Glioblastoma (GBM) is an especially aggressive tumor that accounts for over 50% of brain tissue tumor cases. To better understand GBM’s, we must first have easy access to their image data within MR scans, and this necessitates segmentation of the GBM region from the surrounding brain. Better yet, the GBM can also be classified into four sub-categories: necrosis, edema, non-enhancing, and enhancing.

Goals
- Automatic Segmentation, if proven effective, will save a lot of human time in the segmentation step of GBM image processing, which will allow for highly efficient quantitative feature mining of these images. **Goals:**
  - Find a feature space right for the data.
  - Find the optimal ML algorithm to learn the data.
  - Automatically detect and segment GBM.

Data
- 2015 MICCAI BRATS (Brain Tumor Segmentation):
  - 220 High Grade Glioblastoma (HGG)
  - 54 Low Grade Glioblastoma (LGG).
- MR Modalities: [FLAIR, T1 Pre-Contrast; T2 Weighted, T1 POST-Contrast]
- Pre-processed: Skull-Stripped, Registration, Scale Normalization

Overview

Methodology

Feature Space
- Data Problem: Each patient has millions of voxels of information but only a few hundred patients. Consider voxels independently to increase n. (Bias ↑ Variance ↓)
  - \( X \in \mathbb{R}^{274 \times 6} \rightarrow y \in \{0,1\}^{274 \times 1} \)

Convolution
- Convolution with filters to get features.
  - \([f \ast g](t) = \int_0^\infty f(\tau) g(t-\tau) d\tau\)
- Even though we consider each voxel completely independently, we still couple environmental information.

Neural Network
- 72 Input
- Binary Output
- 2 Hidden Layer
- 10 Neurons Ea.
- 4 Nets for Each Subregion

Results

Choosing Neural Network

GBM Segmentation

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