Brain Tumor Diagnosis and Segmentation

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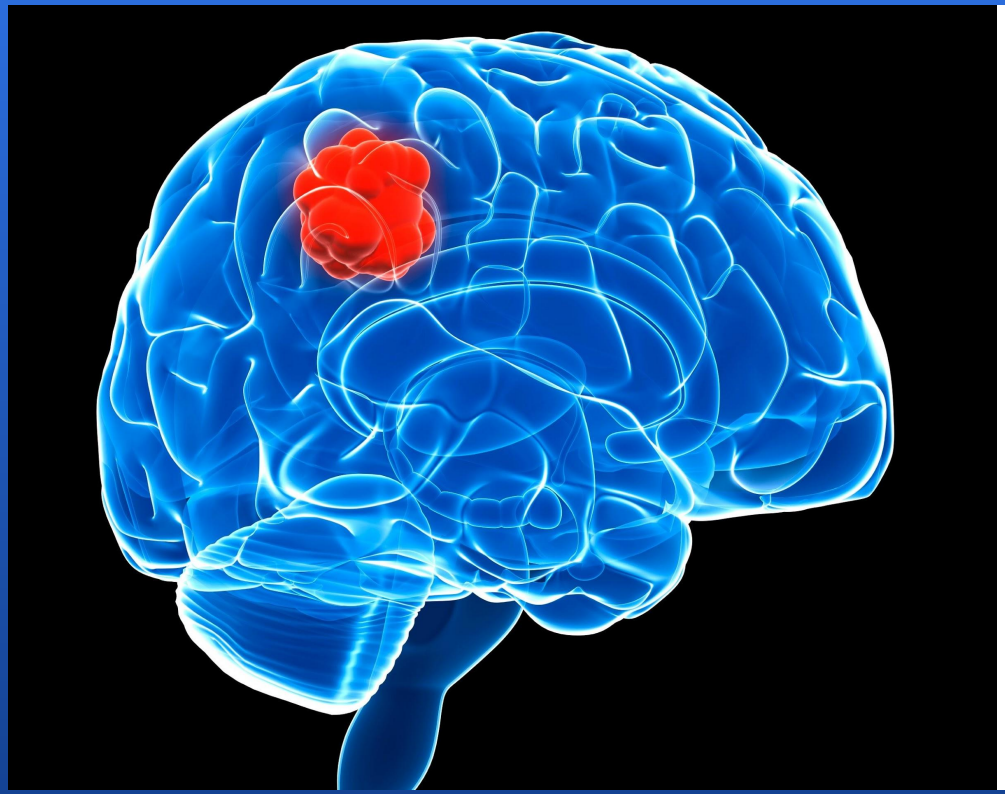
Problem Statement

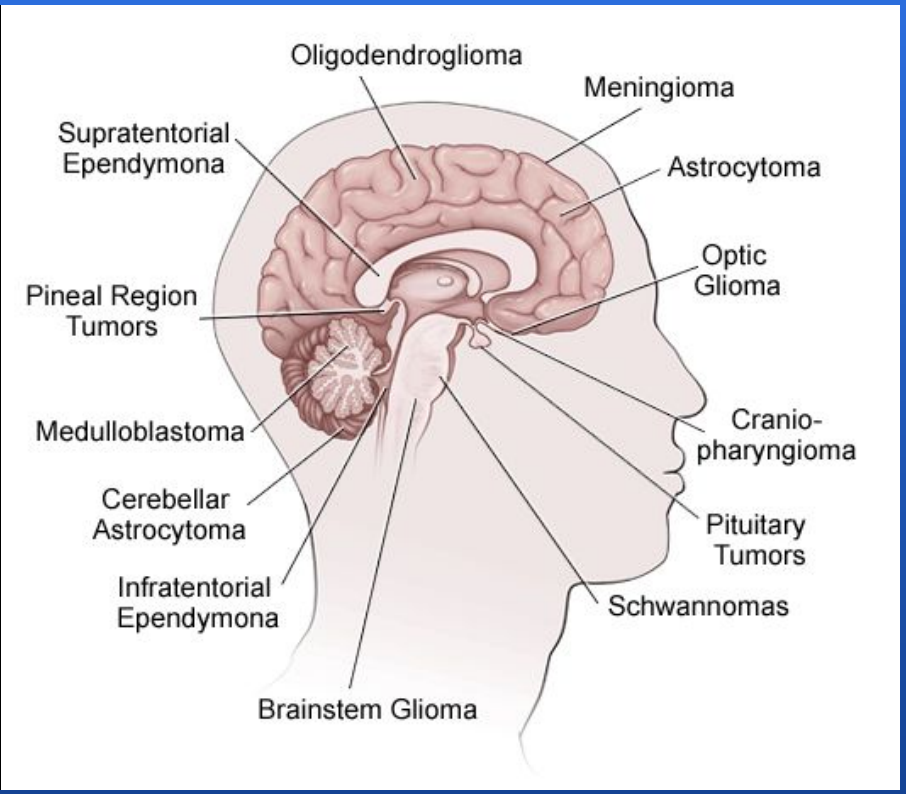
The goal of this project is to develop, test, and evaluate a machine learning algorithm that will be able to perform brain tumor diagnosis and segmentation on a test set of MRI images of the brain.

It will classify cancerous and non-cancerous brain masses, mainly gliomas, and identify the different regions of the tumor, including: active tumor, edema, and necrosis. The most difficult aspect of tumor segmentation is the large imbalance of tumor labels in the training and test data. This leads to a large number of false-negative results, despite a relatively low percentage compared to the entirety of the data set.

We will utilize deep learning and convolutional neural networks to classify the MRI images, as well as a splice-layering technique to create a larger data set.

Brain Tumor Types





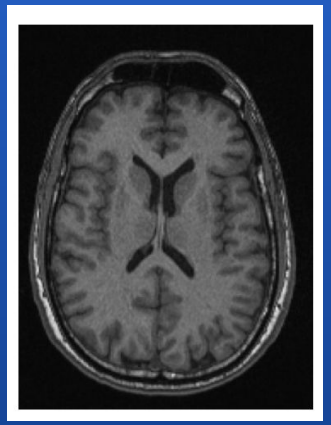
University of Texas MD Anderson Cancer Center

Approach

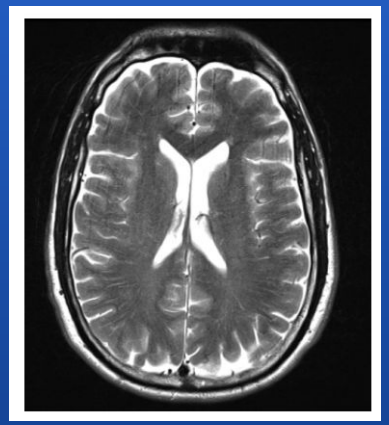
- Data
  - Initially had a relatively small data set (~30-40 images), compared to other traditional machine learning problems, but this was handled by slicing each MRI image into 2D axial images. Each image was subdivided into ~200 slices, yielding a more appropriately-sized data set.
- Normalization / Preprocessing
  - Account for the magnetic field on the MRI by eliminating the highest and lowest 1% intensities.
  - Subtract the mean and divide by the standard deviation within each slice
- Patches
  - Perform mini-batch gradient descent on the patches of each slice.
- Convolutional Neural Network (CNN)
  - Create two CNNS with cascading-architecture, where the output of the first CNN will act as the input of the second.

Problem Formulation: Training Data

- Our project uses training data adopted from BRATS challenge 2013 dataset, consisting of 30 patient datasets, 50 synthetic datasets as well as ground truth data.
- Augment dataset using slicing. Perform segmentation in axial slices.
- Utilizing four different image modalities namely: T1, T2, T1C, and FLAIR.

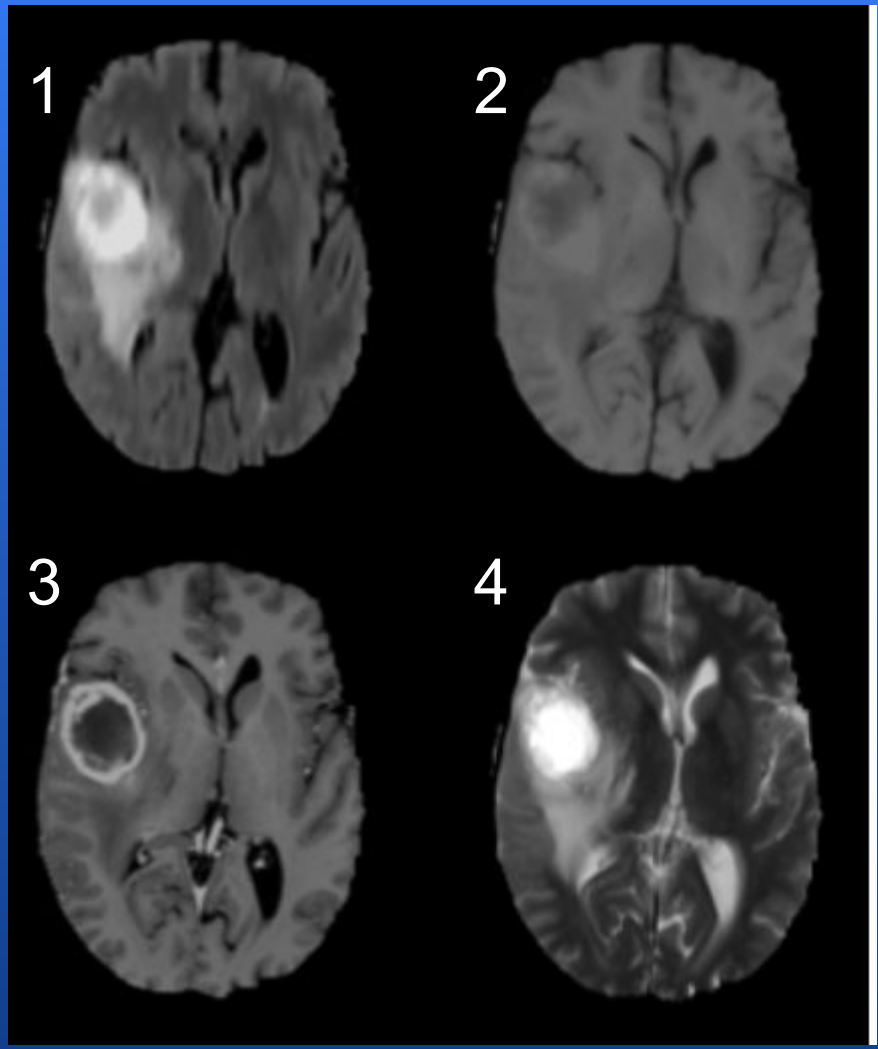


T1: Axial



T2: Axial

("Brain Magnetic Resonance Imaging Technique"2019)



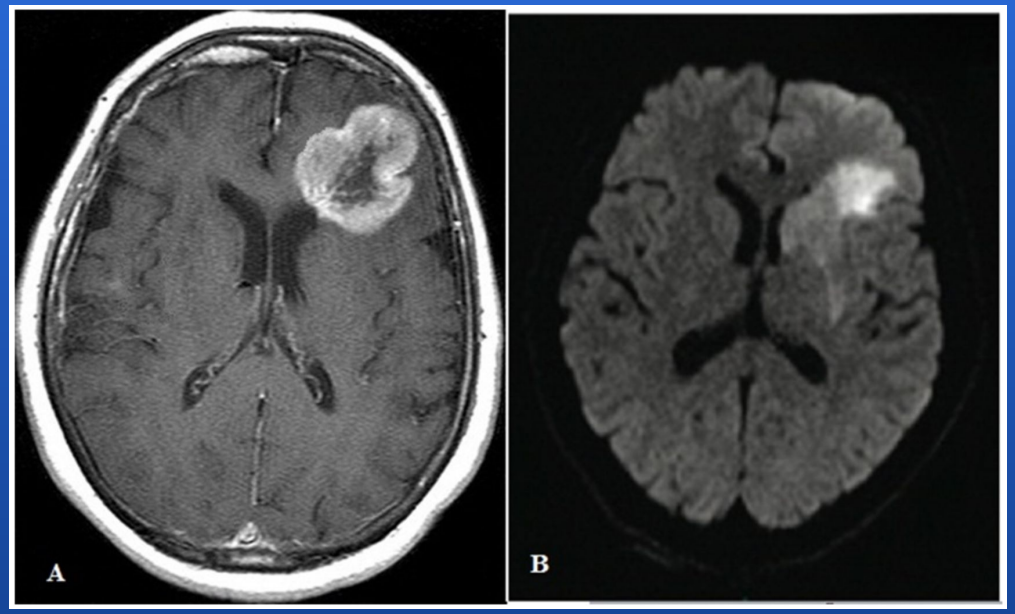
Here is an example of each of the four imaging modalities.

1) FLAIR (Fluid Attenuated Inversion Recovery)
2) T1
3) T1-C
4) T2

Nicole Aldeborgh, 2017

To Visualize...

This is a T1 MRI displaying a high grade glioma in a brain.

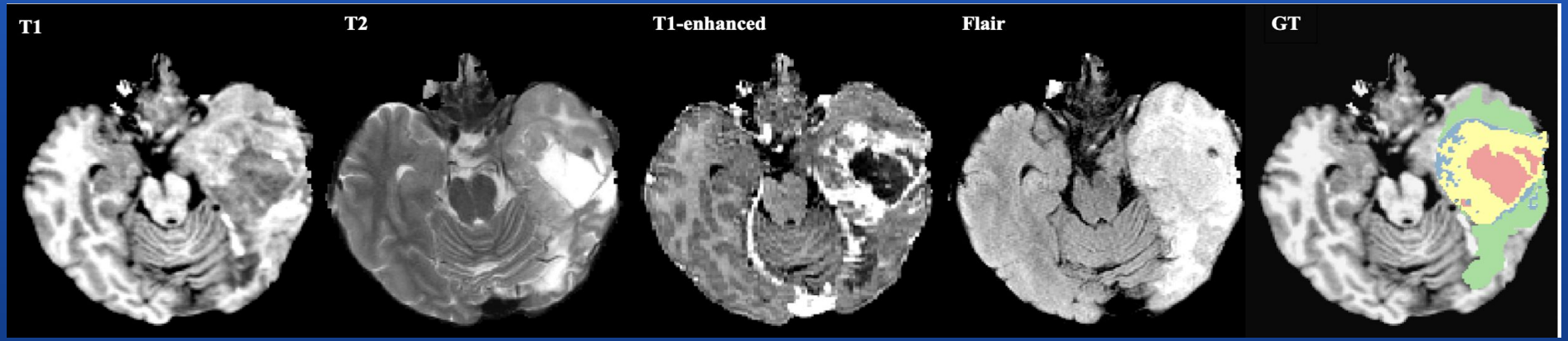


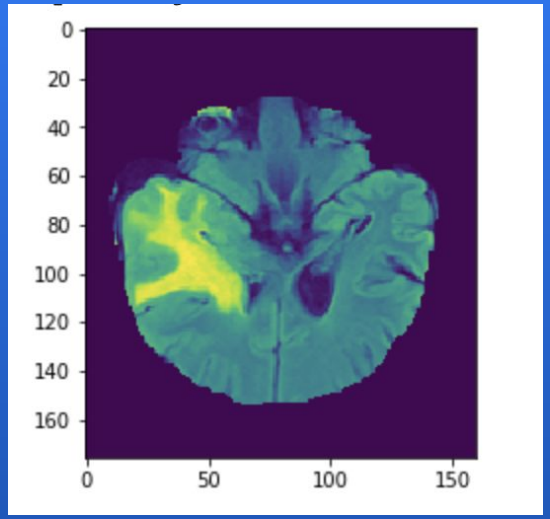
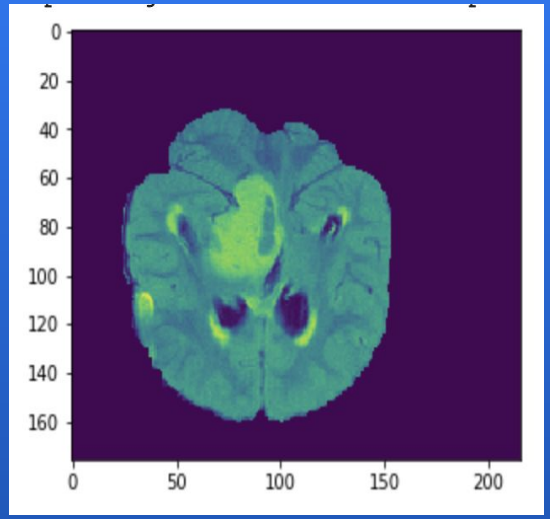
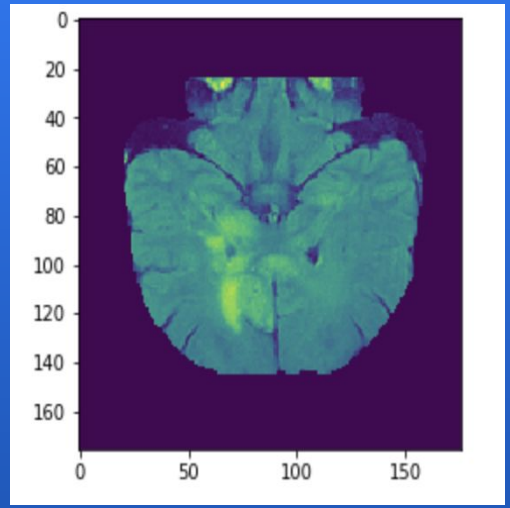
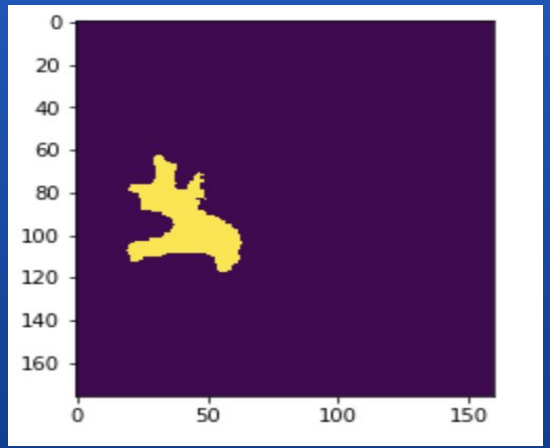
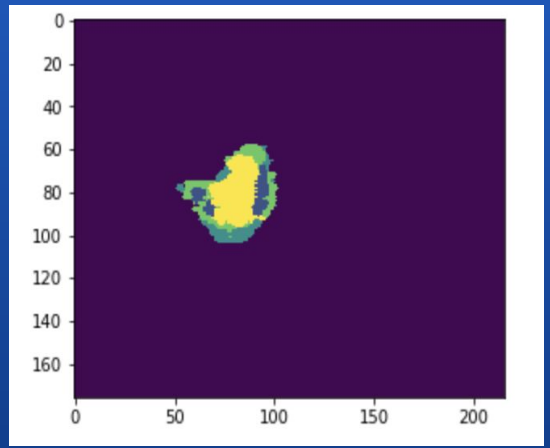
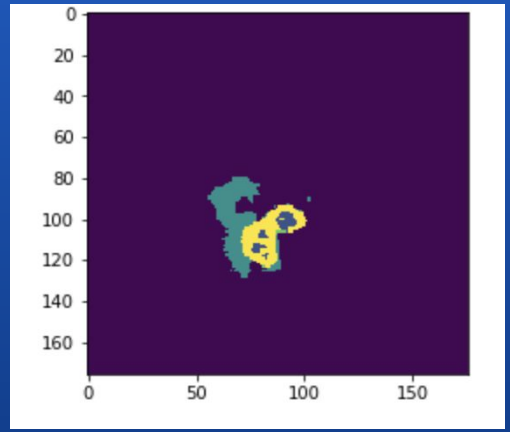
Yasaman Arjmand, Pooya Torkian, Ali Keipourfard

American Journal of Medical Case Reports. **2017**, 5(1), 8-11 doi:10.12691/ajmcr-5-1-3

Training Data, continued…

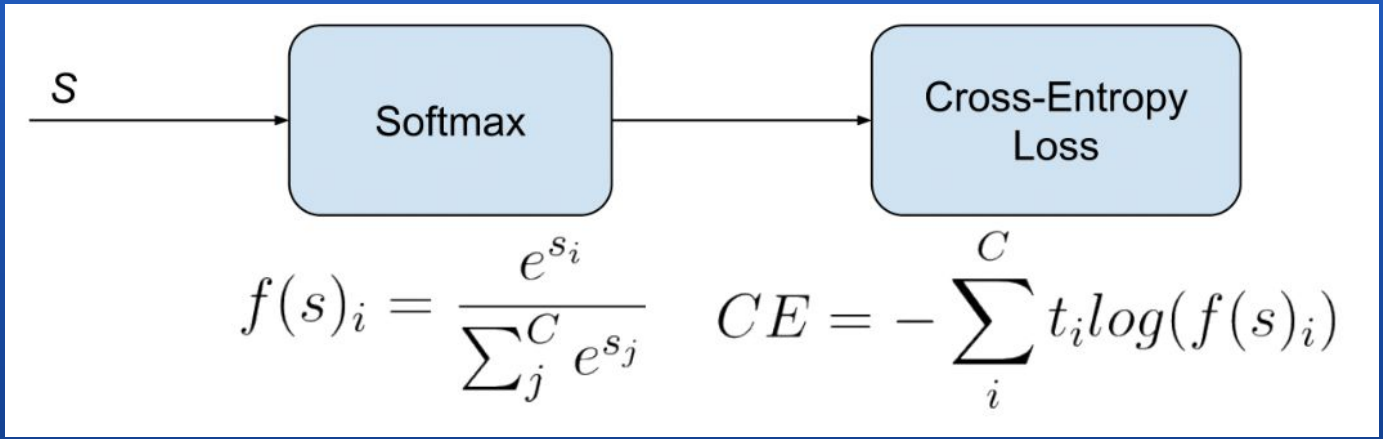
- The training brains come with ground truth for which 5 segmentation labels are provided, namely non-tumor, necrosis, edema, non-enhancing and enhancing tumor.
- In total our model iterates over about 2.2 million examples of tumorous patches and 3.2 million healthy patches, the distribution of examples from all 5 classes is uniform.
- Our model was trained using 2D slices since MRI volumes in the dataset do not possess an isotropic resolution and spacing in the third dimension is not consistent across the data.



Loss Function

- We chose a categorical cross-entropy loss function to use slice by slice on the MRI image pixels.
- Then a weighted loss function was used on the entire set to counteract the skewed nature of the dataset toward healthy voxels instead of tumor tissue.

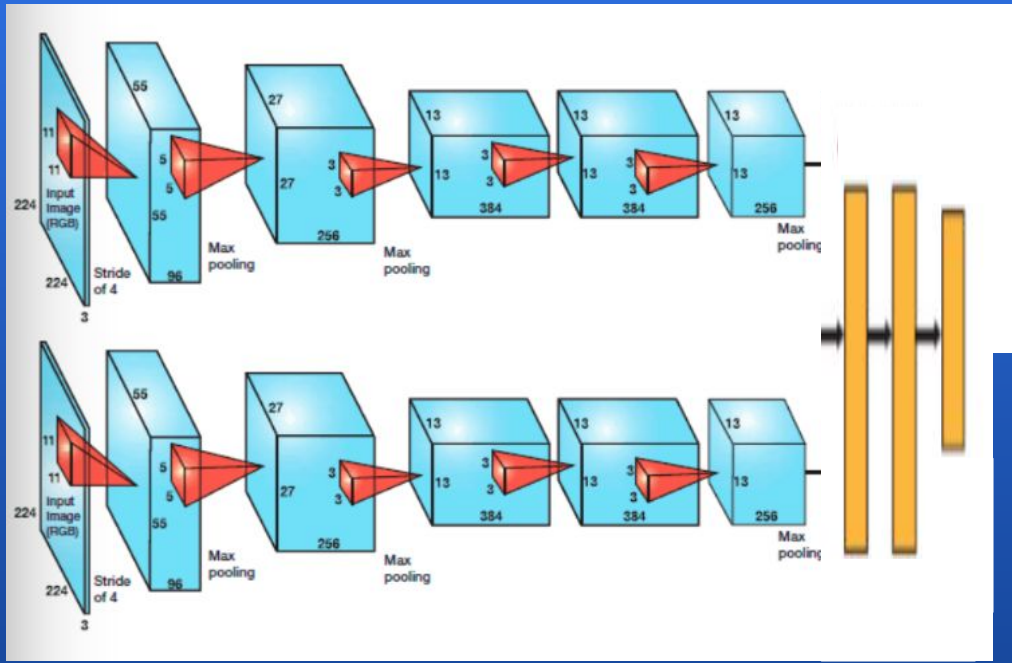


Training Procedure…

- The benefit of using cascading architecture with CNNs is that we are able to achieve a higher degree of discrimination on the images, while still operating at a relatively high performance level.
- Our training criteria is to maximize the probability of all of all labels in our training set which is equivalent to minimizing negative log-probability for each label in the brain, we accomplish this with stochastic gradient descent.
- Due to highly imbalanced nature of our data in the first phase we construct our patches dataset such that all labels are equiprobable. In the second phase we re-train only the output layer, keeping kernels of other layers fixed.
- We used L1/L2 regularization and Dropout to prevent overfitting.

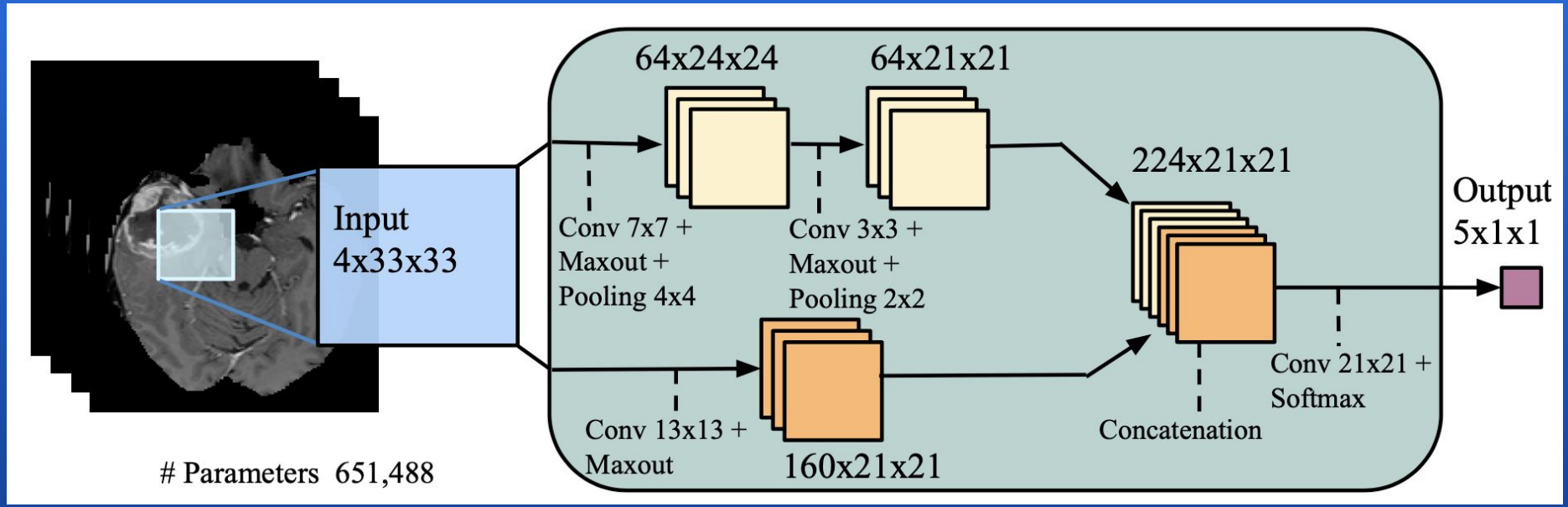
Training Procedure, continued…

The two-path CNN is derivative of multipath convolutional neural network architecture. It creates two paths, one to take source images as input, and the other to take filtered images, then the two paths were concatenated after all the layers were completed. This allows the algorithm to achieve a more comprehensive understanding and classification of image features than if a single-path approach was used. A simple diagram of a classic CNN is shown.

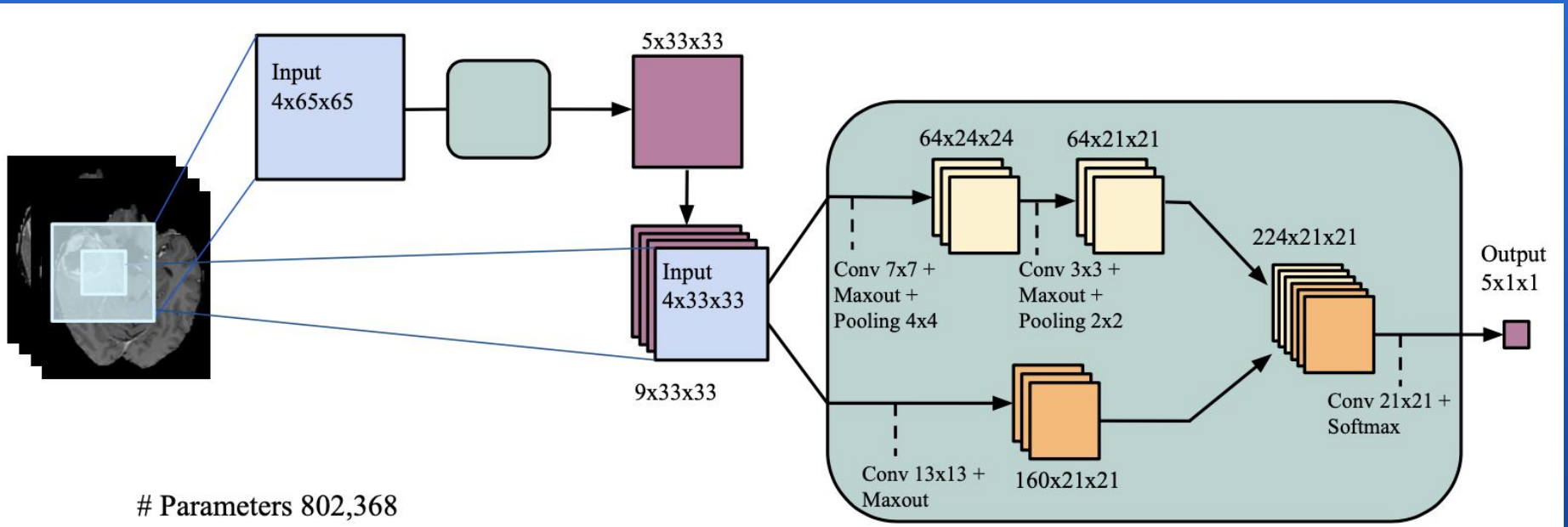


General form of the two-path CNN

Another Visualization of Two-Pathway CNN

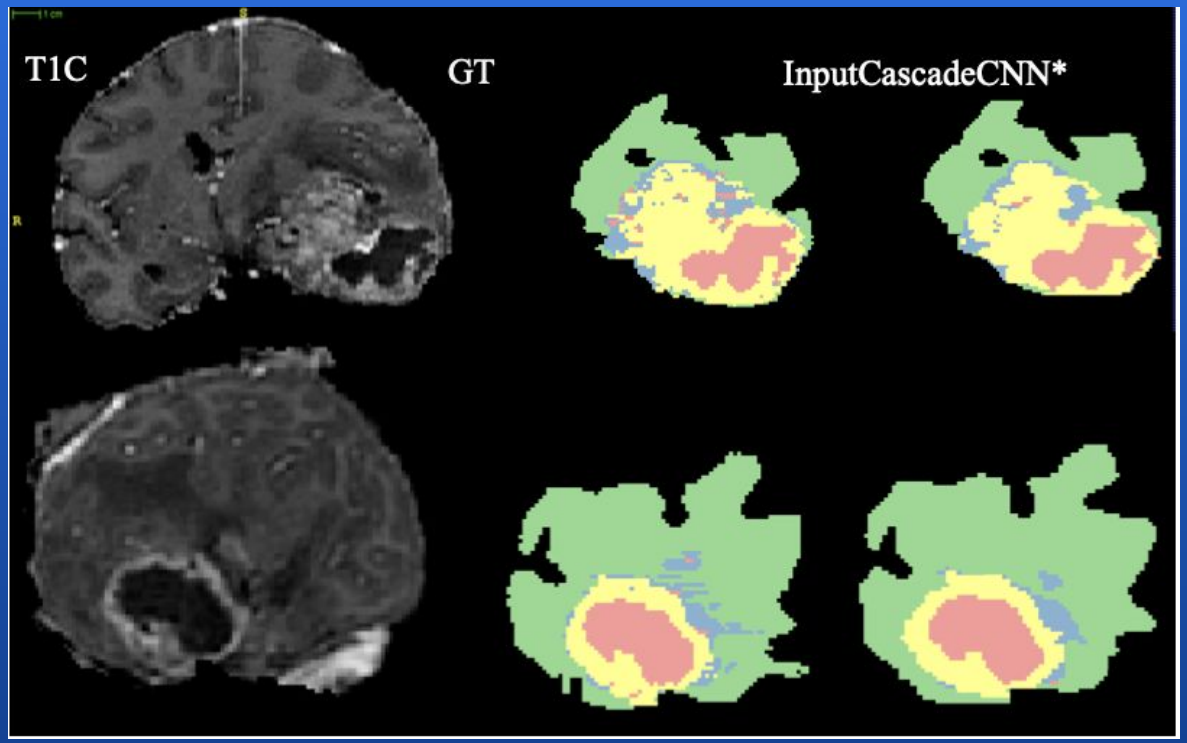


Input Cascade CNN



(a) Cascaded architecture, using input concatenation (InputCascadeCNN).

Evaluation Results Visualization



	BRAIN SLICE	F1 SCORE
0	HG 0004 Slice 113	0.8995
1	HG 0004 Slice 96	0.8375
2	HG 0011 Slice 113	0.9288
3	LG 0004 Slice 113	0.9591
4	LG 0004 Slice 111	0.9626
5	HG 0007 Slice 113	0.9676
6	HG 0007 Slice 96	0.9794
7	LG 0013 Slice 78	0.9878
8	LG 0013 Slice 113	0.9519

Evaluation Results Explained

- The functionality of our model was evaluated by the f1 score. Which takes into the consideration the precision (p) and recall (r) to compute a ratio between 0, and 1. The ideal f1 score is exactly 1, or as close as possible.
- Because our data was an unbalanced class, f1 was more valuable than other evaluation metrics.
- As an intermediary step, the accuracy was used to ensure that the model was working correctly at the epoch level.
    - Can't use accuracy as testing value due to the skewed nature of the dataset (98%:2% ratio of healthy voxels to unhealthy ones).
    - In theory, we could still achieve a high accuracy despite misclassifying images as false negatives, because the number of positive results is so small compared to the rest of the dataset.
- Of the f1 scores on the previous slide, the average value = 0.9375.

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"Figure 2f from: Irimia R, Gottschling M (2016) Taxonomic Revision of Rochefortia Sw. (Ehretiaceae, Boraginales). Biodiversity Data Journal 4: e7720. Https://Doi.org/10.3897/BDJ.4.e7720." doi:10.3897/bdj.4.e7720.figure2f.

Figure 1. A: T1-Weighted MRI Shows Enhanced Lesion with Peripheral Edema on Left Frontal Area, Compatible with High Grade Glioma. B: Left Frontal Area of Same Patient Has Hyper Intense Signal in Diffusion Weighted Imaging (DWI), Compatible with Ischemic Area : Radiologic Evaluation of Patients with Glioblastoma Multiforme Who Initially Presented with Ischemic Stroke: A Case Series : Science and Education Publishing, http://pubs.sciepub.com/ajmcr/5/1/3/figure/1.

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