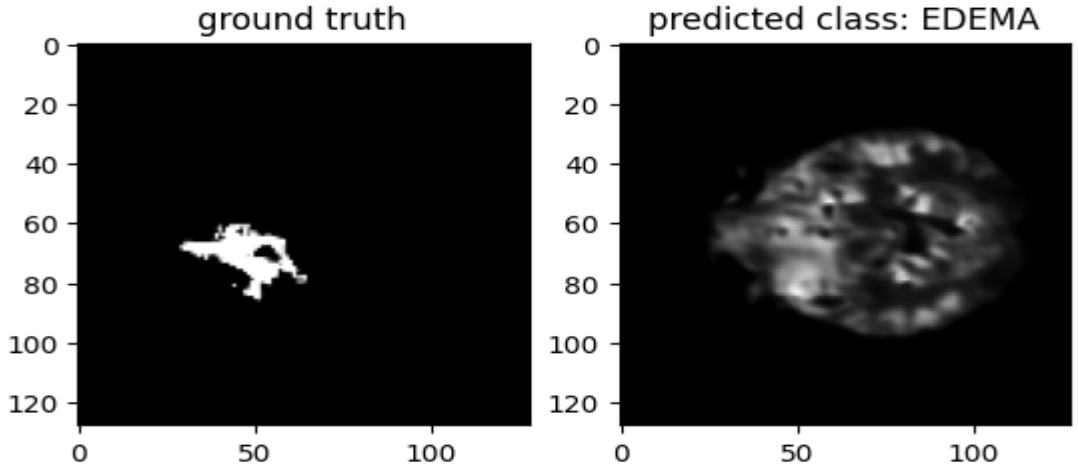
Model: Attention based Resnet+Unet











Model	**Unet**	**Unet++**	**Resnet+Unet**	**Attention based Unet**	**Attention based Resnet+Unet**
Loss	0.0282	0.0301	0.2123	0.0641	0.1422
Accuracy	0.9903	0.9907	0.9478	0.985	0.9622
MeanIOU	0.7713	0.8424	0.3756	0.7667	0.3756
Dice coefficient	**0.4441**	**0.4674**	0.412	0.2801	0.4173
Precision	0.9922	0.9915	0.9518	0.9849	0.9657
Sensitivity	0.988	0.9895	0.9459	0.9848	0.9595
Specificity	0.9973	0.9971	0.9842	0.995	0.9887
Dice coef Necrotic	0.2884	0.2672	0.3267	0.0712	0.3588
Dice coef Edema	0.6169	0.5453	0.2569	0.1644	0.325
Dice coef Enhancing	0.383	0.4757	0.4147	0.0655	0.4043

Conclusion

Among the evaluated models, U-Net++ emerges as the most effective for brain tumor segmentation on raw T1ce and T2-FLAIR MRI scans from the BraTS 2020 dataset, achieving the highest Mean IoU (0.8424), Dice coefficient (0.4674), and enhancing tumor Dice (0.4757), with competitive performance across other metrics. Its nested skip connections and robustness to raw data variability make it ideal for clinical applications, where accurate segmentation of enhancing tumors is critical. However, all models face challenges with class imbalance (background dominance) and small tumor regions (low necrotic and enhancing Dice scores), exacerbated by raw data noise and variability. U-Net is a strong alternative with the lowest loss and high edema Dice, while Attention-based ResNet+U-Net excels for necrotic regions but underperforms overall. To improve performance, future work should focus on revisiting preprocessing to address raw data challenges. These improvements could further enhance segmentation accuracy.