Brain Tumor Segmentation

By Anna Douville

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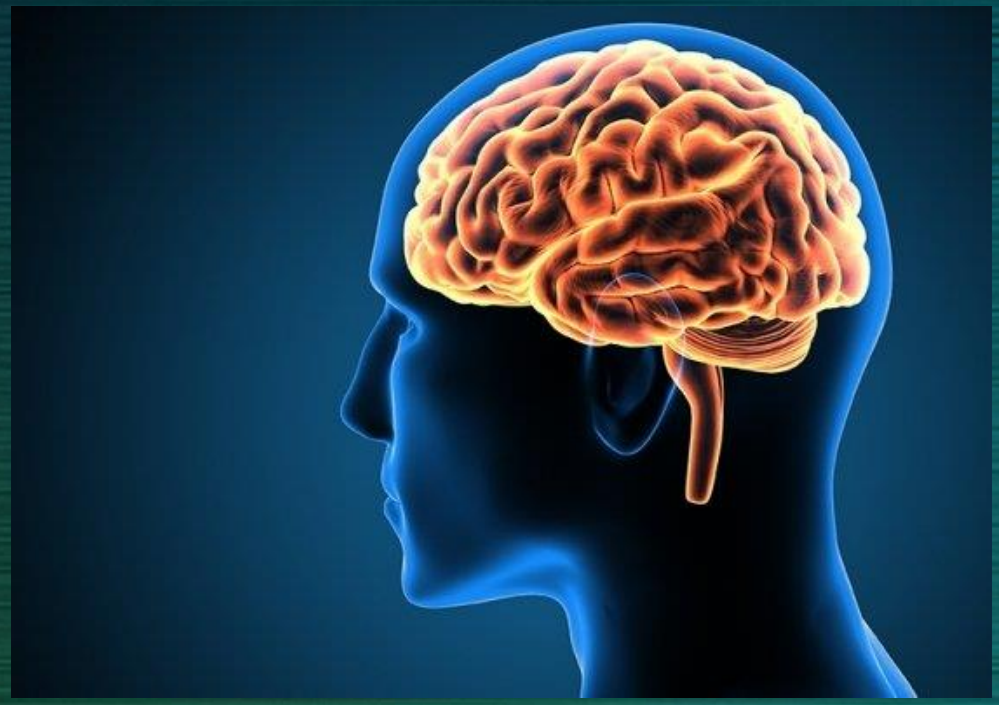
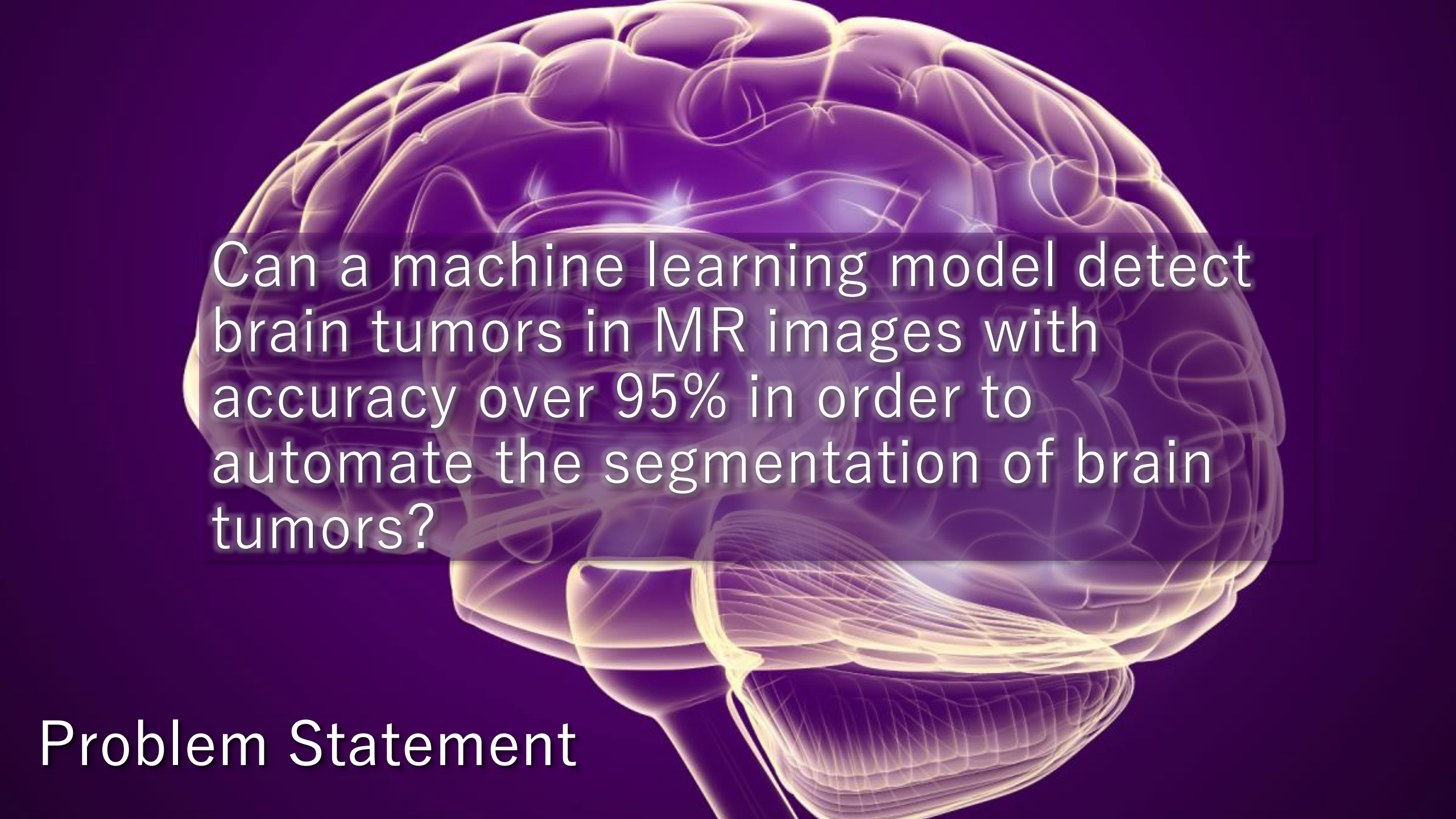
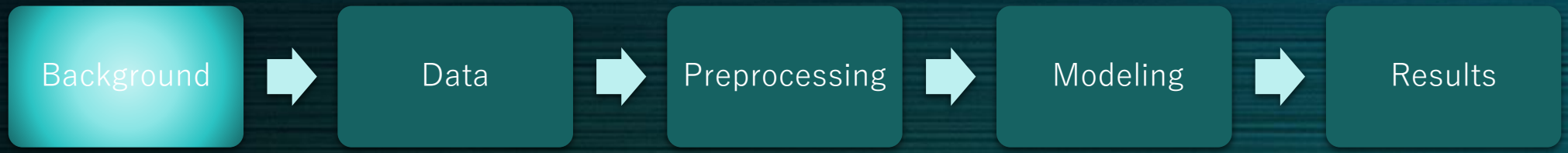




Problem Statement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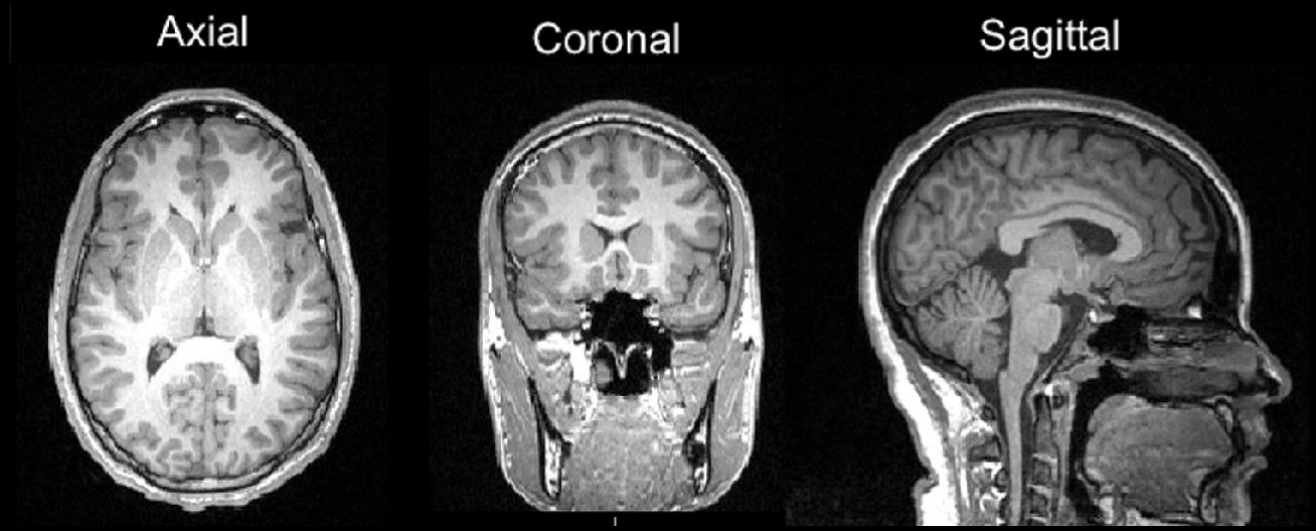
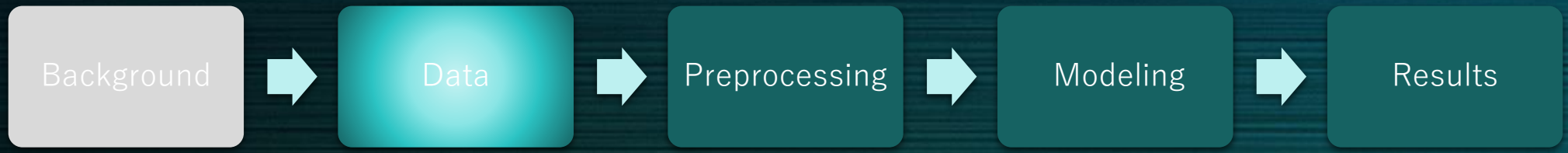
Background

- Brain tumor: cluster of mutated cells that is potentially life-threatening
- Magnetic Resonance Imaging (MRI): non-invasive technique used to capture images of the brain
- Brain tumor segmentation: separating the tumor pixels from the non-tumor pixels in an MRI for measuring, diagnosing, informing treatment
  - Manual segmentation is extremely time consuming and difficult for radiologists

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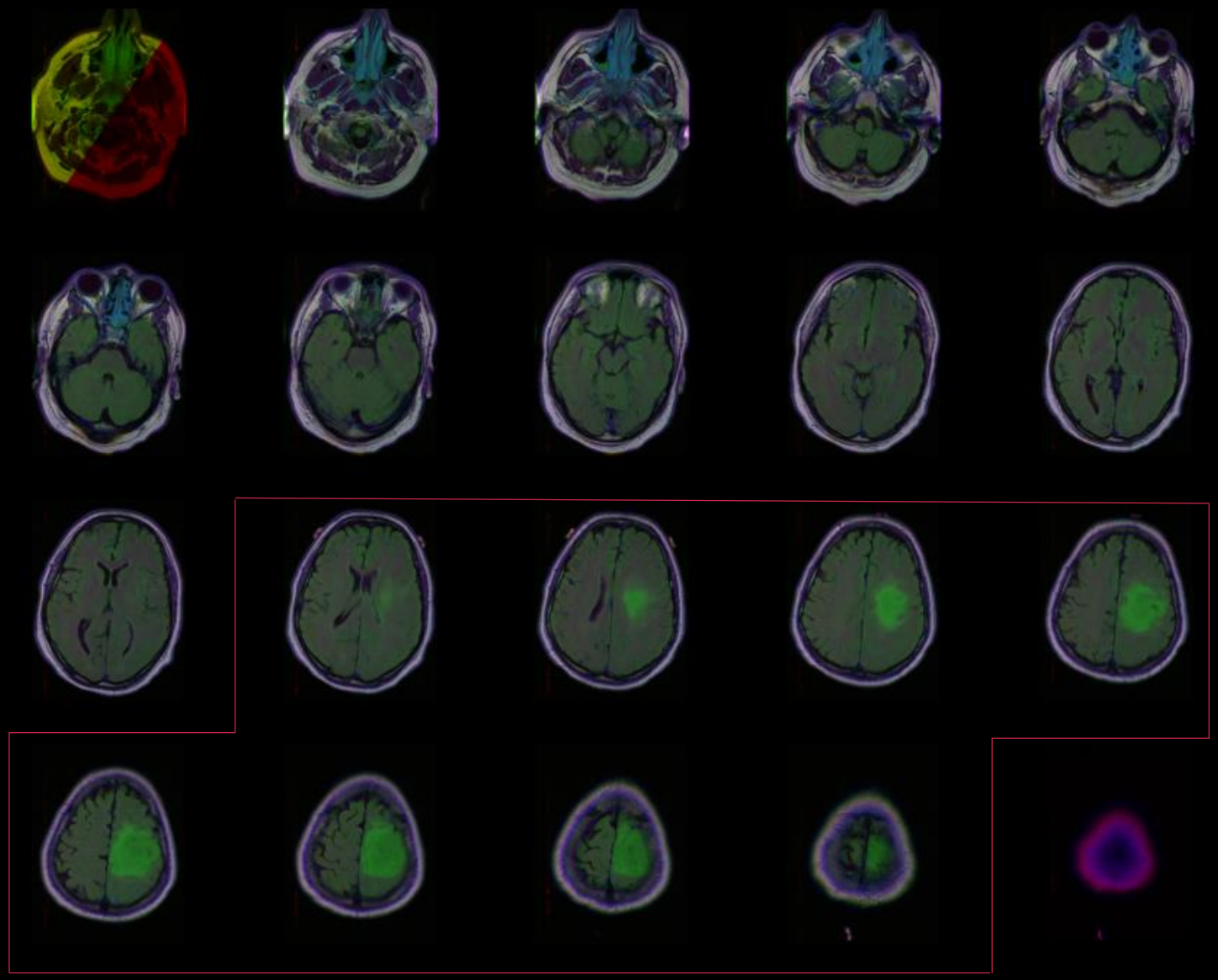
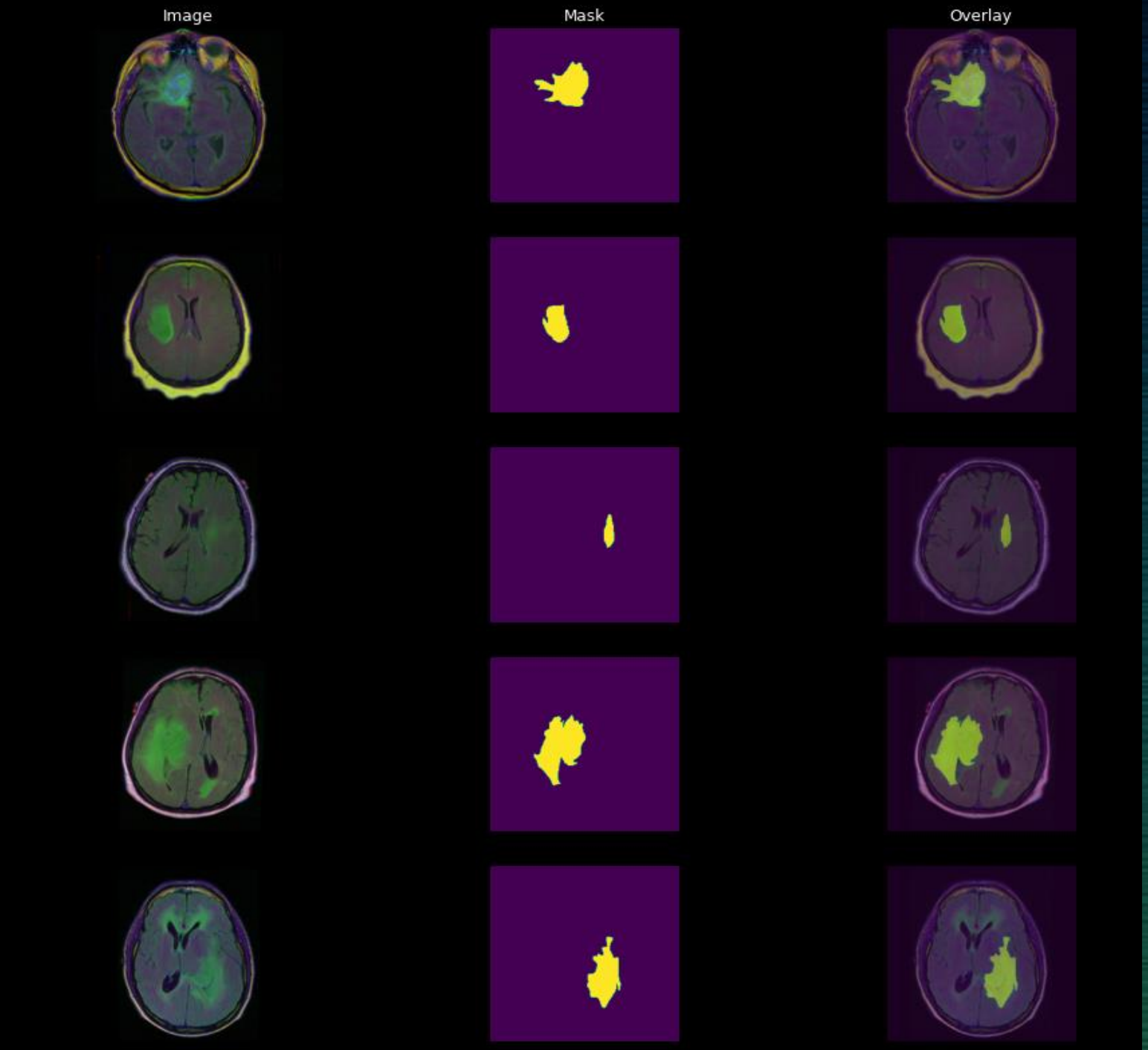


MR Images

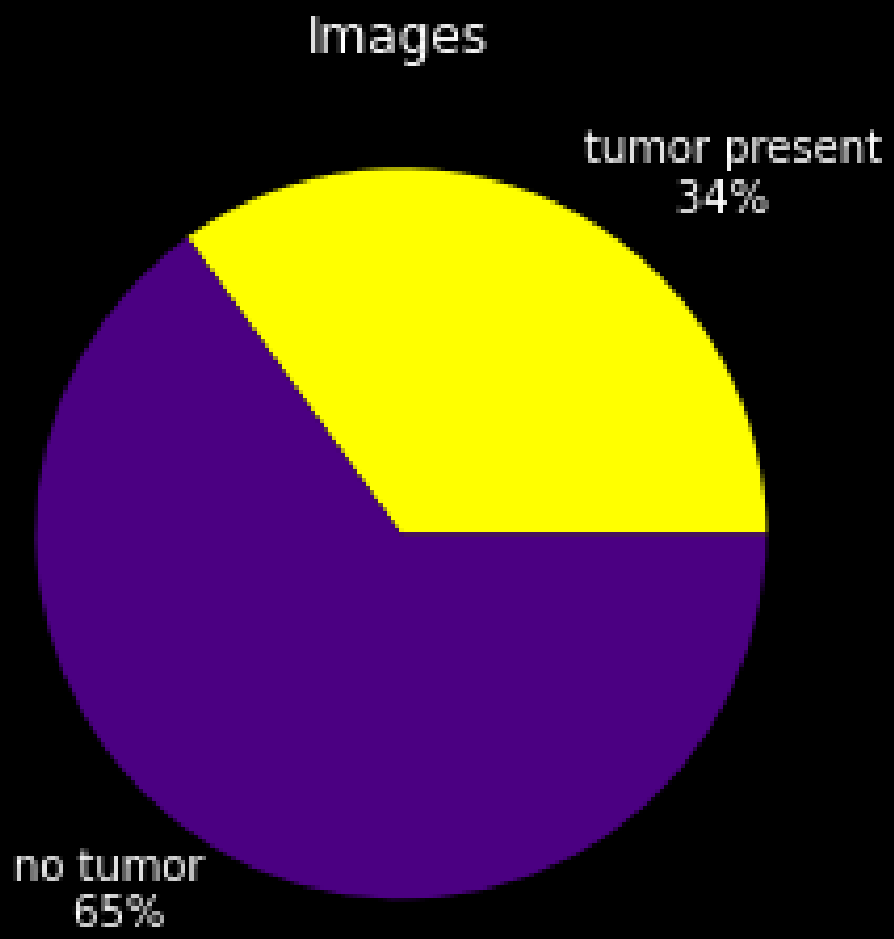
- Subset of The Cancer Genome Atlas Low Grade Glioma (TCGA-LGG) dataset
- 3,292 MR images from 65 different patients with LGGs
- 256x256 axial cross sections
- Tumors can be seen a green mass

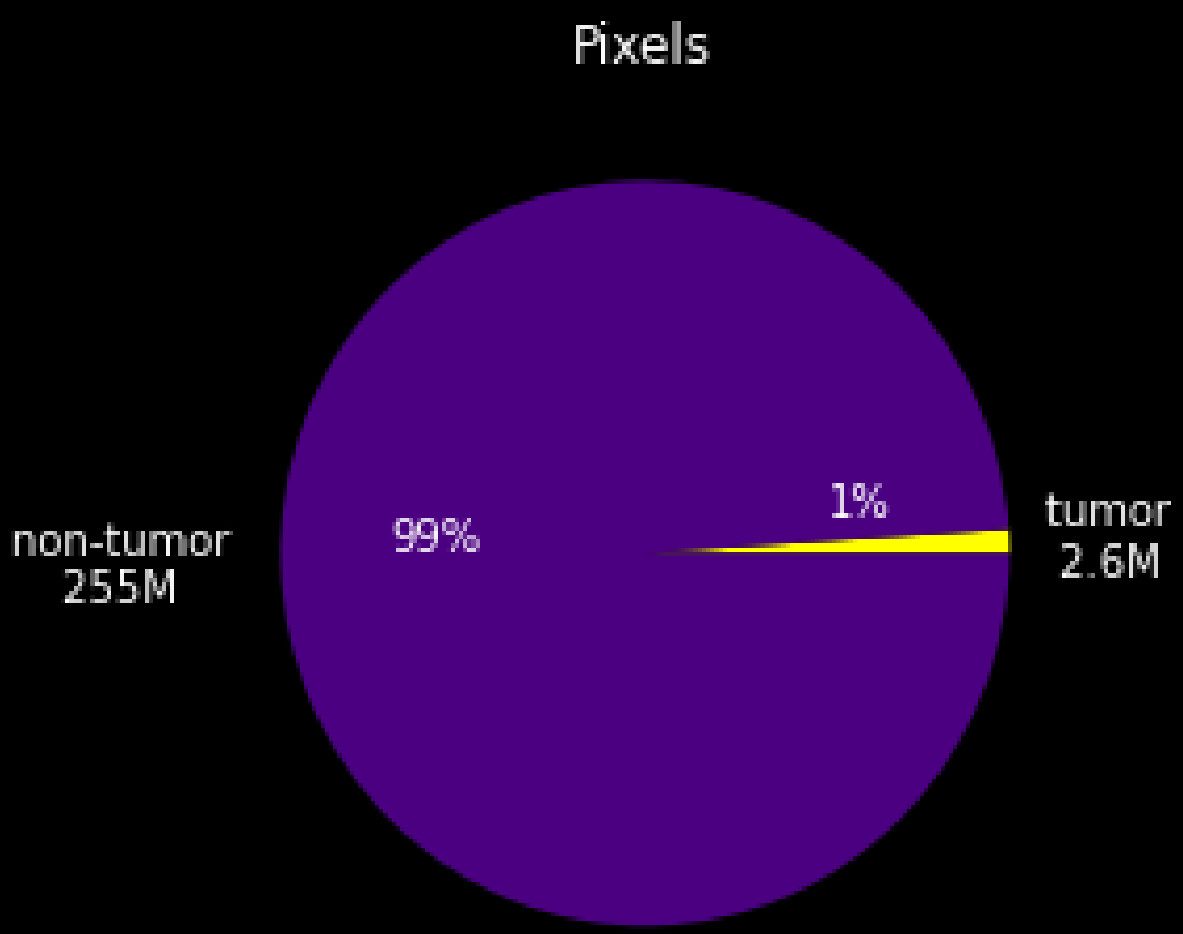


Masks

- Each MRI has a corresponding mask
- Masks label all tumor pixels (yellow) as 255 and all non-tumor pixels (purple) as 0
- Validated by board-certified radiologist

Exploratory Analysis





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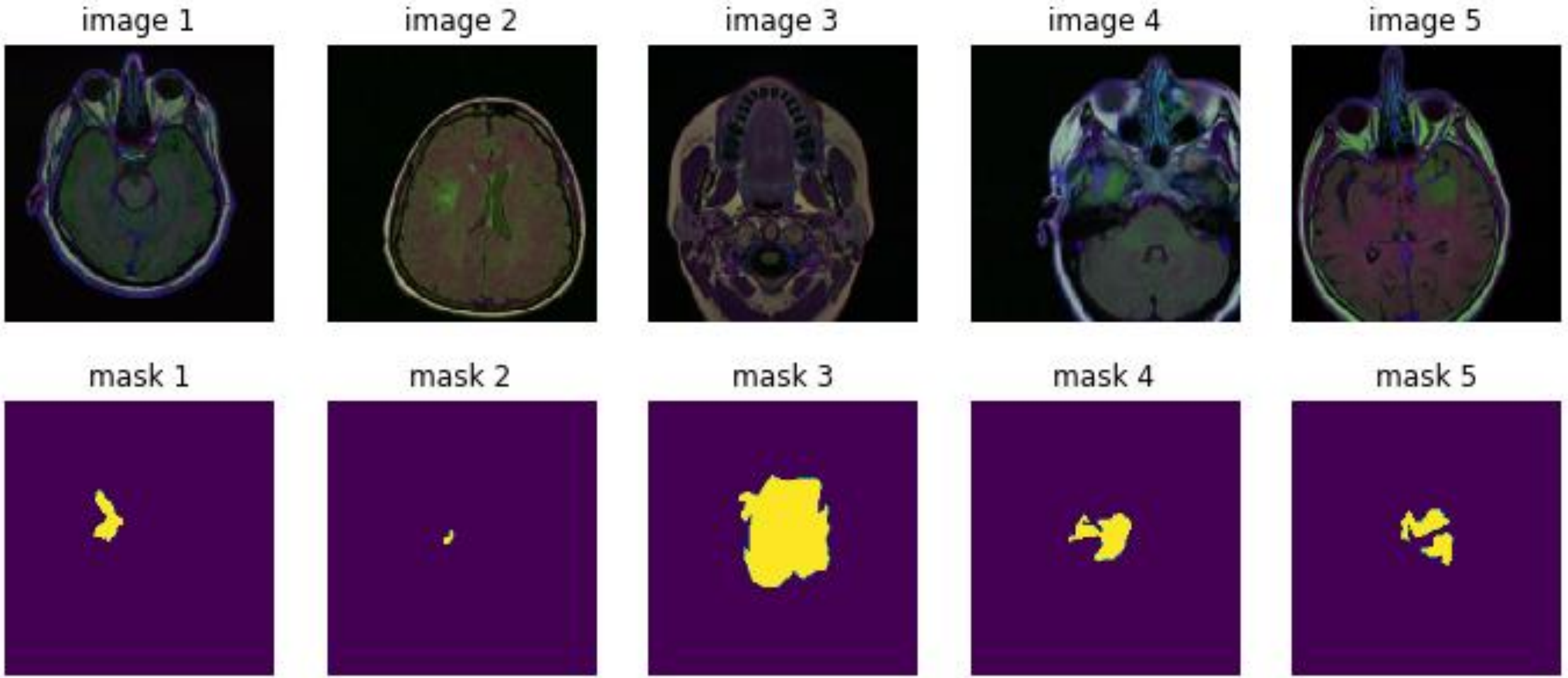
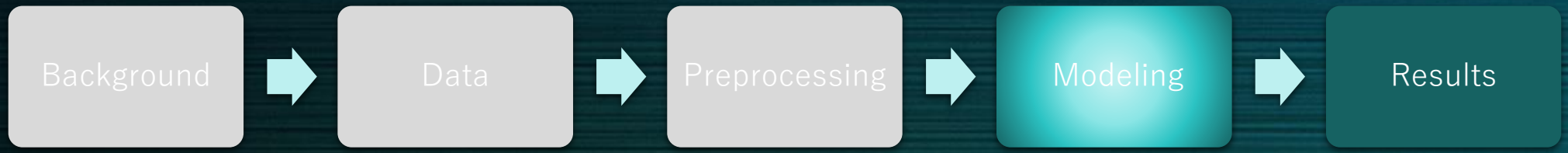
Preprocessing

- Dropped all 2,556 images w/o a tumor present
  - increased the percentage of tumor pixels to 2.9%
  - decreased size of the dataset to 1,373 image & mask pairs
- Cropped images around the tumor w/ random amount of padding on each side
  - Increased percentage of tumor pixels to 6% w/o sacrificing too much context
- Resized images back to 256x256
- Scaled images by 255 to normalize data from 0 to 1

Transformations

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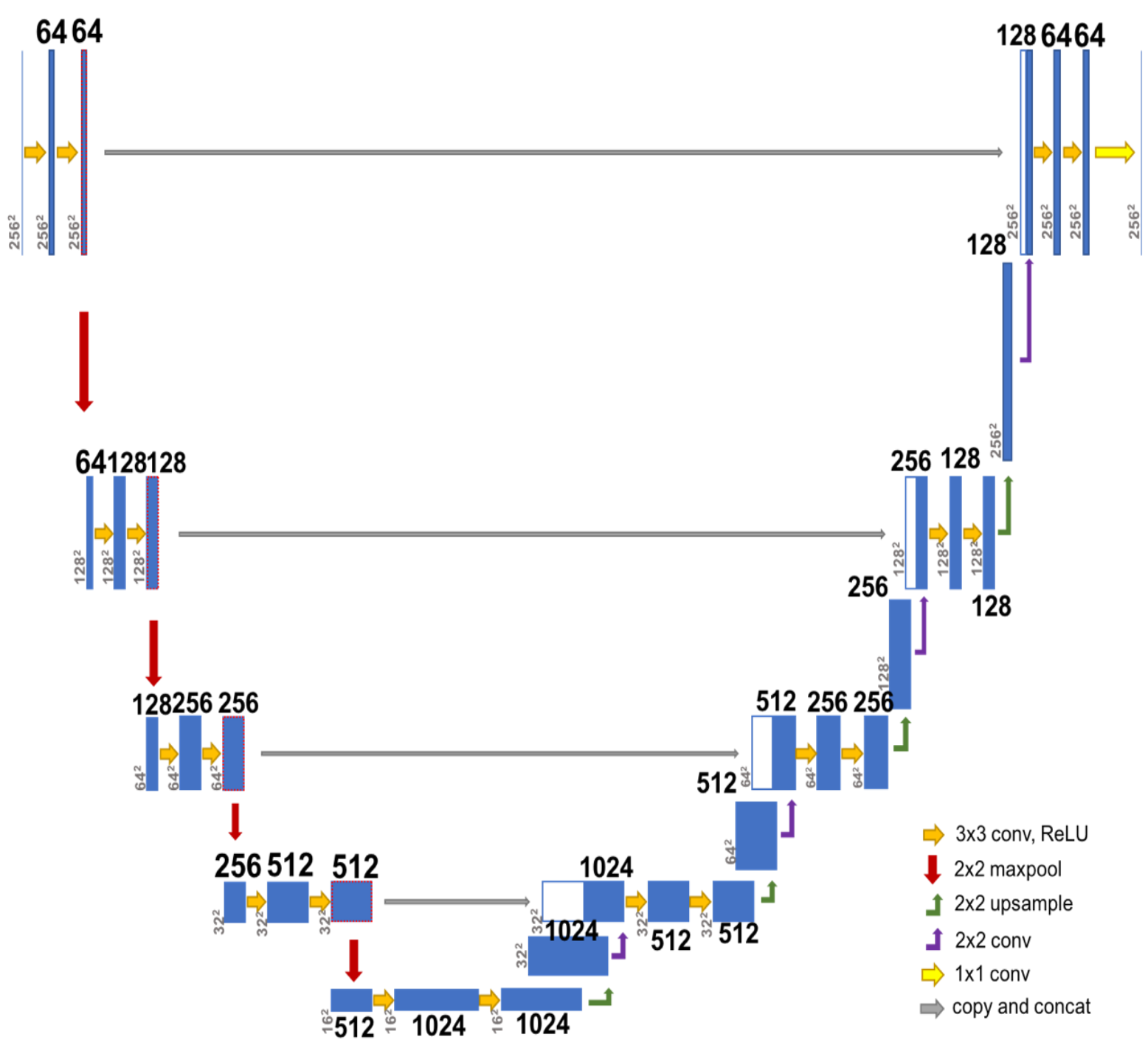
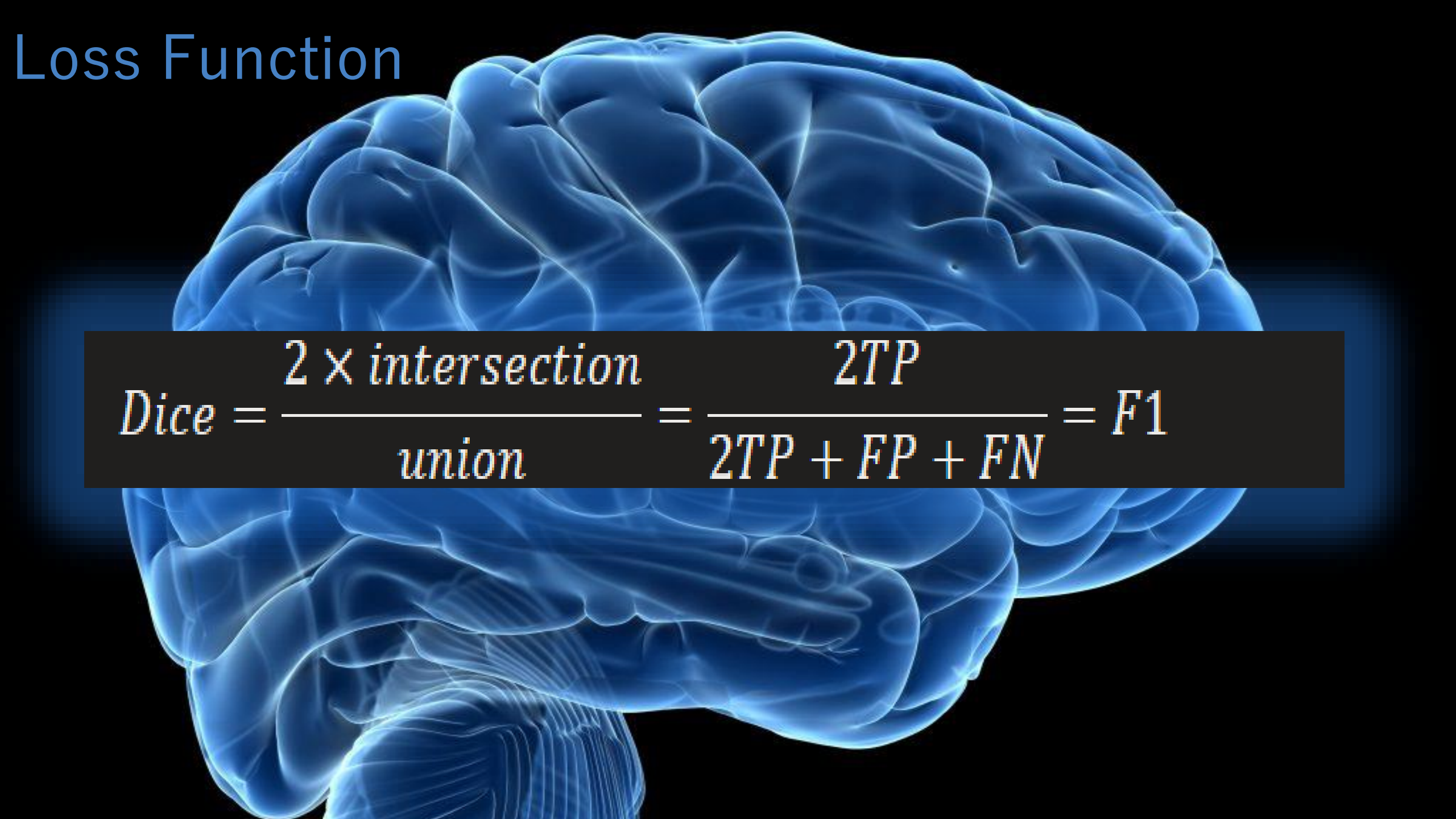


U-Net

- FCN developed for biomedical image segmentation
- Encoder path
  - pooling
  - convolutions
  - provides context information
- Decoder path
  - upsampling
  - convolutions
  - provides spatial information
- Skip connections
  - ensure context is not lost
- Binary output for every pixel
- 22,384,577 parameters to train

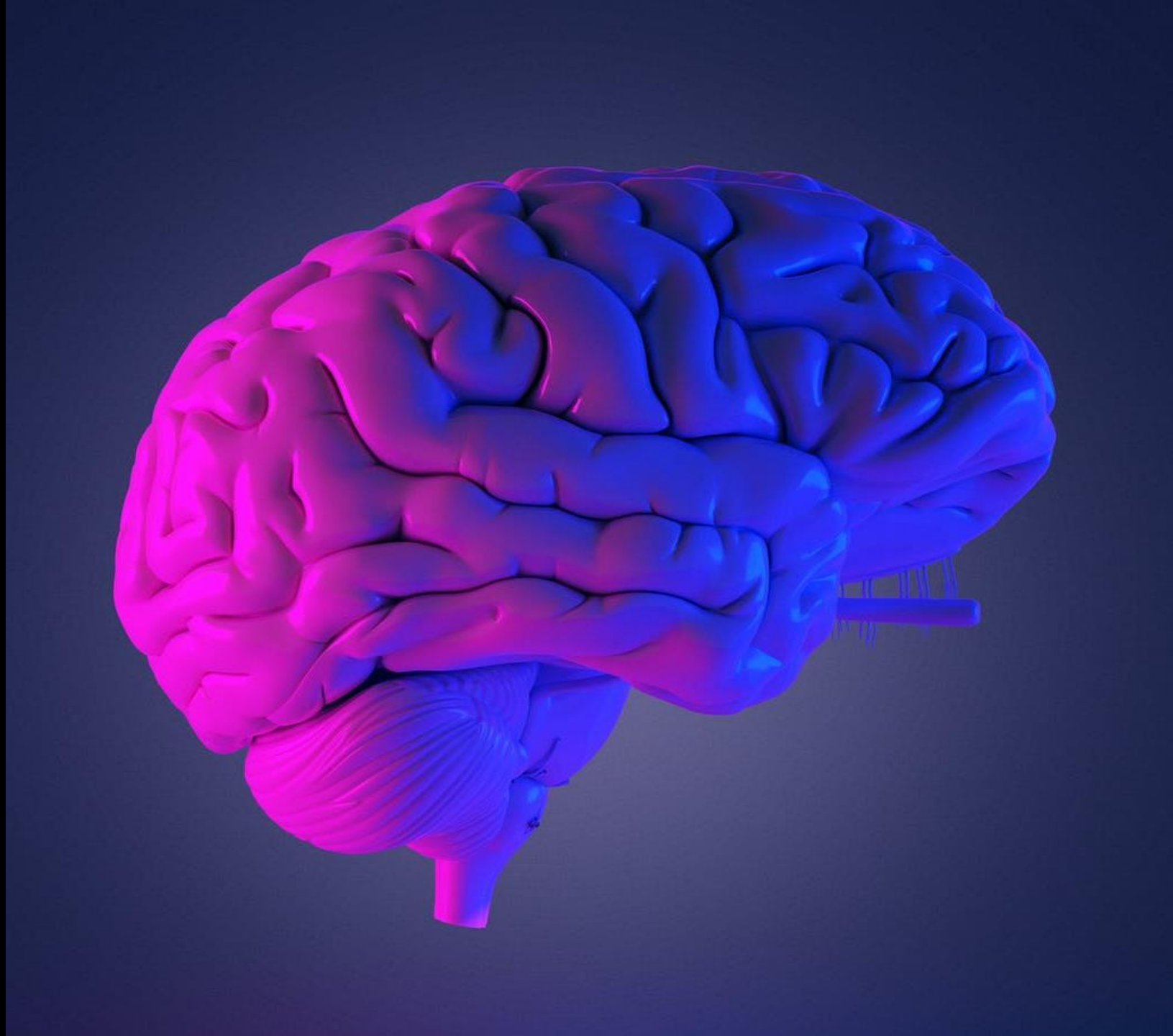
Loss Function



$$Dice = \frac{2 \times intersection}{union} = \frac{2TP}{2TP + FP + FN} = F1$$

Hyperparameters

- Adam Optimizer
  - Learning rate = .001
  - Decay = learning rate / # epochs
  - Epsilon = None
- Convolution Layers
  - Activation = ReLU
  - Kernel initializer = HeNormal
  - Padding = Same
- Batch size: 32
- Epochs: 100
- Callbacks: ModelCheckpoints



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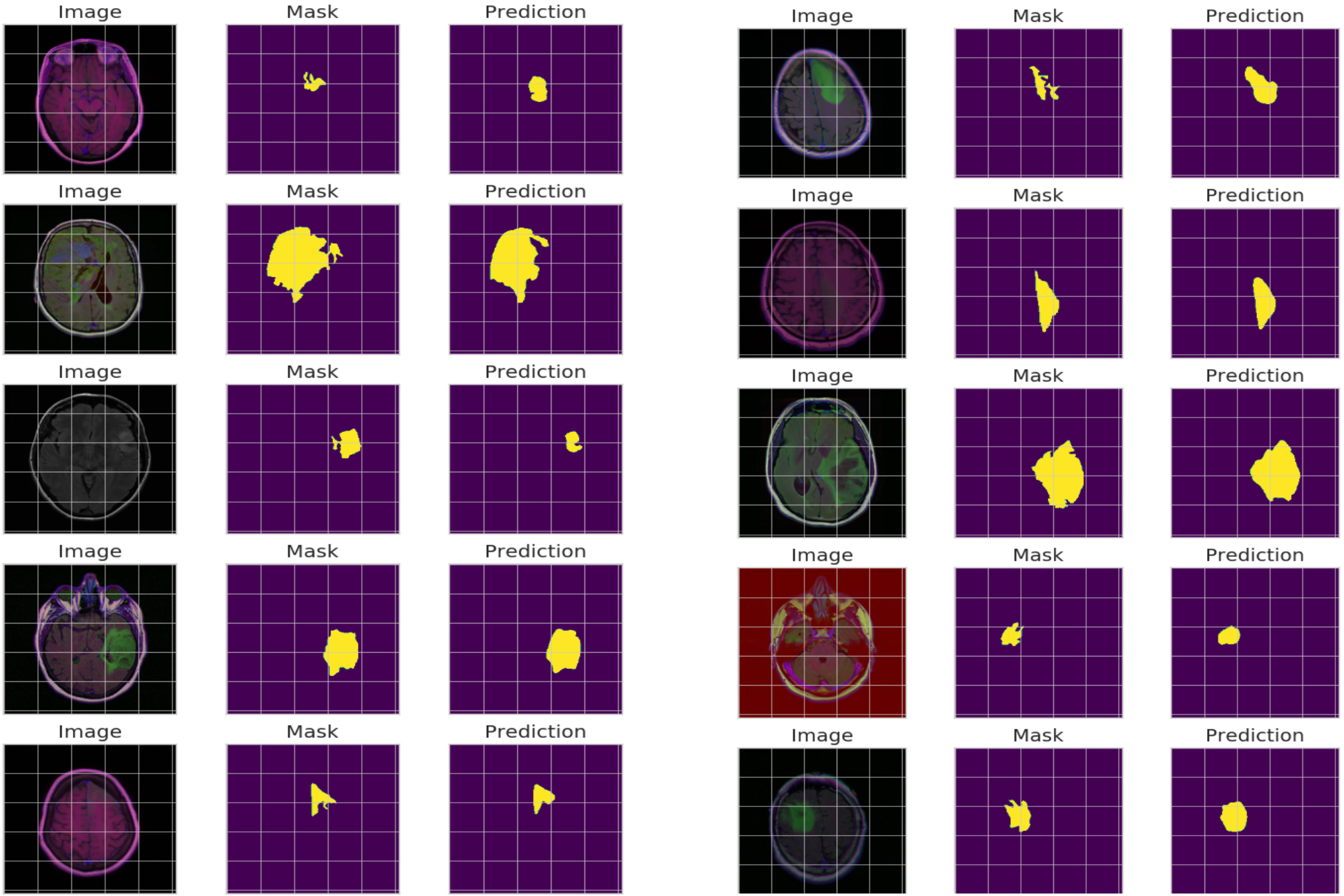
Model Performance

Accuracy: .98
Dice Coefficient: .68

	loss	accuracy	dice
train	0.200864	0.986188	0.799399
test	0.331611	0.983733	0.677358

Predictions



Summary

- Brain tumor segmentation is crucial for the proper measurement, treatment, and diagnosis of a tumor
- Previously, radiologists had to spend hours manually segmenting brain tumors from MRI
- Radiologists can use a deep learning model with a U-Net architecture for semi-automated brain tumor segmentation with a binary accuracy of 98%
- Model performance may improve with a much larger dataset or with different variations of the U-Net that may allow for fully automated brain tumor segmentation