Optimizing Brain Tumor Segmentation by Multi-Slicing images with T1, T1CE, FLAIR Modalities using U-Net

Brandon Bahr-Maravilla, Yoonji Lee, Abdoulfatah Abdillahi

Abstract

Our goal in this project was to determine the best modality for whole tumor segmentation using T1, T1CE, and FLAIR multi-slice images. We used the U-Net model to train and evaluate the model's performance on the BraTS dataset, using the Jaccard and Dice coefficient metrics. We hope our results revealed which modality produced the best segmentation for binary brain tumors. The study underscores the effectiveness of the U-Net model and highlights the significance of multi-modal approaches in achieving accurate brain tumor segmentation.

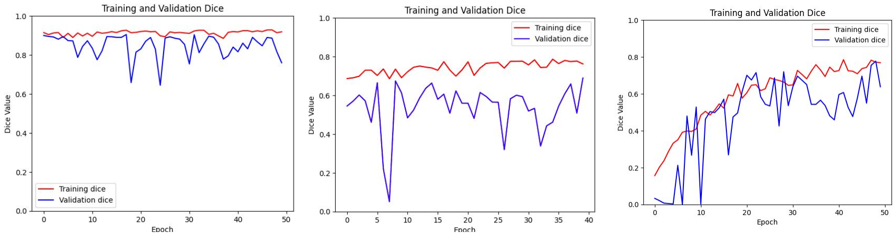
Background

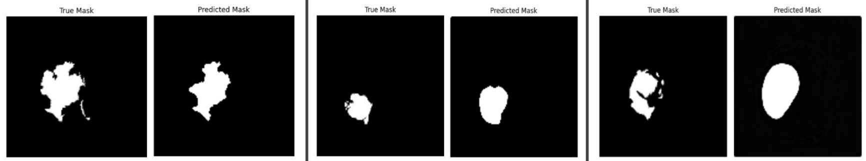
- **U-Net** is a deep learning network commonly used for image segmentation tasks that includes an encoder to capture image features, a decoder to generate the segmentation mask, and skip connections to allow the decoder to use information from the encoder at different scales.
- Magnetic Resonance Imaging (MRI) images:
  - **T1 images**: A type of MRI that provides information on the brain's anatomy.
  - **T1CE images**: A type of MRI that is similar to T1, but with a contrast agent that highlights certain areas of the brain.
  - **FLAIR images**: A type of MRI that suppresses the signal from cerebrospinal fluid and highlights pathology in the brain.
- **Multi-slice images** are a collection of 2D MRI scans representing slices of the brain used to construct a 3D image, with this project selecting the center slice and skipping several slices before and after to acquire the next in the sequence.
- **Jaccard coefficient**: Measures the similarity between predicted and ground truth segmentation masks as the ratio of their intersection to their union, with a range of 0 to 1.
- **Dice coefficient**: Measures the similarity between predicted and ground truth segmentation masks as twice the ratio of their intersection to the sum of their areas, with a range of 0 to 1.

Methods

- **Data**: We used the BraTS dataset, which contains multi-modal MRI images of brain tumors.
- **Model**: We employed the U-Net model architecture, as it excellent at image segmentation problems such as the one we're looking into.
- **Image Preprocessing**: We used multiple MRI image modalities including T1, T1CE, FLAIR. For multi-slice images, we selected the center slice of the brain and skipped several slices before and after it to acquire the next in the sequence for each modality.
- **Training**: We trained the U-Net model using the T1, T1CE, FLAIR, and multi-sliced each of these modalities into multiple images from the BraTS dataset. During training, we used the Jaccard and Dice coefficient metrics to evaluate the performance of the model.
- **Evaluation**: We evaluated the performance of the U-Net model using the Jaccard and Dice coefficient metrics to measure the similarity between predicted and ground truth segmentation masks.

Results





FLAIR | T1 | T1CE

Conclusion

- In the end, the model with the best performance is **FLAIR** with the loss dice using these hyperparameters: **Learning rate**=0.00005, **Batch size** = 4, **Buffer size** = 1000, **Epoch** = 50 ,**Early stopping** = No, **Images acquired before/after middle slice** = 2 (5 total per patient id), **Image spacing** = 4
- We hope for further study to instead of just outlining the whole tumor, to now highlight and segment out each individual part of the tumor, such as necrosis, edema, & enhancing tumor parts from the whole.

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