Uncertainty-Aware Brain Tumor Segmentation for Enhanced Clinical Decision Support

CSIT 574 - IMAGE PROCESSING

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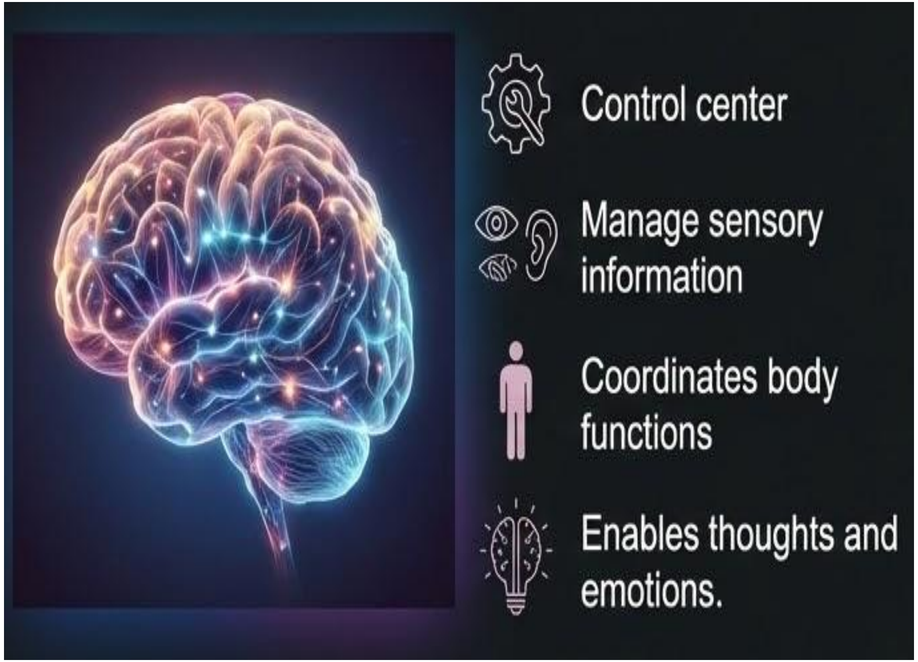
Background and Motivation



BRAIN - Most complex organ of human body

These processes can be significantly disrupted by the presence of brain tumors leading to major impairments in daily lives.

The heterogeneous nature of brain tumors, makes segmentation of tumor regions a tough and time-intensive job performed only by specially trained neuroradiologists.

Automatic and robust methods for brain tumor segmentation

> U-Net
> V-Net (Extend U-Net to 3D processing)
> Swin UNETR (combine CNN and Transformers)

And many more…..

Despite the impressive performance of modern deep learning models, clinicians often find themselves **not trusting** the model predictions.

European Union’s Artificial Intelligence Act (the “AI Act”) – August 1, 2024.

It introduces a risk-based framework for AI deployment . AI-driven medical imaging systems, classified as high-risk, must meet strict requirements to ensure safety, accountability, and trustworthiness.

The EU parliament recognized the importance of addressing the uncertainty in AI systems,particularly in healthcare. The EU’s Scientific Foresight Unit emphasized that healthcare AI must estimate uncertainty to help clinicians assess prediction confidence.

CLINICAL CONTEXT

Types of Brain Tumors:

1. Primary
2. Secondary (meningiomas and gliomas)

Gliomas account for almost 80% of all malignant tumors in adults.

Glioma sub-regions:

1. Necrotic core (NCR): The area of cellular death inside tumors.
2. Edema (ED): The region surrounding the tumor.
3. Enhancing tumor (ET): This sub-region contains active and aggressive tumor cells, making it a focal point for medical treatments.

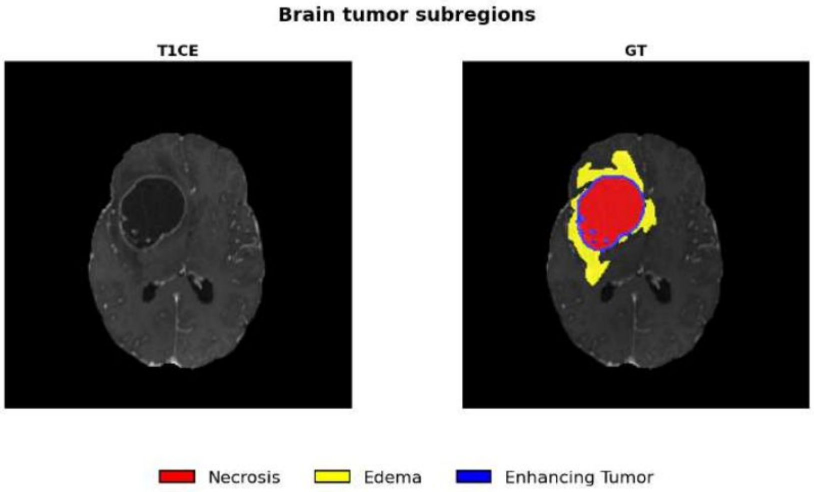


Fig : Visualization of glioma tumor sub-regions in T1CE MRI. The example scan comes from the BraTS 2021 Adult Glioma Challenge dataset.

Evolution of segmentation techniques

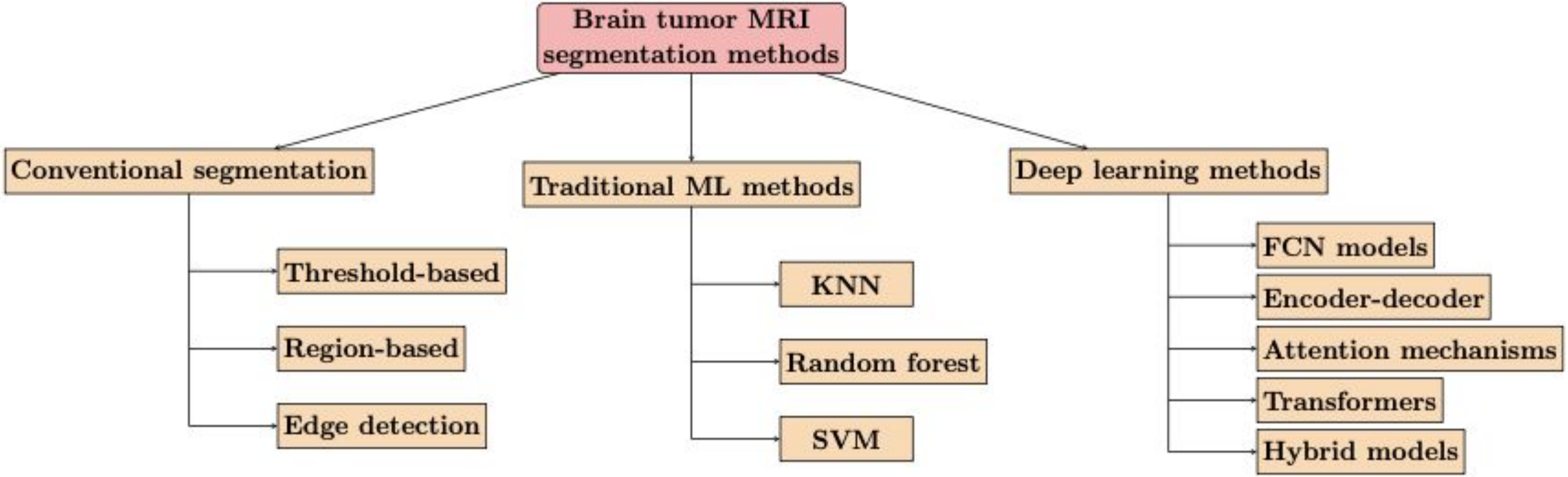


Fig : Overview of brain tumor MRI segmentation approaches.

Dataset and Preprocessing

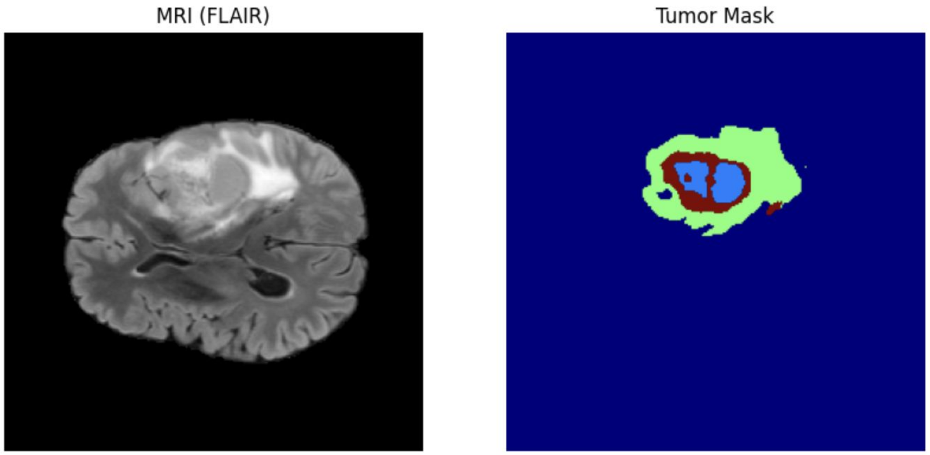
Name: BraTS 2021 Adult Glioma Challenge.

Modalities: T1, T1CE, T2, **T2-FLAIR**.

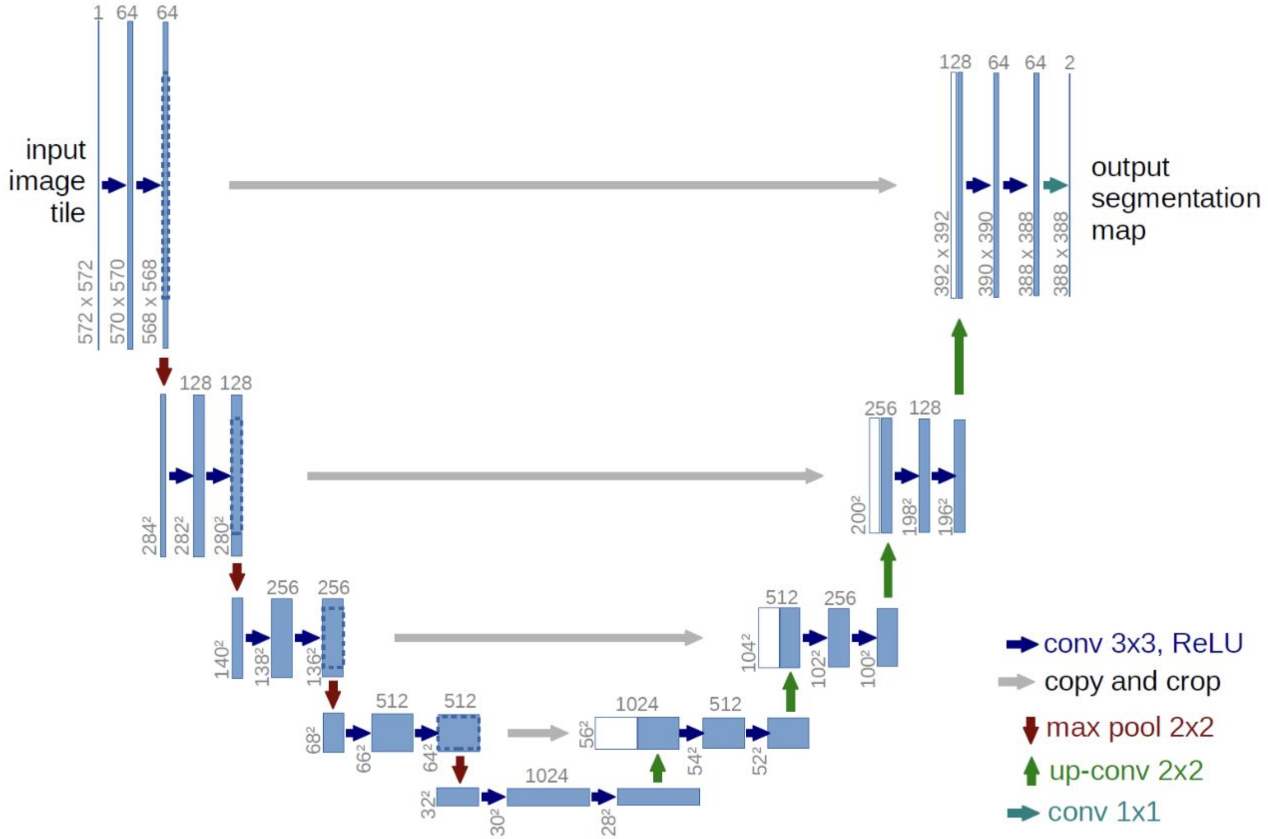
T2-FLAIR (Chosen for high edema/tumor contrast).

Preprocessing (Technical Specs):

- **3D → 2D:** Slice extraction optimized for GPU resources.
- **Normalization:** Scaling pixel intensity to [0,1].
- **Evaluation Strategy:** 80% Train / 20% Test.

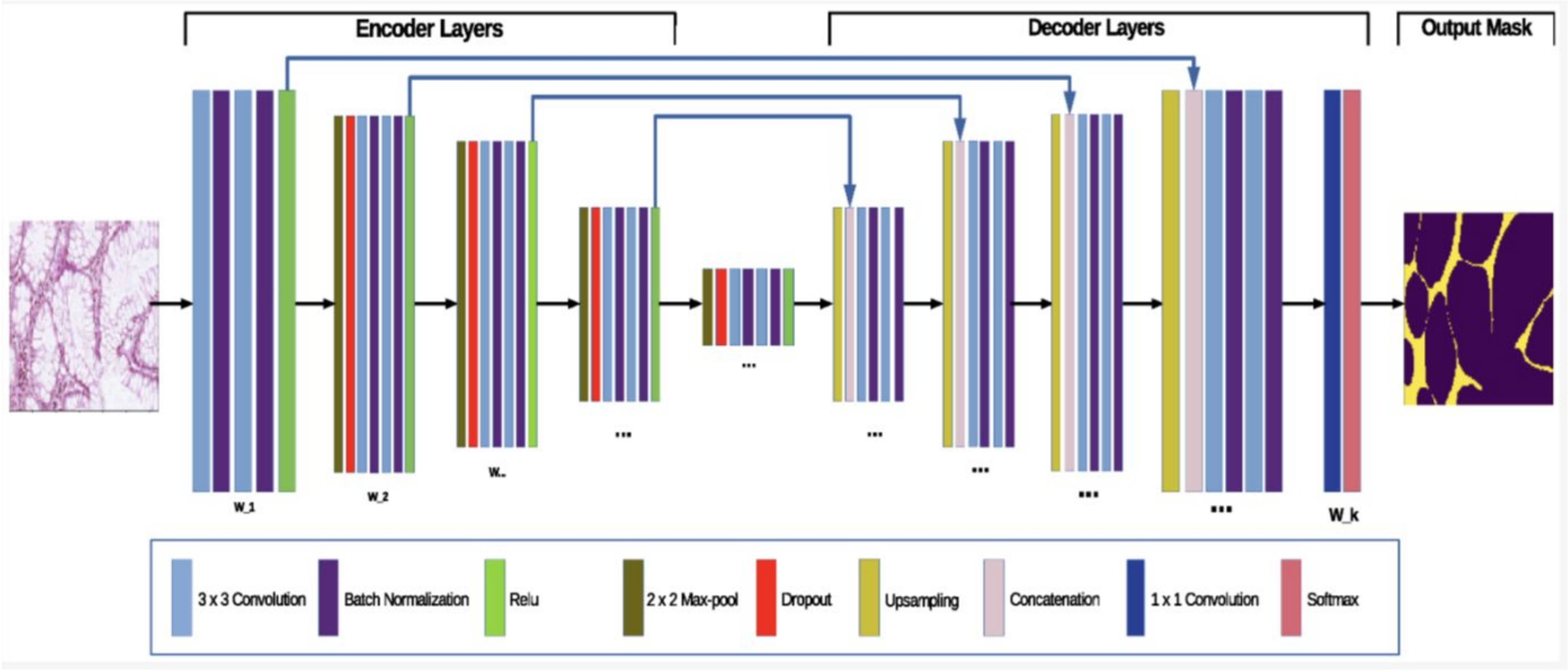


Theoretical Framework: 2D U-Net architecture



Source : U-Net: Convolutional Networks for Biomedical Image Segmentation By Olaf Ronneberger, Philipp Fischer, and Thomas Brox

U-Net with Dropout



Source : Research Gate - Comparing multiple AI strategies for segmentation

Architecture & Training (Monte Carlo Dropout)

Model Implementation:

- **Layers:** 4 Encoder Blocks / 4 Decoder Blocks.
- **Activation:** ReLU (Hidden) + Sigmoid (Output).
- **Regularization:** Dropout(p=0.2) injected after convolutional blocks.

Training Dynamics:

- **Loss Function:** BCEWithLogitsLoss (Sigmoid + Cross Entropy for numerical stability).
- **Optimizer:** Adam
- **Early Stopping** : 5 Epochs

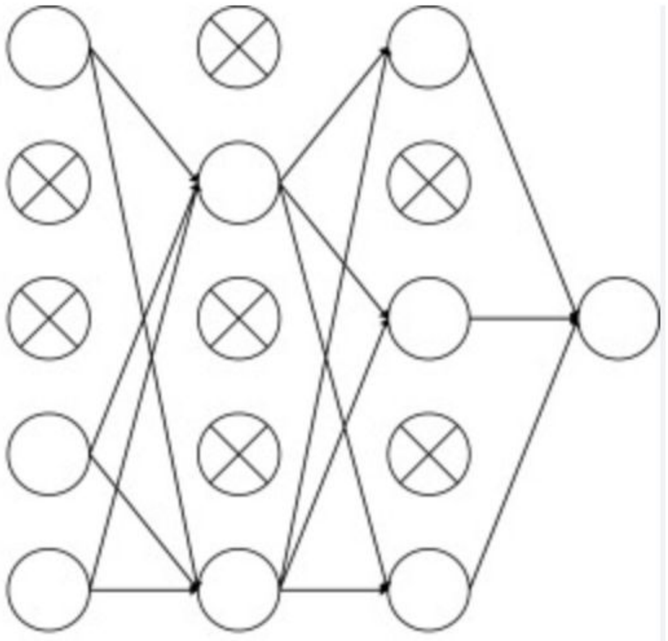


Fig: Monte Carlo Dropout

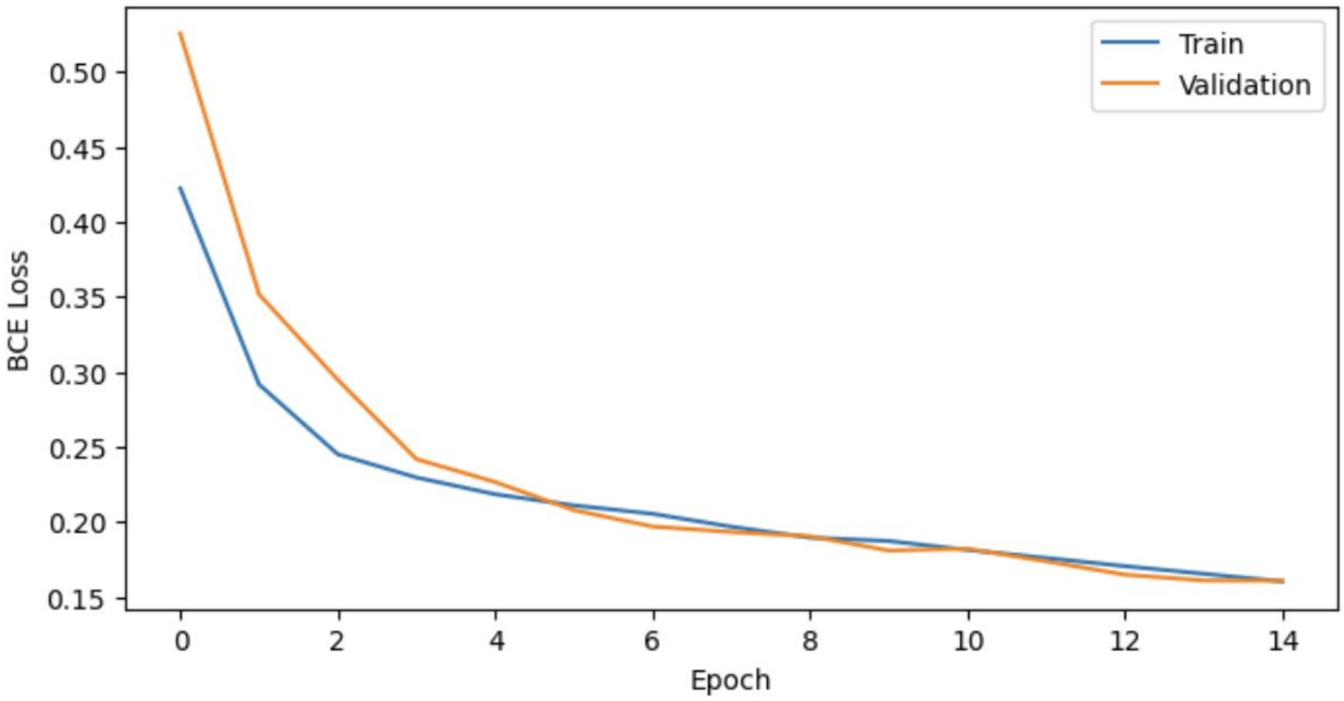
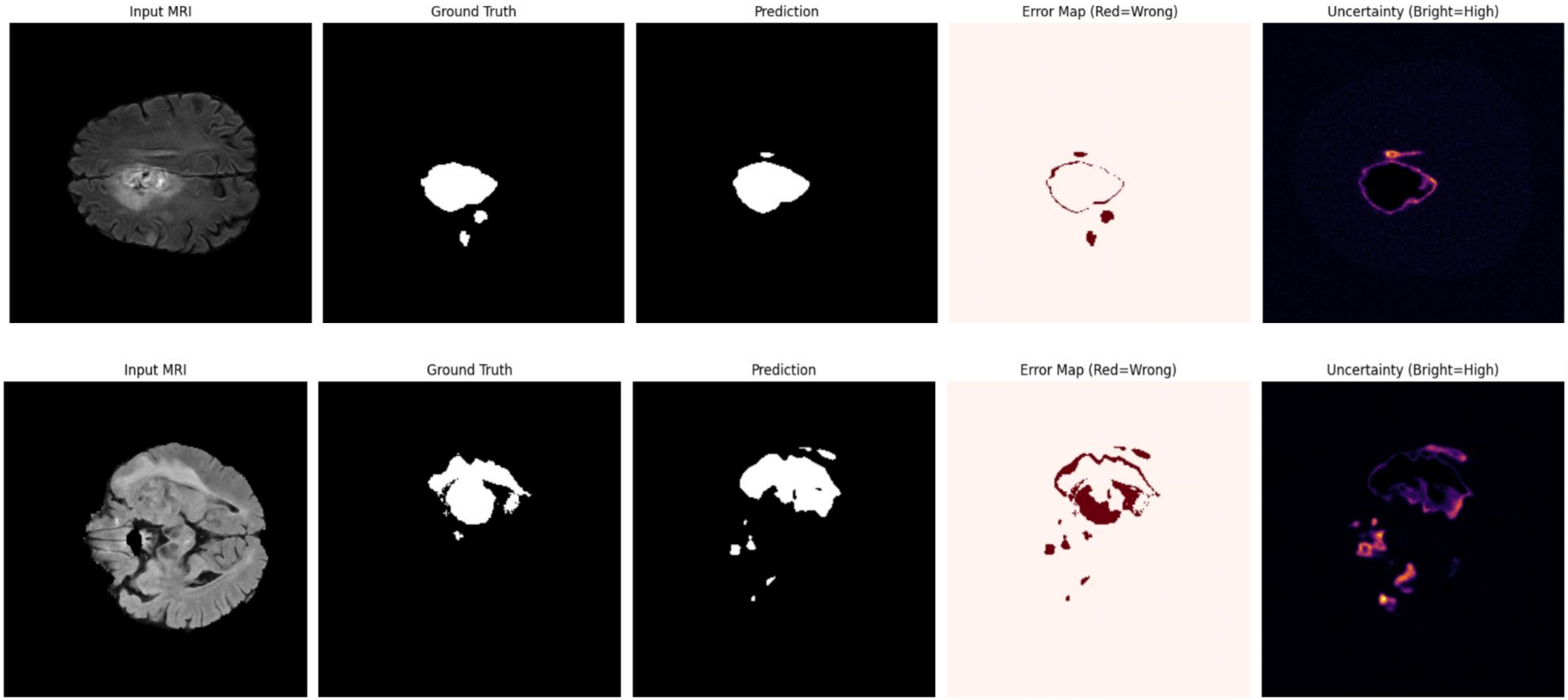


Fig : Loss Curve

Results



Input MRI
Ground Truth
Prediction
Error Map (Red=Wrong)
Uncertainty (Bright=High)
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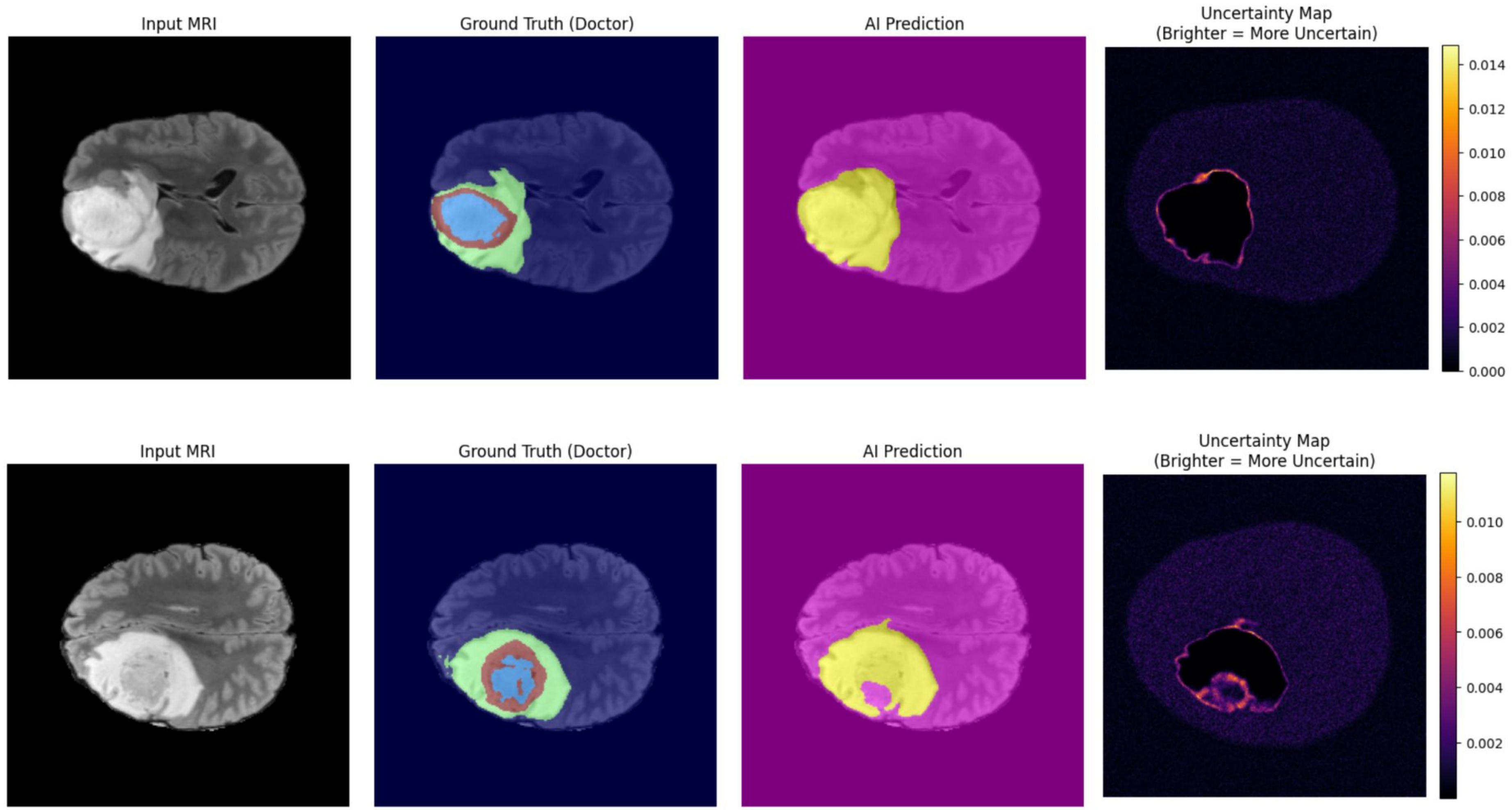
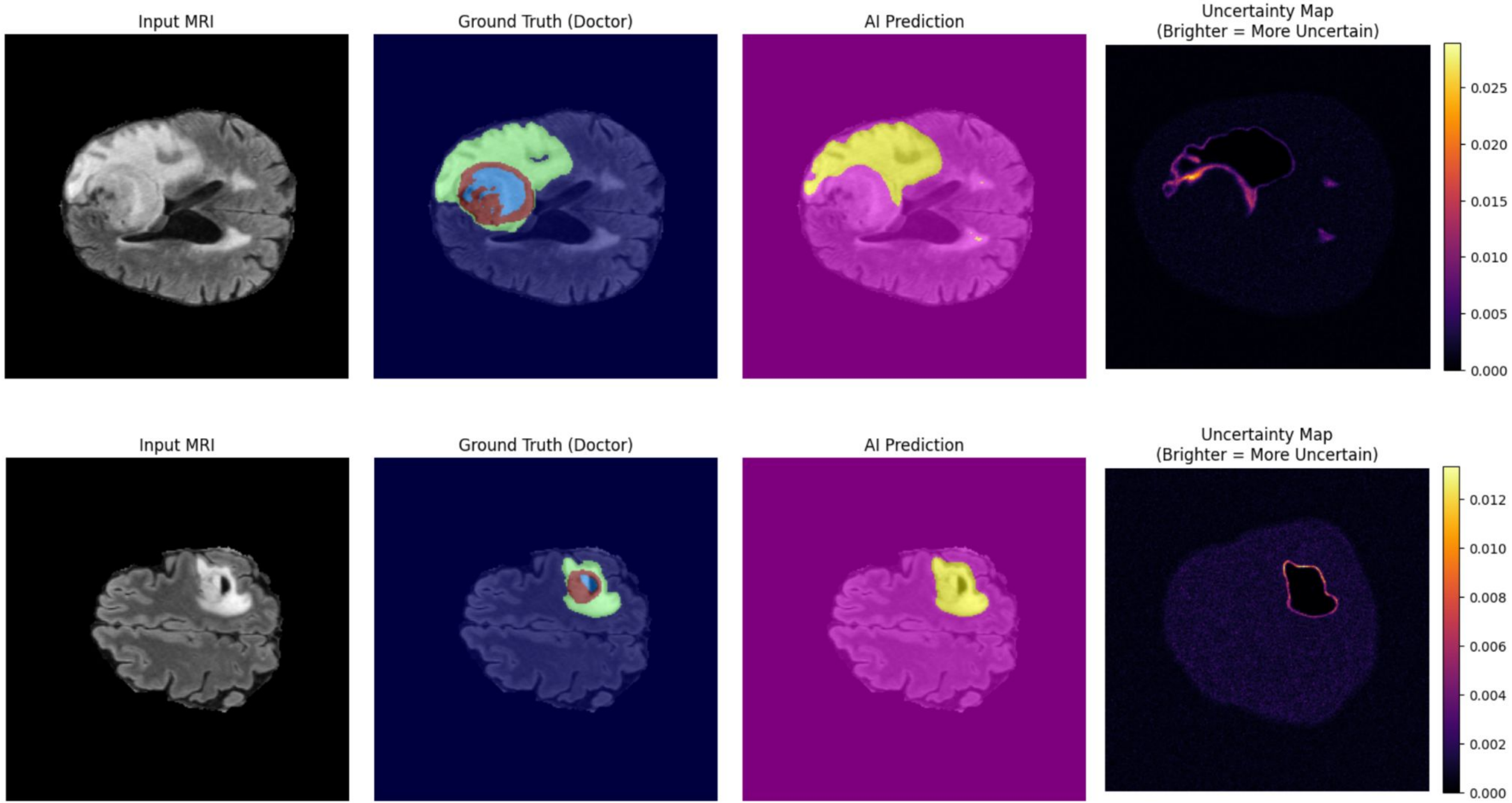
Ground Truth
Prediction
Error Map (Red=Wrong)
Uncertainty (Bright=High)


Input MRI
Ground Truth (Doctor)
AI Prediction
Uncertainty Map
(Brighter = More Uncertain)
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Input MRI
Ground Truth (Doctor)
AI Prediction
Uncertainty Map
(Brighter = More Uncertain)
0.010
0.008
0.006
0.004
0.002


Input MRI
Ground Truth (Doctor)
AI Prediction
Uncertainty Map
(Brighter = More Uncertain)
0.025
0.020
0.015
0.010
0.005
0.000
Input MRI
Ground Truth (Doctor)
AI Prediction
Uncertainty Map
(Brighter = More Uncertain)
0.012
0.010
0.008
0.006
0.004
0.002
0.000

Quantitative Reliability Assessment

Formula:

$$DSC = \frac{2|X \cap Y|}{|X|+|Y|} = \frac{2TP}{2TP+FP+FN}$$

X: The set of pixels predicted as "Tumor" by your AI model.

Y: The set of pixels labeled as "Tumor" by the expert doctors (Ground Truth).

Purpose: The standard metric for medical image segmentation. It measures spatial overlap between the Prediction (X) and Ground Truth (Y), penalizing False Positives and False Negatives equally.

Range: 0 (No Overlap) to 1 (Perfect Match).

Result : High Dice Score (**≈0.86**).

Conclusion

Successfully engineered a U-Net using Monte Carlo Dropout to transform a standard model into a probabilistic sampler capable of quantifying epistemic uncertainty.

Demonstrated a strong spatial correlation where high uncertainty correctly flags ambiguous tumor boundaries and potential segmentation errors.

Quantitatively validated that the model is well-calibrated, achieving significantly higher Dice scores.

THANK YOU