Synthesizing Missing MRI Modalities for Brain Tumor Segmentation

As we are all Maths and Computer Science students, we did not understand most of the terminology at first, so we began our research by understanding the Medical Context of the project.

Introduction

We went through the reference paper of the Sailunez. According to Sailunez et al. (20003, brain tumors arise due to abnormal, uncontrolled cell growth in brain tissue. The areas where brain tumors can occur include the nerves, the pituitary gland, the pineal gland, and the membranes that cover the surface of the brain. Often, it can lead to the spread of cancer to the brain from other parts of the body. These tumors are secondary brain tumors, also called metastatic brain tumors.

And if the patient is suffering from a Brain Tumor, the survival rate for them is relatively low, hence making early and accurate detection critical. Therefore, the practice of Medical imaging plays a central role in diagnosis. And, for this, MRI is considered the primary imaging modality for diagnosing brain conditions, so understanding how MRI modalities work is essential.

The four most common modalities are: T1-weighted, T1-weighted contrast-enhanced(T1ce), T2-weighted (T2), and FLAIR (Fluid Attenuated Inversion Recovery). Here, the work of each modality is to provide different but correlated information about the same anatomy. However, in real-world scenarios such as hospitals, obtaining accurate results requires all modalities, and this is often challenging due to patient motion, time constraints, or contraindications to contrast agents. Due to these constraints, a modality remains missing, significantly reducing the performance of automated tumor segmentation systems.

This project aims to synthesize missing MRI modalities from available ones using deep learning techniques to enable tumor segmentation models to function effectively.

Methodology

This project employs a three-stage approach:

1. **Preprocessing:** Standardization and augmentation of public multimodal BraTS MRI data by simulating missing sequences via masking.
2. **Model Implementation:** Will try to adapt a U-Net for modality synthesis (translation), which will help reconstruct missing modalities using available data.
3. **Downstream Validation:** Compare the Dice and Jaccard performance of a pre-trained segmentation model on synthesized data versus complete real data.

Keywords

Deep Learning, MRI Modality Synthesis, U-Net, Brain Tumor Segmentation, Conditional Generative Model, Image Reconstruction, BraTS Dataset.

Brain Tumor Detection vs Segmentation

The analysis of the brain tumor generally consists of two major tasks. The first is Tumor Detection (a classification problem: whether a given image contains a cancer), and the second is Tumor **Segmentation** (a pixel-wise labeling task that extracts tumor regions from MRI images).

This project focuses on enabling segmentation under incomplete data conditions by reconstructing missing MRI modalities.

Deep Learning in Brain Tumor Segmentation

The earliest practices relied primarily on thresholding, morphology, and clustering. However, current methods, such as deep learning, dominate the field of medical image analysis.

Convolutional Neural Network (CNN)

CNNs can automatically learn hierarchical features from images. Early convolutional layers capture low-level patterns, such as edges and gradients (similar to the Sobel or Canny operators studied in class. In contrast, the deeper layers of CNNs extract more abstract, semantic information. The architectures that we learned in the class, such as AlexNet and InceptionNet, have already demonstrated the power of deep convolutional feature extraction. Using them might enable end-to-end learning for our model.

U-Net Architecture

For segmentation tasks, the most influential architecture is the U-Net. U-Net consists of:

- A contracting path (encoder) for feature extraction.

- An expanding path (decoder) for spatial reconstruction.
- Skip connections that preserve fine-grained spatial details.

The U-Net architecture enables pixel-level prediction, which is essential for medical image segmentation.

Expected Outcomes

By the end of this project, the expected deliverables include:

- A trained model capable of synthesizing a missing MRI sequence.
- A trained model capable of synthesizing a missing MRI sequence and PSNR.
- Downstream Validation: A report showing segmentation accuracy comparisons when running a standard tumor detector on real vs.
- synthesized images.

And for the upcoming week, we will be looking more into the data and starting its integration.

Conclusion

To conclude, Brain tumor segmentation relies heavily on multi-modal MRI data. But as we saw, clinical constraints often lead to incomplete imaging data, reducing the reliability of automated systems.

The literature demonstrates that CNN- and U-Net-based architectures can be highly effective for medical image analysis. Building upon these foundations, this project proposes to synthesize missing MRI modalities to maintain segmentation performance.

The next stage of the project will focus on dataset exploration, preprocessing, and implementation of a baseline U-Net model for modality synthesis.