Brain Tumor Segmentation:

As a part of brain tumor study, we at BrainsightAI are developing deep learning algorithms for automated brain tumor segmentation. Brain tumor segmentation is one of the most challenging problems in medical image processing due to their variable shape and appearance in multimodal MRI scans.

We used large , high quality dataset consisting of multi modal MRI brain scan with corresponding segmentation mask from The Brain Tumor Segmentation Challenge(BraTS).

BraTS dataset consists of four different modalities -

1.) Native T1w
2.) Post-contrast T1-weighted(T1Gd)
3.) T2-weighted
4.) T2 Fluid Attenuated Inversion Recovery(T2-FLAIR)

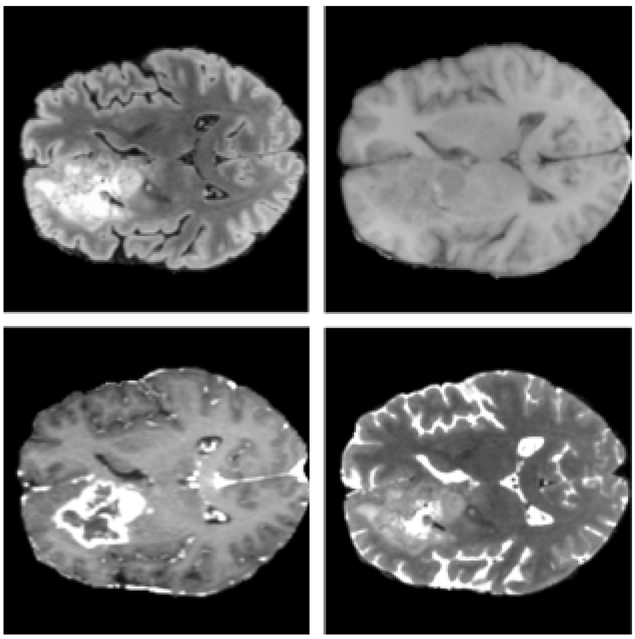


Fig. 1. Example with ID 00000 from the BraTS21 training dataset. Each subplot presents a different modality. From top left to bottom right: FLAIR, T1, T1Gd T2.

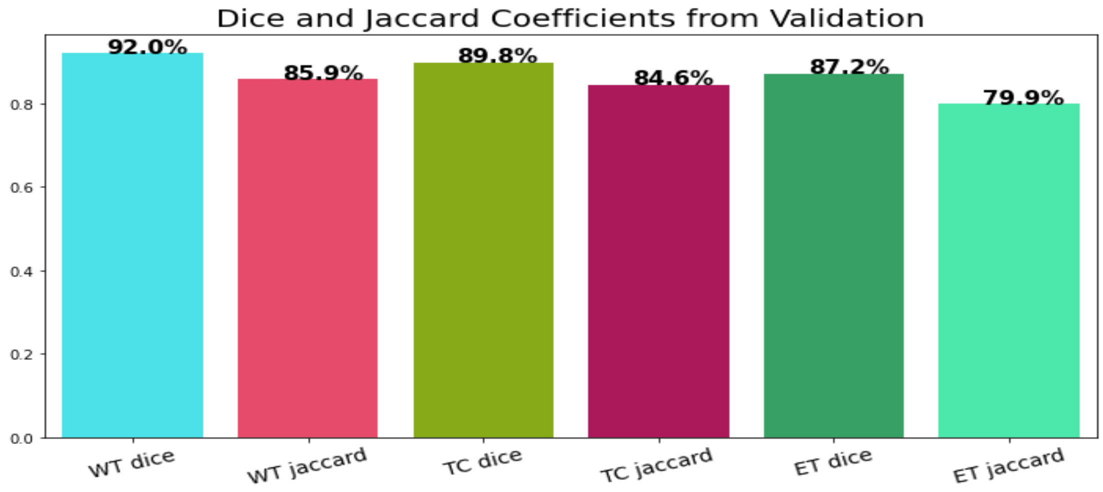
Annotation consists of four classes -

1.) Enhancing Tumor - **ET**
2.) Peritumoral edimatous tissue - **ED**
3.) Necrotic Tumor Core - **NCR**
4.) Background - Voxels that are not part of the tumor

For the purpose of training the model the classes present in the label were converted to partially overlapping region - Whole tumor (WT) , Tumor Core (TC) and Enhancing tumor (ET)

Results:

- **Mean Dice score - 89.6**
- **WT dice score - 92**
- **ET dice score - 87.2**
- **TC dice score - 89.8**
- **NCR dice score - 88.1**



WT - Whole Tumor
TC - Tumor Core
ET - Enhancing Tumor
NCR - Necrotic Tumor core

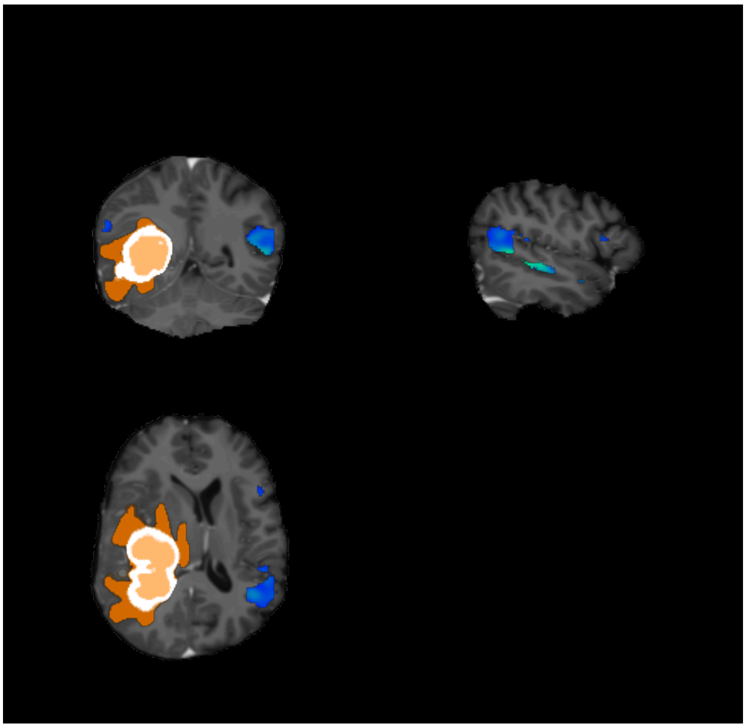
References:

1. **nnU-Net for Brain Tumor Segmentation:** https://arxiv.org/pdf/2011.00848.pdf
2. **Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks:** https://arxiv.org/pdf/1705.03820.pdf
3. **Optimized U-Net for Brain Tumor Segmentation:** https://arxiv.org/pdf/2110.03352.pdf
4. **NVIDIA Brain Tumor Segmentation Results for MICCAI BRATS 2021 Dataset:** https://developer.nvidia.com/blog/nvidia-data-scientists-take-top-spots-in-miccai-2021-brain-tumor-segmentation-challenge/
5. http://braintumorsegmentation.org/

Connectomic Analysis using VoxelBox Plus - Network Mapping & Functional Connectivity of the brain using rs-fMRI:

VoxelBox Plus generates functional connectivity within the regions of the brain based on different atlas parcellations (like Human Connectome Project's Atlas), and localises the activity of the brain's functional networks like Visual, Language, Motor, Sensory, Salience, Default Mode Network, Central Executive Network, Auditory using the processed resting state functional MRI with statistical algorithm called Dynamic Independent Component Analysis (DynICA).

The DynICA algorithm decomposes the processed resting state fMRI into independent network components that match with the networks from Human Connectome Project's atlas (Primary Visual, Visual, Language, Motor, Sensory, Salience, Central Executive Network, Auditory, Default Mode Network). The individual network components are mapped based on a statistical target network comparison algorithm that compares individual network components with HCP based networks to dynamically threshold the network component based on statistical significance and Region-of-Interests as per networks to obtain clean and accurate maps of the networks.



Tumor Segmentation & Language Network Localization using VoxelBox+

Future Works:

- Develop a deep learning algorithm (Generative Adversarial Network or Convolutional Neural Network) that uses functional connectomes obtained from rs-fMRI to localise the subject's scan into several functional networks based on activations from rs-fMRI and tb-fMRI to map task positive and resting state networks.
- Optimise network localization to produce robust and accurate activations in ROIs.

References:

1. **ReStNeuMap: a tool for automatic extraction of resting-state functional MRI networks in neurosurgical practice:** https://thejns.org/view/journals/j-neurosurg/131/3/article-p764.xml

   a. **Methodology:** Independent Component Analysis based network activity localization using rs-fMRI for language, sensorimotor, and primary visual cortical areas using a template matching algorithm based on FIND atlas.
   b. **Intent:** An automated algorithm to do network localization of the brain using rs-fMRI for presurgical planning.
2. **Mapping language function with task-based vs. resting-state functional MRI: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7394427/**
   a. **Methodology:** Statistical group-level analysis of tb-fMRI and rs-fMRI for language network of 35 patients done during the course of pre-surgical evaluation to find out inter-subject variability of response magnitude and sensitivity/specificity analysis of response topography.
   b. **Observations/Results:** Both tb-fMRI and rs-fMRI were able to localise the language network's components. tb-fMRI also activated task-general areas not specific to language while rs-fMRI produced specific and more symmetrical activations of the language system.
3. **Replication of Resting State-Task Network Correspondence and Novel Findings on Brain Network Activation During Task fMRI in the Human Connectome Project Study: https://www.nature.com/articles/s41598-018-35209-6**
   a. **Methodology:** Statistical analysis of task based activations vs resting state activations of different task positive and resting state networks using the Human Connectome Project's dataset of 1100 individuals.
   b. **Observations/Results:** Networks localised using Task-based fMRI are in correspondence with networks slocalized by rs-fMRI and resting state networks are also replicated by task based fMRI. Some network's activations in rs-fMRI as well as tb-fMRI were degraded due to machine specific scenarios such as high noise.
4. **A multi-modal parcellation of human cerebral cortex (Glasser Atlas/Human Connectome Project's atlas): https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4990127/**
   a. **Intent:** An atlas parcellation of the brain using gradient-based parcellation, & Independent Component Analysis on the Human Connectome Project's dataset of 1200 healthy control subjects.
5. **Mapping of the Language Network With Deep Learning:** https://www.frontiersin.org/articles/10.3389/fneur.2020.00819/full
   a. **Intent:** A 3DCNN based approach to localise language networks using rs-fMRI in patients with tumors and comparison of the same with tb-fMRI. The model has achieved ~95% ROC-AUC in localising Broca's and Wernicke's area.

Tractography using Diffusion Tensor Imaging (DTI):

Generation of Optic Radiation, Inferior Longitudinal Fasciculus, Superior Longitudinal Fasciculus, CorticoSpinal Tract, Arcuate Fasciculus, Frontal Aslant Tract, Inferior Fronto-Occipital Fasciculus Tracts using Diffusion Tensor Imaging with tensor-based processing pipeline (distributed computing for speed) and deep learning based eddy current correction and denoising (for accuracy).

Future Works:

- Building an Eddy Current Correction and Denoising algorithm for DTI using Deep Learning to produce high-resolution and accurate tracts.
- Tract Generation and Optimization using Deep Learning algorithm for accurate polygons of the subject’s tracts.

References: