Deep Learning for Brain Tumor Segmentation on MRI

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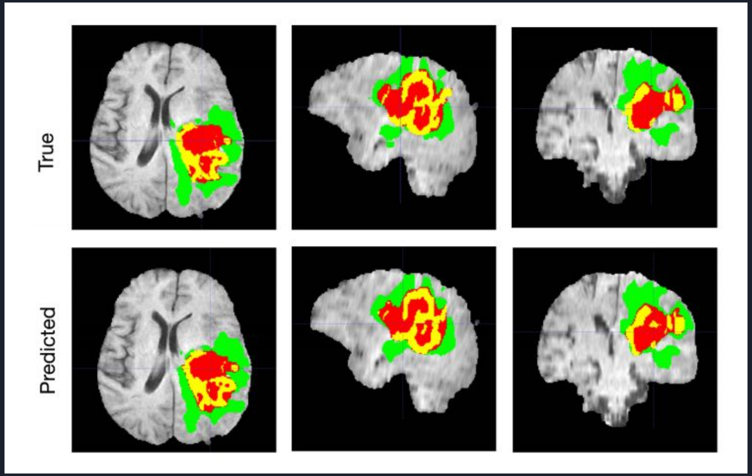
Motivation

- Brain tumors are life-threatening diseases
  - Glioblastoma (focus of this project) are fast-growing and very aggressive
- MRI is necessary, though analysis is time-consuming and often difficult
  - Manual tumor outlining is not only tedious but also biased
    - May not even be performed in busier hospitals
  - Segmenting tumor into different subregions is important to improve diagnosis/treatment
    - It’s important to know where the tumor is and how big each subregion is

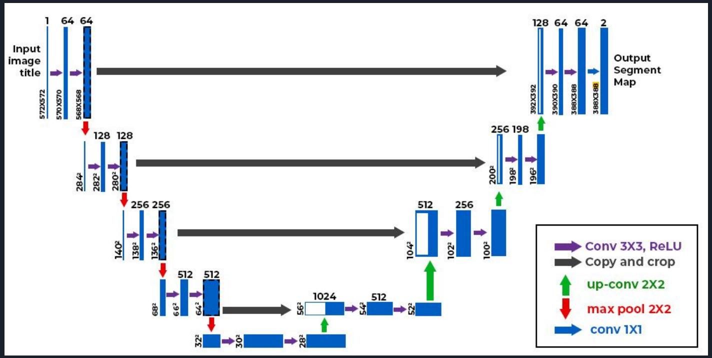


Background

- **Dataset:** Brain Tumor Segmentation Challenge (BraTS)
  - Input: uses magnetic resonance imaging (mpMRI) scans
  - Output: segmentation of different glioma subregions
- The different glioma subregions include:
  - Enhancing tumor (ET)
  - Tumor core (TC)
    - ET + NCR (necrotic core – dead/non-enhancing)
  - Whole tumor (WT)
    - TC + ED (edema – surrounding tissue)

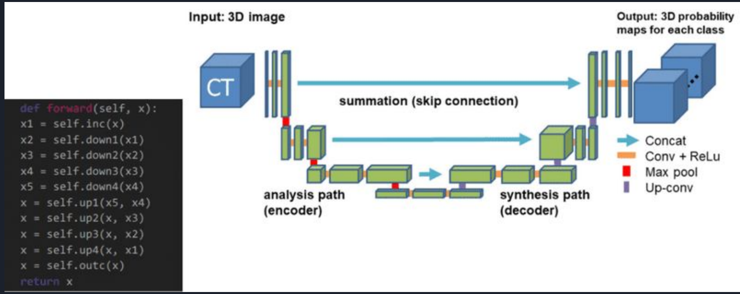
Related Work

- U-Net (including 3D U-net)
  - Popular convolutional neural network architecture used for image segmentation
  - Contracting path: repeated convolutions + max pooling
  - Expansive path: upsamples feature maps
  - Encoding/decoding is strictly CNN
- Transformers (TransUNet)
  - Some new methods have combined CNNs with transformers as a novel hybrid approach
  - Uses vision transformer later in encoding
  - They perform well, though are much harder to implement and train
- It seems that the best and most reliable choice here would be a 2D U-Net.



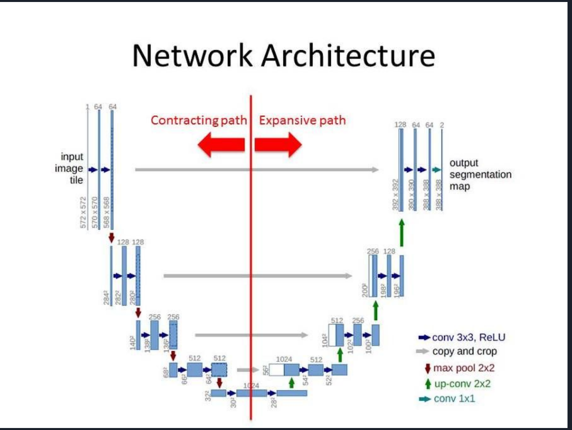
Target Task

- Input
  - Multimodal brain MRI scans (T1, T1Gd, T2, FLAIR)
    - 3D volumetric brain MRI scans
    - Get 2D slices, where each slice has different channels corresponding to different modalities
- Intermediary: pass through a U-Net CNN
- Output
  - For every pixel, predict which tumor subregion it belongs to
    - Necrotic and non-enhancing tumor core (NCR/NET)
    - Peritumoral edema (ED)
    - GD-enhancing tumor (ET)



Proposed Solution

- Preprocessing
  - 3D volumes of T1, T1Gd, T2, FLAIR
  - Slice 3D into 2D slices and create channel images
- Model architecture
  - Repeatedly feed slices
  - Contracting path:
    - Conv → ReLU → Conv → ReLU → Max pool
    - Repeat about 4 times over
  - Expansive path:
    - Up-convolution until original resolution is reached
  - Softmax to predict class per each pixel

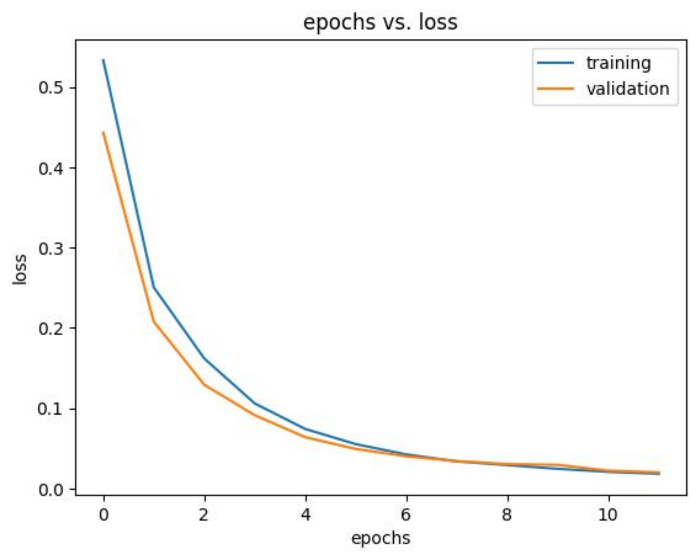


Implementation

- Data splitting
  - Split data by volumes instead of slices to prevent data leakage
- Preprocessing
  - Use Keras Sequence to feed batches and save RAM
  - Only after splitting, shuffle slices
  - Convert multi-channel mask to a class map (0=BG, 1=NCR, 2=ED, 3=ET)
  - Model predicts NCR, ED, or ET
- Training
  - Input: (240, 240, 4) slice of T1, T1Gd, T2, FLAIR
  - Feed through U-Net
  - Output: (240, 240) softmax
  - Loss: sparse categorical crossentropy

Results

- Test loss: 0.0194
- Test accuracy: 0.9954



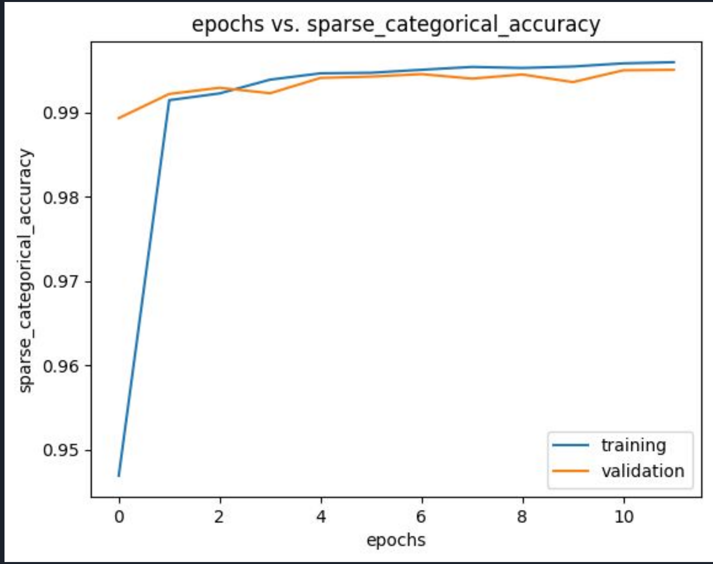
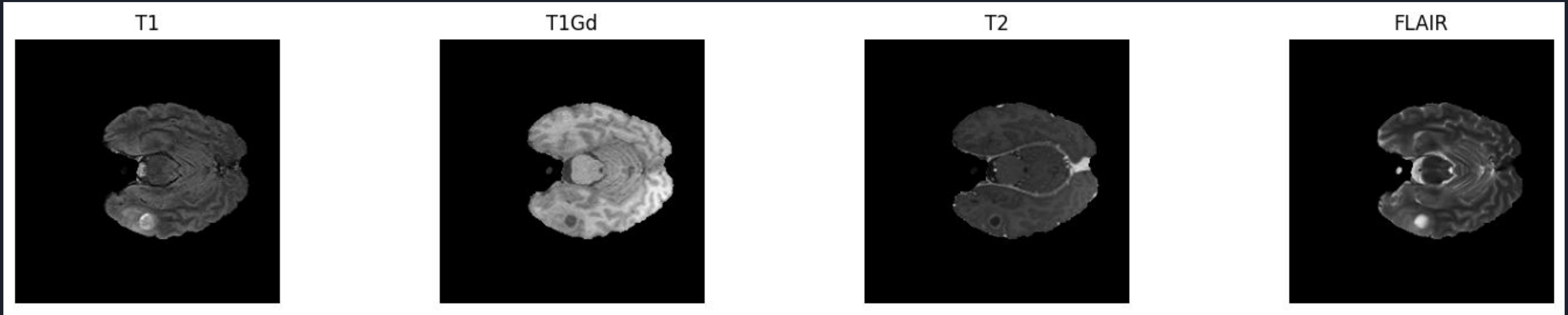
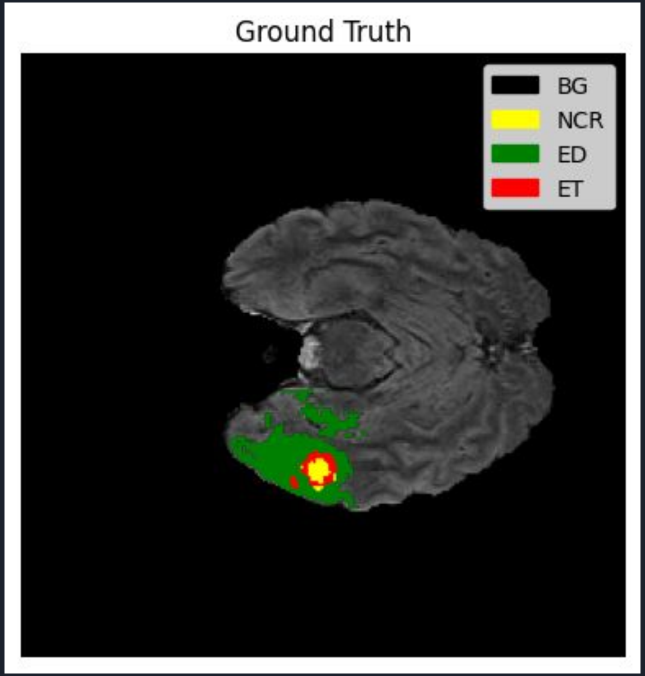


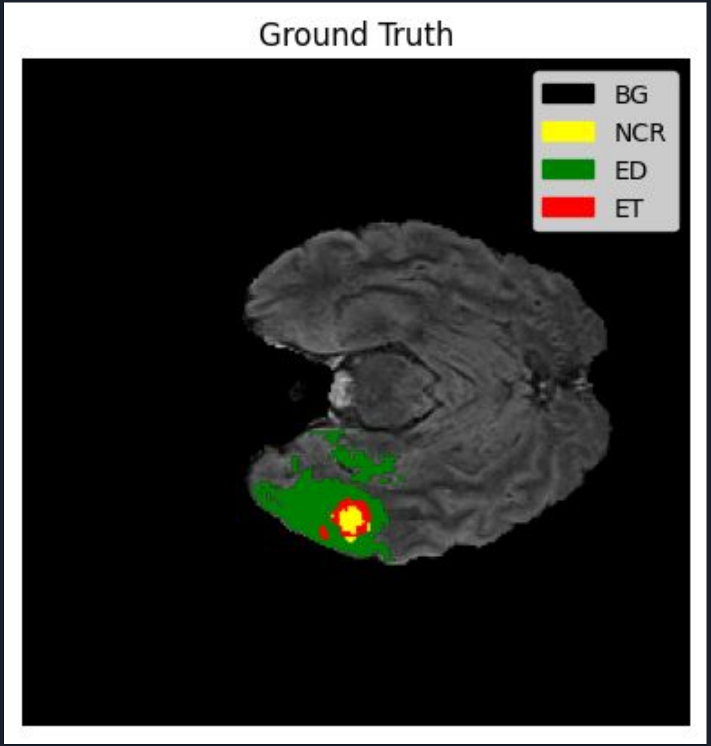
Image Example

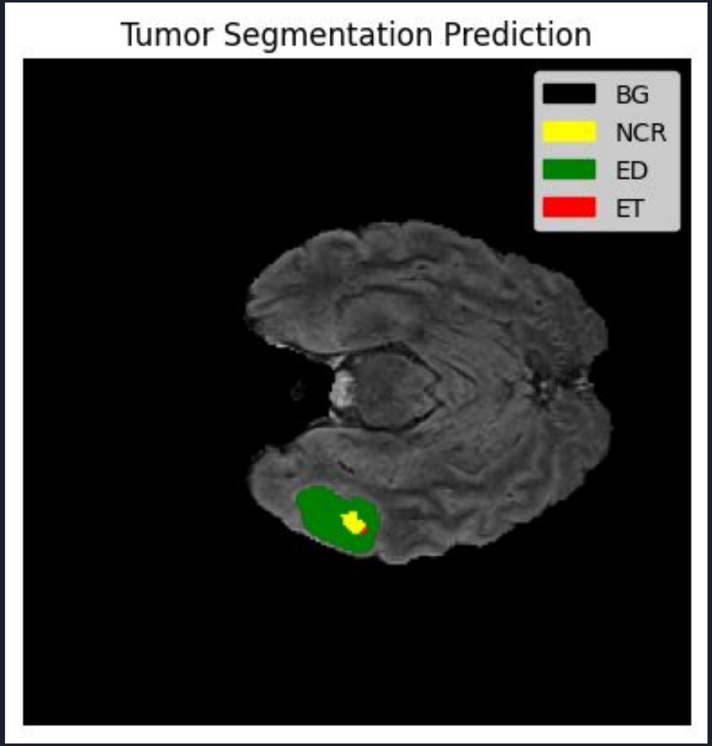


Mask Example

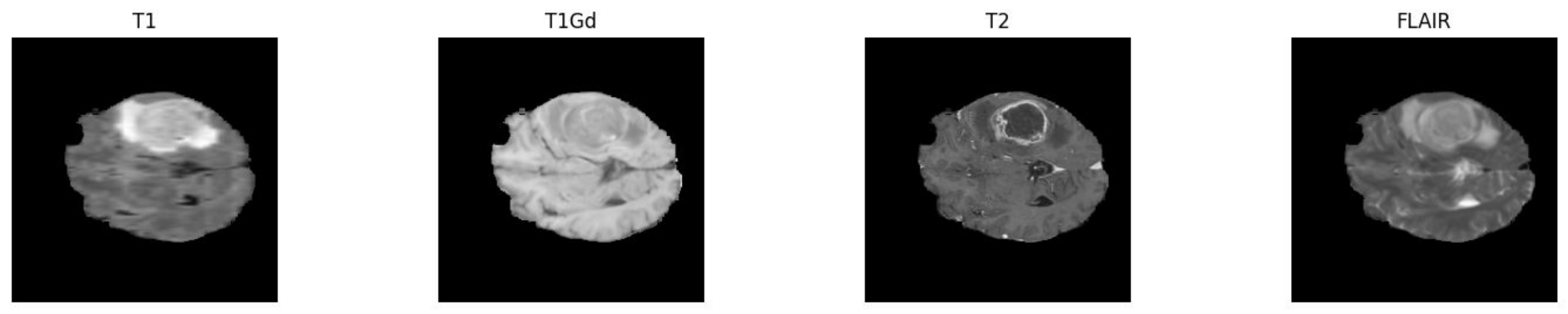


Prediction Example

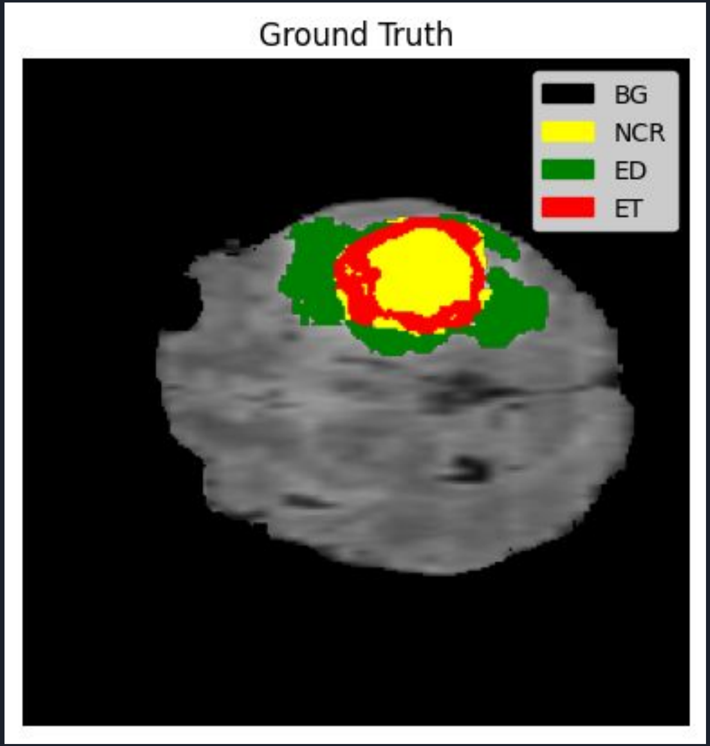




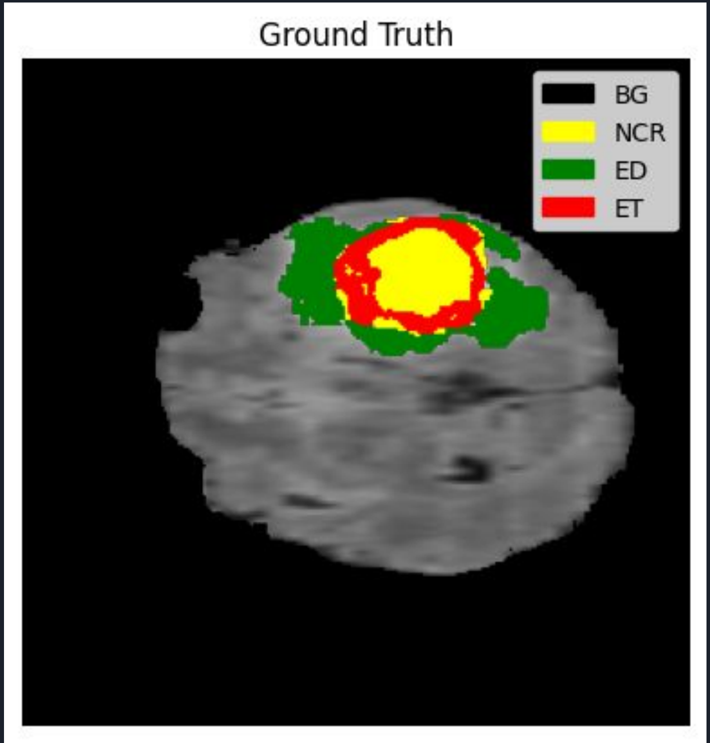
Another Image

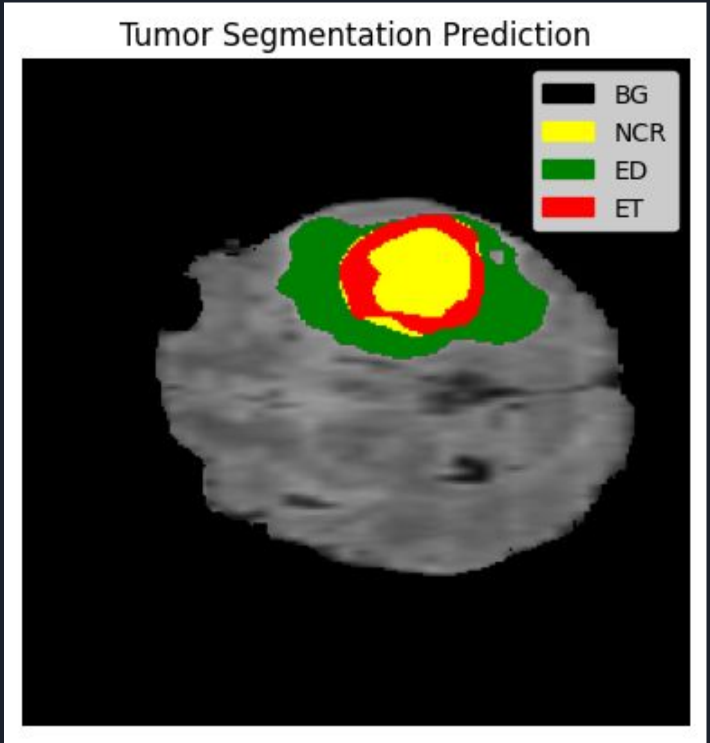


Mask



Prediction


Ground Truth
BG
NCR
ED
ET


Tumor Segmentation Prediction
BG
NCR
ED
ET

Extra Video

https://youtu.be/jqPlX29tkfM

References

Kamara, Alpha Alimamy. “Comprehensive Guide to Mastering the UNET Model for Image Segmentation.” Medium, 15 Oct. 2024, medium.com/@alphaalimamykamara/unet-is-a-well-known-convolutional-neural-network-cnn-architecture-introduced-by-olaf-ronneberger-005a5ec4351f.

Chen, Jieneng, et al. “TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation.” arXiv.Org, 8 Feb. 2021, arxiv.org/abs/2102.04306.