AI 395T | AI IN HEATHCARE

PROFESSOR YING DING

Final Project

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THE AGENDA

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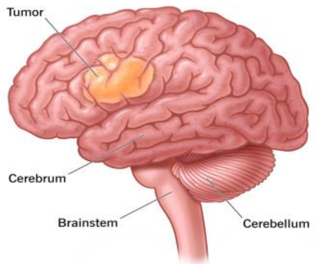
1. Introduction

Topic Selection – Brain Tumor Segmentation



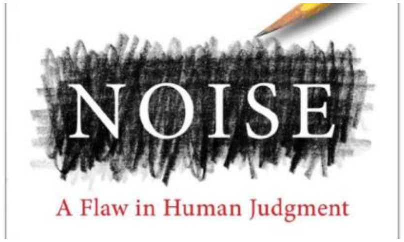
Brain Tumor is a significant health concern, and its early and precise detection is essential for planning an effective treatment for patients.

Despite recent advancements in imaging technology, the error rate of radiologists remains as high as it was in 1949, around 30% per annum. [2]

MRI is the best and most commonly used non-invasive method for brain tumor detection.

One possible way to address the error rate and help radiologists catch more missed or incidental findings is by using AI [3].

Error in image interpretation as radiology's "Achilles' heel" [1]



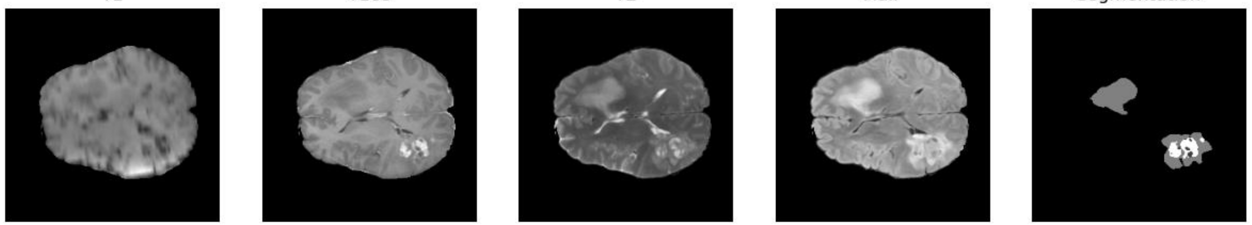
[1]: https://pmc.ncbi.nlm.nih.gov/articles/PMC6540865/
[2] https://www.rsna.org/news/2022/march/human-error-in-radiology
[3] https://healthimaging.com/topics/healthcare-management/healthcare-quality/error-rates-radiology-have-not-changed-75-years

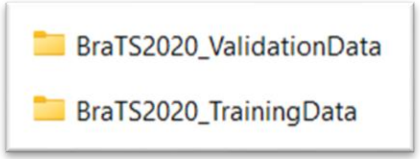
2. Dataset and Methodologies

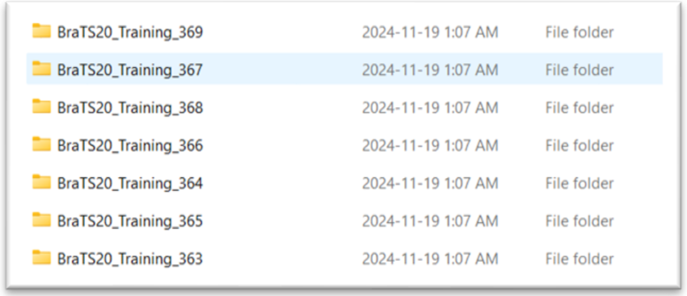
The Dataset

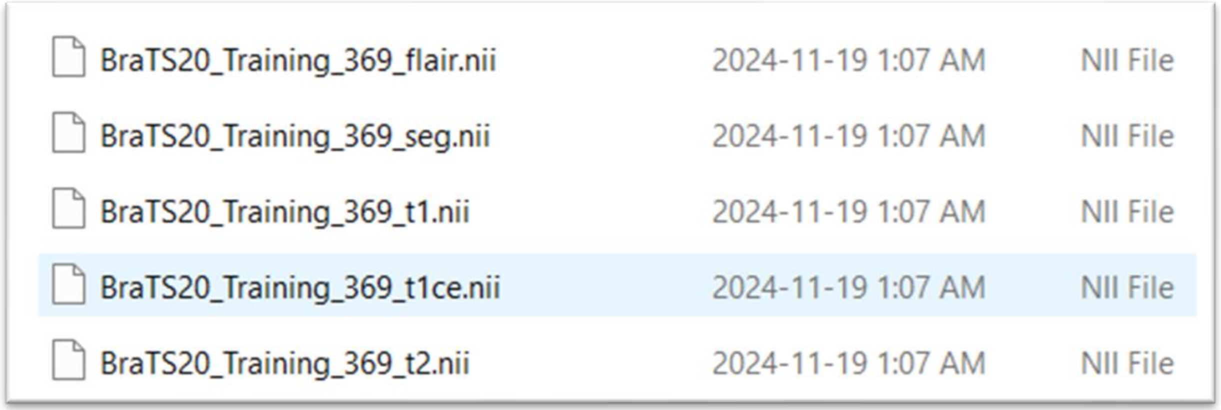
The [BraTS2020 dataset] was used for this study. It includes multi-modal MRI scans (T1, T1ce, T2, and FLAIR) and corresponding ground truth masks with annotated brain tumor regions, all stored in **.nii** format. [4]

The dataset consists of 369 cases with ground truth stored in the Training Data folder and 125 cases without ground truth stored in the Validation Data folder.







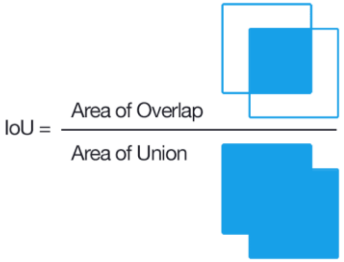


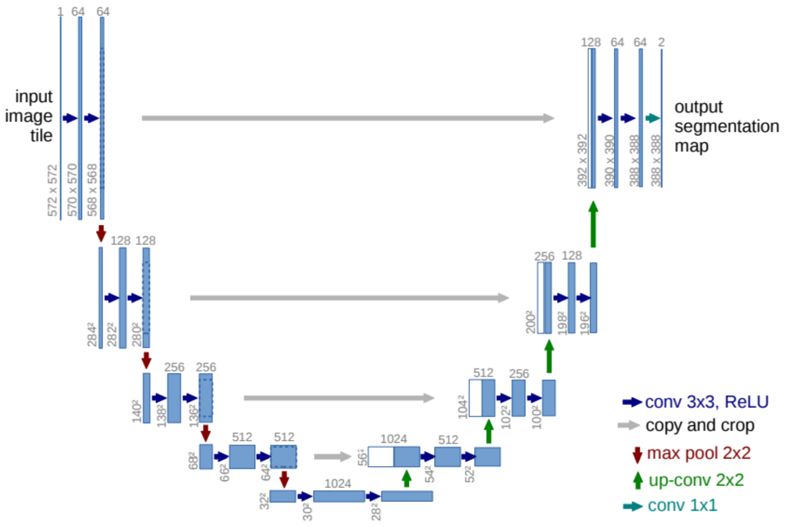
[4] https://www.kaggle.com/datasets/awsaf49/brats20-dataset-training-validation/data

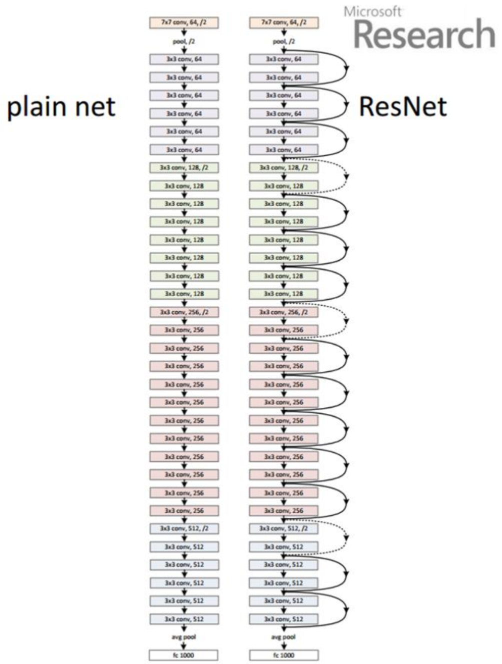
The Methodologies

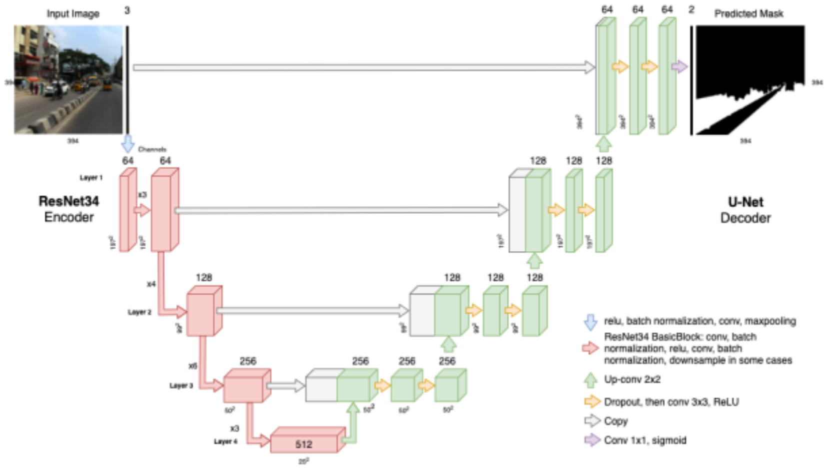
Model's key techniques: CNN, encoder-decoder structure, skip connection, and residual connection.
Loss function: Binary Cross-Entropy Loss and IoU Loss.

BINARY CROSS-ENTROPY LOSS +





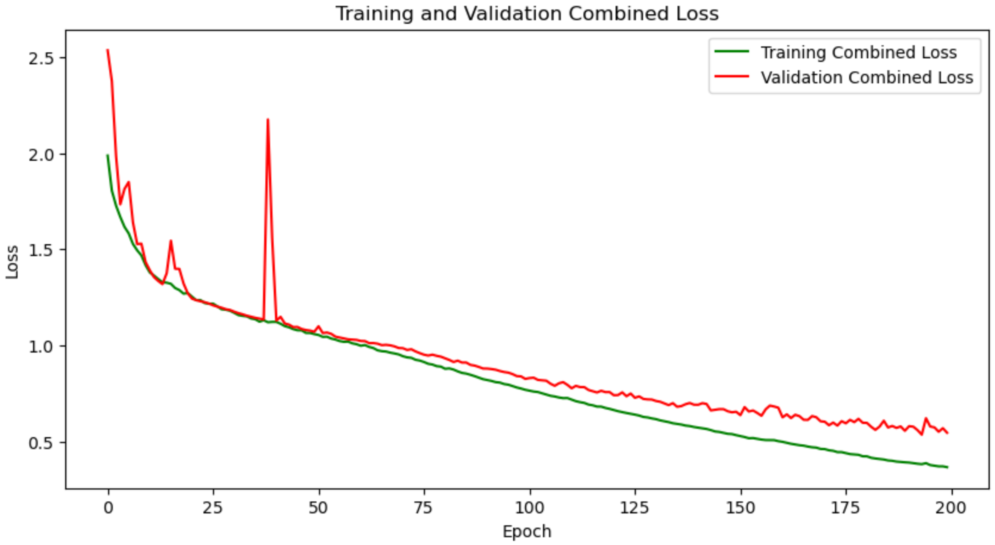


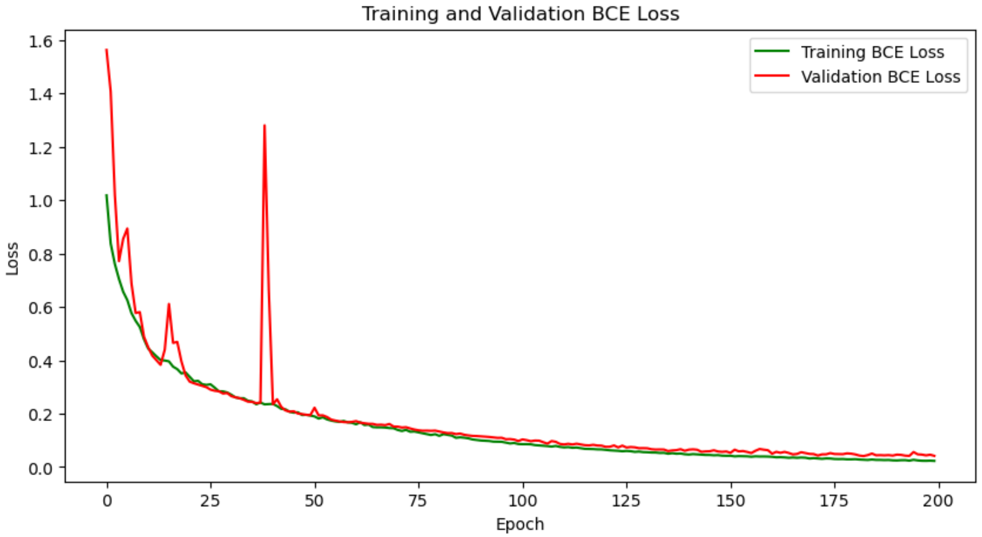


UNET + ResNet = UNET with ResNet encoder

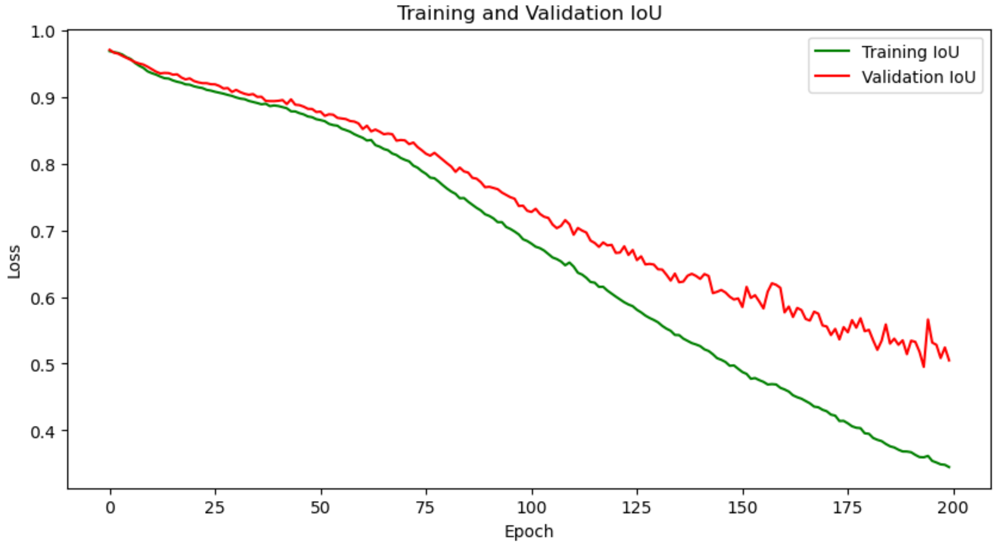
3. Result

The Training Loss & Score



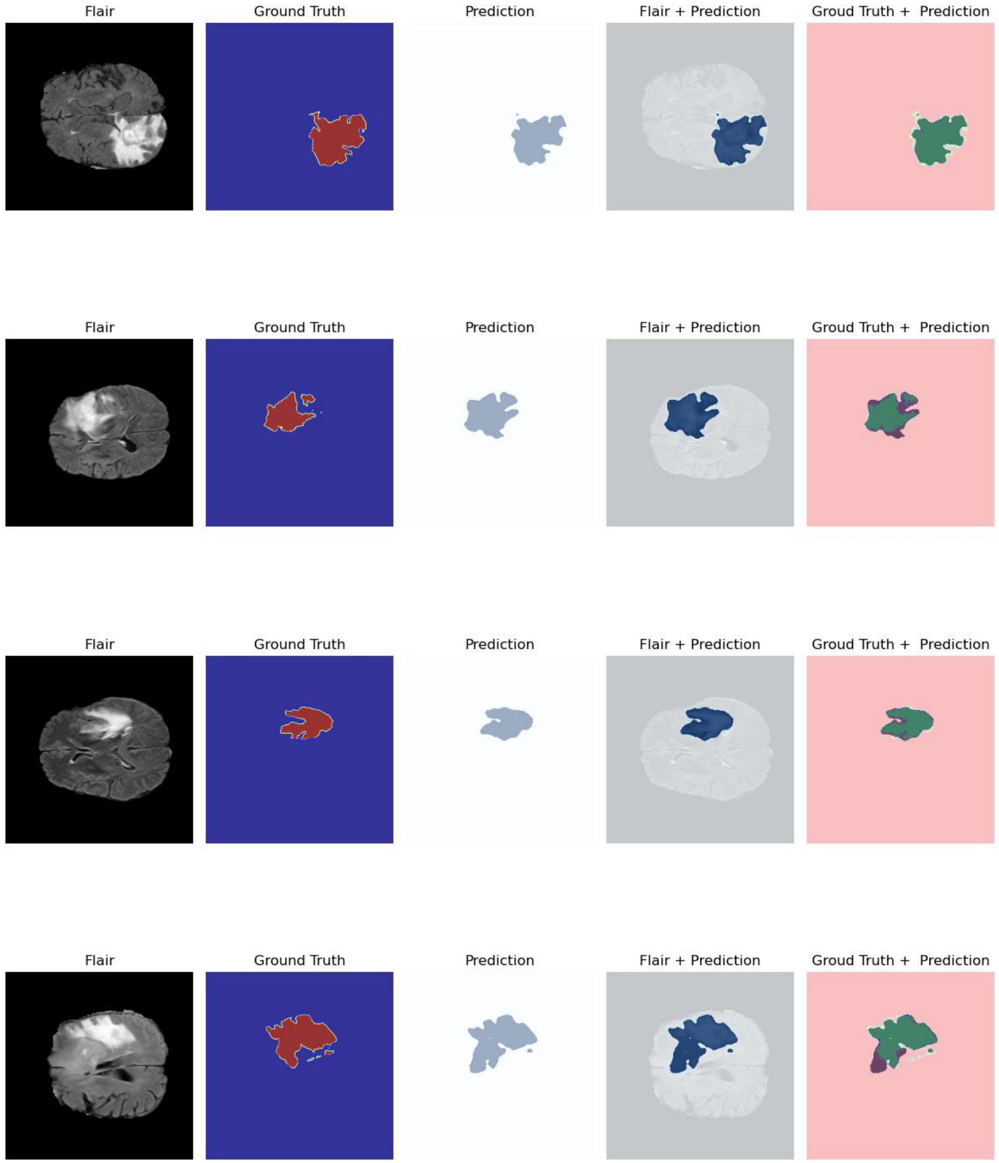


Conclusion: Overall, the model effectively learns the task, achieving high performance on the training set, but shows some slight issues with generalization on the validation set.



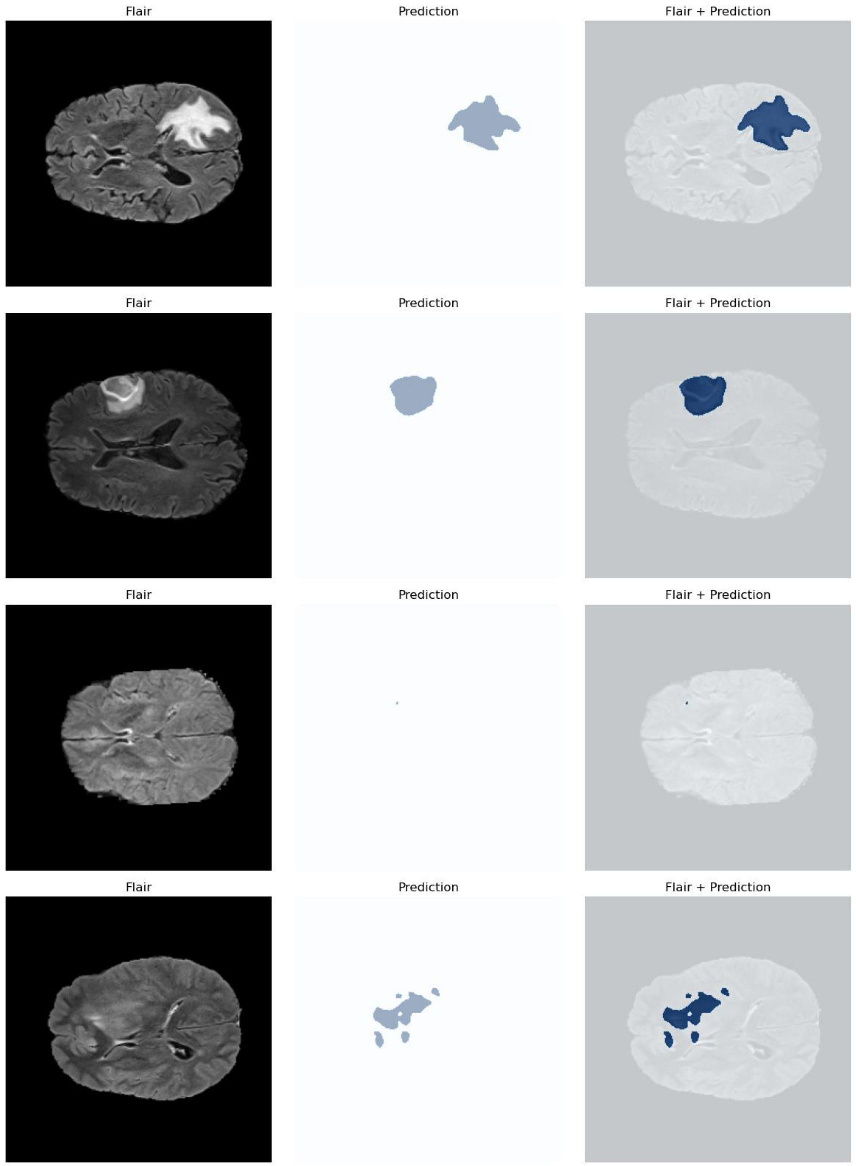
The Segmentation outcome

Validation Set



Limitation: The model has slight issues segmenting the curve edges and tiny objects.

Test Set



4. Future Direction

Future Direction

- **Increase Dataset Size:** The current train dataset includes 300 samples. While augmentation adds variability, increasing the dataset size with additional real samples will improve generalization.

- **Hyperparameter Fine-tuning:** Hyperparameter optimization can further refine the training process. Due to the computing constraints, the model is not fine-tuned with different hyperparameters such as optimizers, learning rates, and batch size.

- **Incorporate Dice Loss:** Dice Loss is particularly effective for addressing class imbalance, which is common in medical imaging datasets where the tumor region (positive class) is significantly smaller than the background (negative class). By incorporating the Dice coefficient, the model can focus more on overlapping areas between the predicted and actual masks, thereby achieving better segmentation results.

- **Incorporate Classification task:** the model can be extended to perform a dual task: tumor segmentation and classification (benign vs. malignant, or different tumor types), thereby providing comprehensive diagnostic insights in a single step.

THANK YOU!