Brain Tumor Image Segmentation using Deep Learning

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Introduction

Brain tumors are a serious medical condition. Manual segmentation of a brain tumor is a time-consuming task and depends on knowledge and experience of physicians.

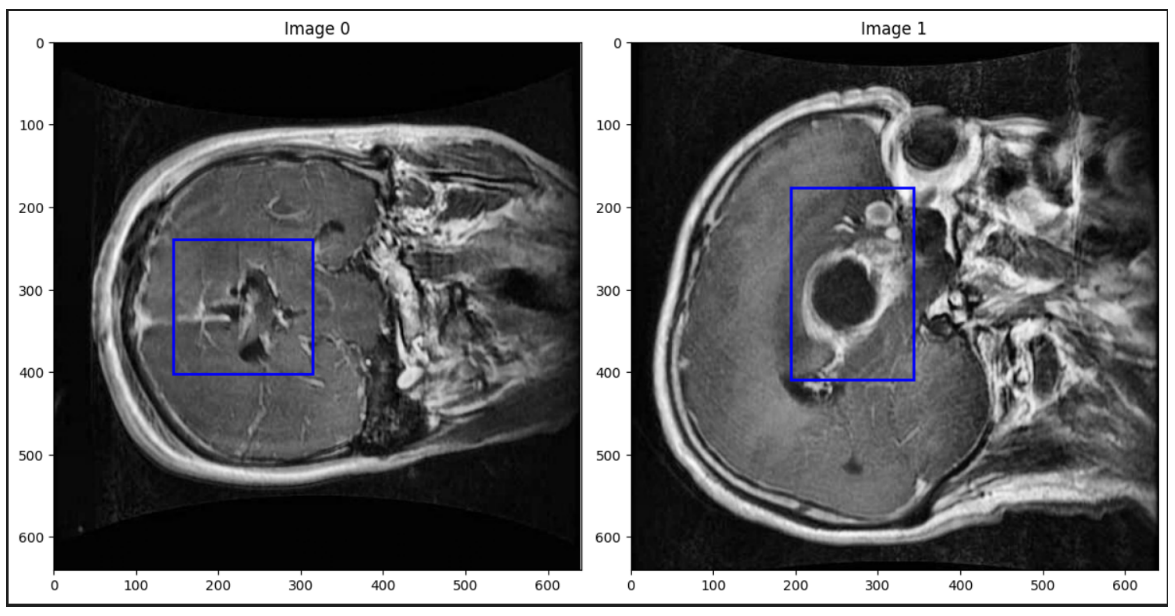

Figure 1: Very relevant image

Why Use Image Segmentation for Brain Tumors?

- Rapid tumor Identification
- Faster treatment decisions
- Reduces manual effort analyzing larger datasets

Image segmentation significantly aids radiologists in identifying and locating tumors.

Methodology

Image segmentation techniques have been extensively explored, including methods such as Attention Res-UNet with Guided Decoder.[3], which offers improved performance in segmenting brain tumors.We used UNet model for our project.

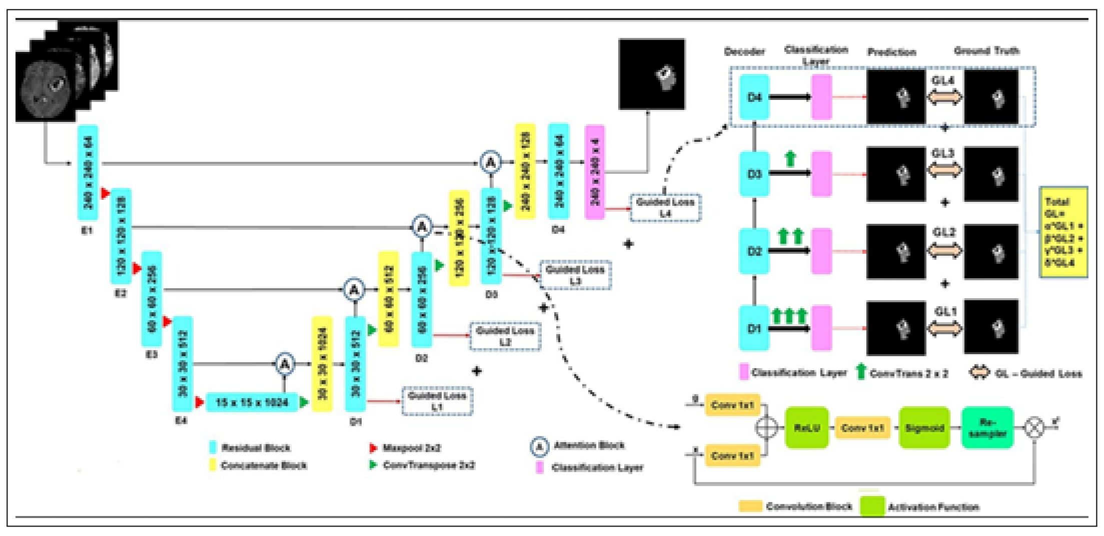

Figure 2: UNet architecture for segmentation

UNet key blocks:

- **Downsampling**: Captures spatial features
- **Upsampling**: Reconstructs image resolution
- **Encoder-Decoder structure**: Compresses and expands image features
- **Skip Connections**: Retain fine-grained details by combining encoder and decoder layers

Theory

- Mathematical Representation

The Dice loss is calculated as:

$$\text{Dice Loss} = 1 - \frac{2\sum(\hat{y} \cdot y) + \text{smooth}}{\sum\hat{y} + \sum y + \text{smooth}}[1]$$

First, the Binary Cross-Entropy (BCE) loss is computed as:

$$\text{BCE Loss} = -(y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y}))$$

The Focal Loss is then calculated as:

$$\text{Focal Loss} = \alpha \cdot (1-\hat{p})^{\gamma} \cdot \text{BCE Loss}[2]$$

where $\hat{p} = \exp(-\text{BCE Loss})$. Finally, the combined loss function is given by the weighted sum of the Dice loss and the Focal loss:

$$\text{Combined Loss} = w_{\text{dice}} \cdot \text{Dice Loss} + w_{\text{focal}} \cdot \text{Focal Loss}$$

Project Steps

- **Method:**
- Brain tumor image dataset from Kaggle:
  - 2146 images labeled in 2 classes: 0 (Non-tumor), 1(Tumor)
- Model:UNet(Encoder-Decoder) with dropout
- Optimizer: Adam
- Loss function:Combined Dice and Focal loss
- **Results:**
- Achieved a validation accuracy of around 60%
- Improved IoU scores, demonstrating better segmentation performance over time.

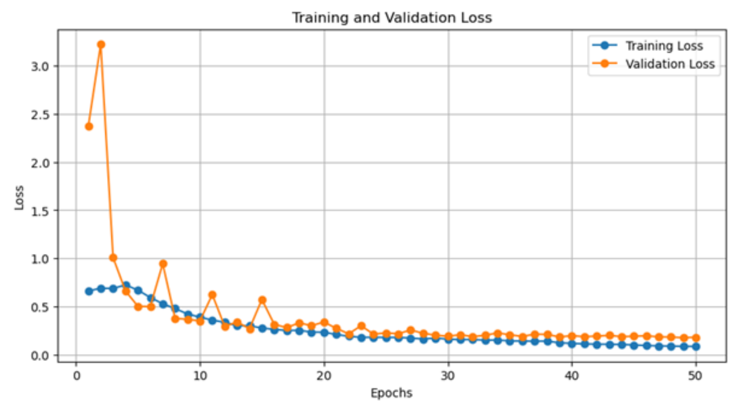

Figure 3: Train-Validation loss

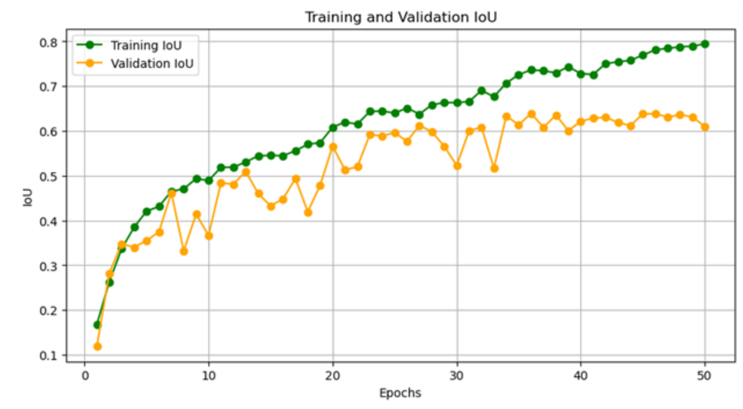

Figure 4: Validation IoU

- Test results
  - Global accuracy: 0.98
  - Mean accuracy: 0.99
  - Mean IoU: 0.98
  - Weighted IoU: 0.98
  - Mean F-score: 0.75
  - Dice score: 0.75
- **Conclusion:**
- The model IoU of validation (0.614) improves on test set (IoU of 0.9827, accuracy of 0.9831),indicating strong tumor segmentation. Moderate F-score and Dice scores suggest boundary delineation challenges. Better test performance may result from data similarities, requiring further tuning.

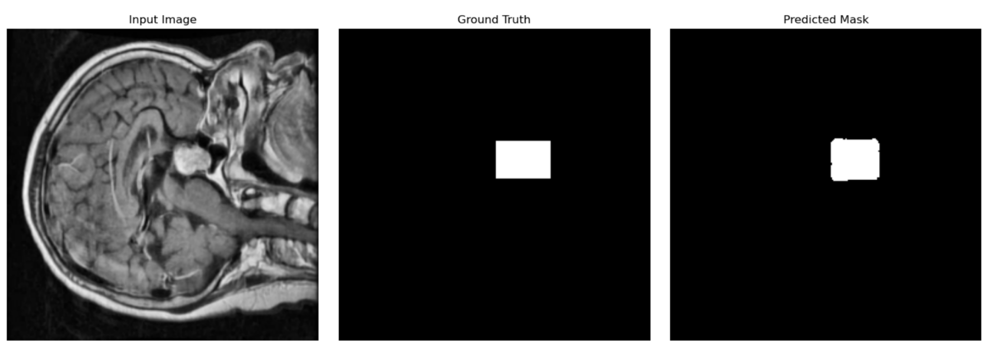

Figure 5: Ground truth and predicted masks of test image

References

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[3] D. Maji, P. Sigedar, and M. Singh.
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