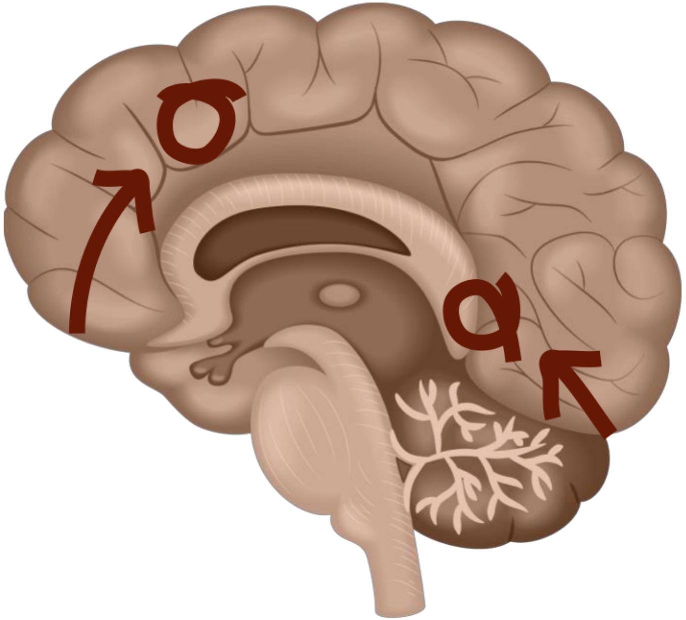
Low-Grade Glioma Segmentation

Prepared By Eda AYDIN



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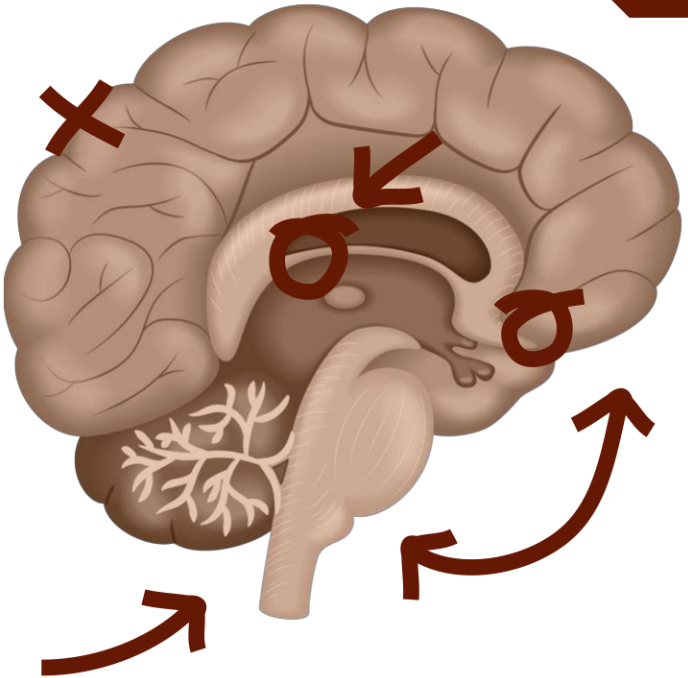
My Journey



My Journey

B.Eng. in Computer Engineering

2014 - 2019

Got a job as an Artificial Intelligence Intern

2019

Micro Master in Artificial Intelligence - Neural Engineering Program

2021 - Present

Graduate Research Student in AI for Neuroscience

2021- Present

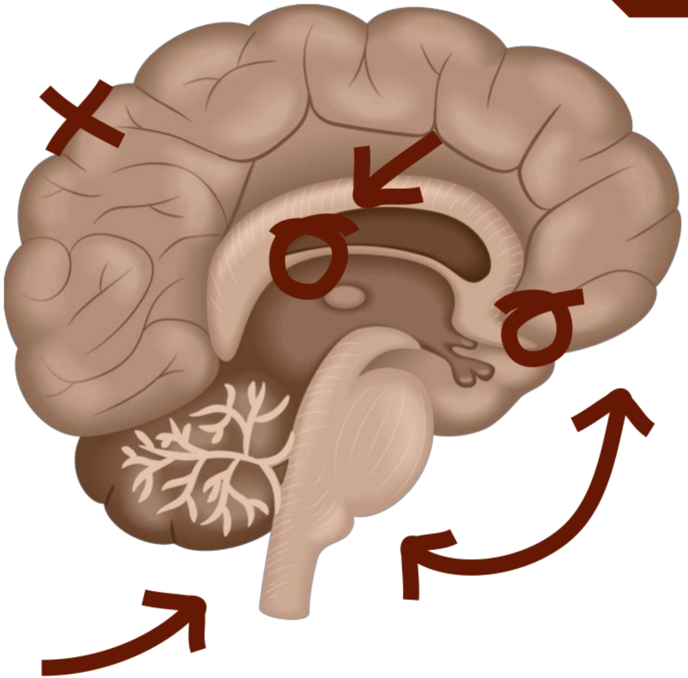
UpSchool - Google Developers

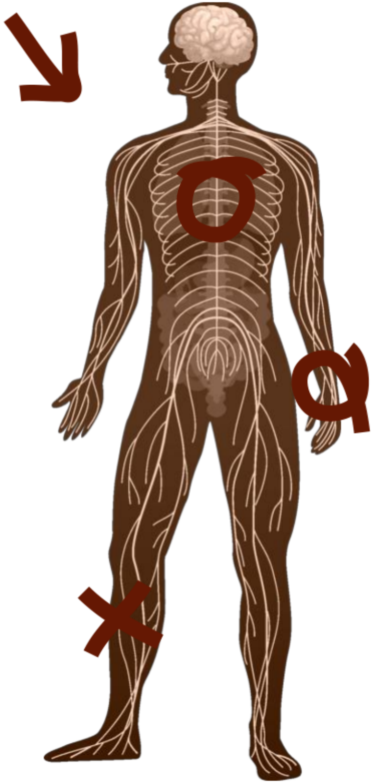
ML Program

2022- Present

02

Business Understanding



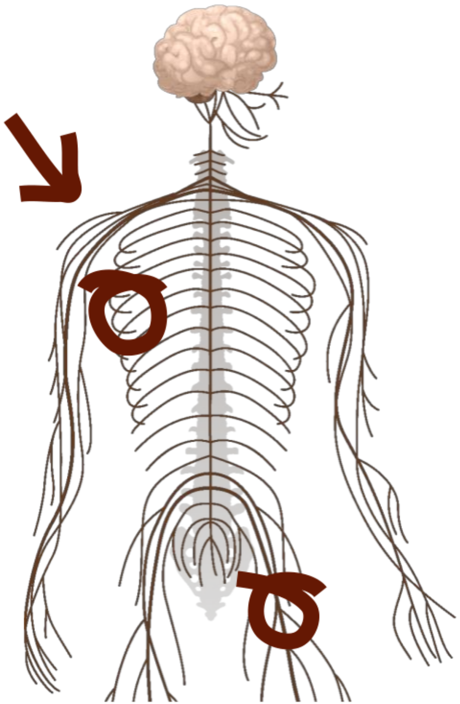


What is the Low-Grade Glioma?

- A type of brain tumor is classified as a grade II and III tumor
- Arises from the supporting cells of the brain called glial cells
- Generally benign
    - Cause significant neurological symptoms
    - Pressure on the surrounding brain tissue
- Most common in adults, but also occurs in children
- Treated with surgery, radiation therapy

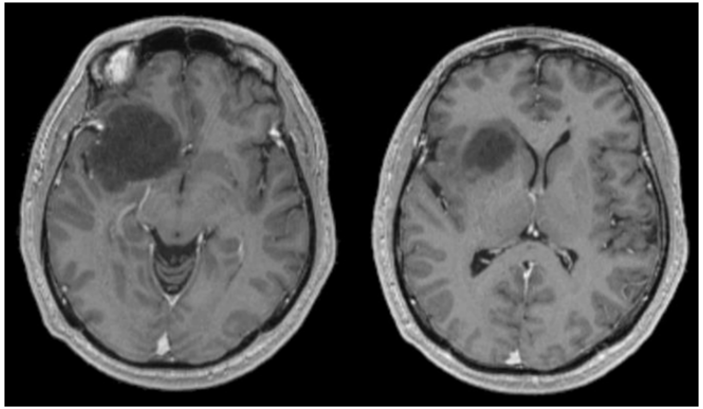
Why deep learning should be used?

- Allows for the accurate identification of tumor boundaries in MRI scans.
- Without deep learning, time-consuming
- Can be challenging due to the infiltrative nature
- Leading to potential misdiagnosis
- Improve efficiency and accuracy

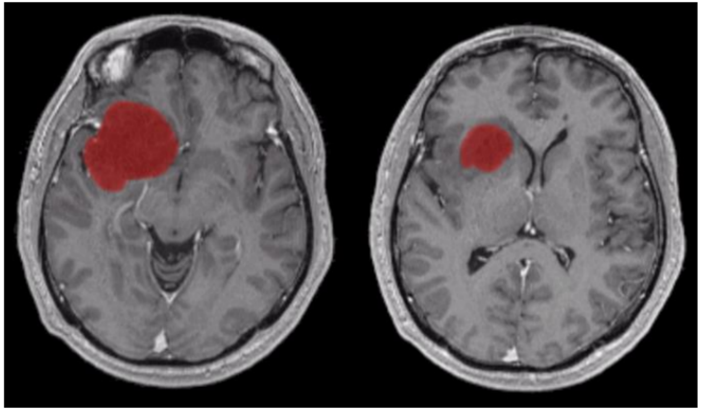


UP School

Example of Low-Grade Glioma



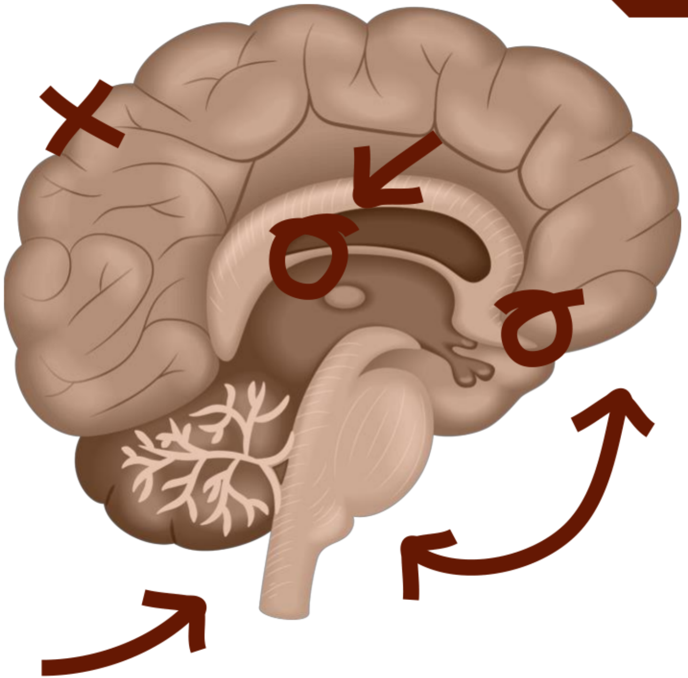
Without Segmentation



With Segmentation

03

Data Understading



Data Information

- Obtained from The Cancer Imaging Archive (TCIA)
- Contains Brain MRI images with manual FLAIR abnormality segmentation masks
- 110 patients
- CSV dataset
  - 110 rows – 18 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110 entries, 0 to 109
Data columns (total 18 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Patient                     110 non-null    object
 1   RNASeqCluster               92 non-null     float64
 2   MethylationCluster          109 non-null    float64
 3   miRNACluster                110 non-null    int64
 4   CNCluster                   108 non-null    float64
 5   RPPACluster                 98 non-null     float64
 6   OncosignCluster             105 non-null    float64
 7   COCCluster                  110 non-null    int64
 8   histological_type           109 non-null    float64
 9   neoplasm_histologic_grade   109 non-null    float64
 10  tumor_tissue_site           109 non-null    float64
 11  laterality                  109 non-null    float64
 12  tumor_location              109 non-null    float64
 13  gender                      109 non-null    float64
 14  age_at_initial_pathologic   109 non-null    float64
 15  race                        108 non-null    float64
 16  ethnicity                   102 non-null    float64
 17  death01                     109 non-null    float64
dtypes: float64(15), int64(2), object(1)
memory usage: 15.6+ KB
```

Taking a look at dataset

10 rows ∨ 10 rows × 18 columns

	Patient	RNASeqCluster	MethylationCluster	miRNACluster	CNCluster	RPPACluster	OncosignCluster	COCCluster
0	TCGA_CS_4941	2.0	4.0	2	2.0	NaN	3.0	2
1	TCGA_CS_4942	1.0	5.0	2	1.0	1.0	2.0	1
2	TCGA_CS_4943	1.0	5.0	2	1.0	2.0	2.0	1
3	TCGA_CS_4944	NaN	5.0	2	1.0	2.0	1.0	1
4	TCGA_CS_5393	4.0	5.0	2	1.0	2.0	3.0	1
5	TCGA_CS_5395	2.0	4.0	2	2.0	NaN	3.0	2
6	TCGA_CS_5396	3.0	3.0	2	3.0	2.0	2.0	3
7	TCGA_CS_5397	NaN	4.0	1	2.0	3.0	3.0	2
8	TCGA_CS_6186	2.0	4.0	1	2.0	1.0	3.0	2
9	TCGA_CS_6188	2.0	4.0	3	2.0	3.0	3.0	2

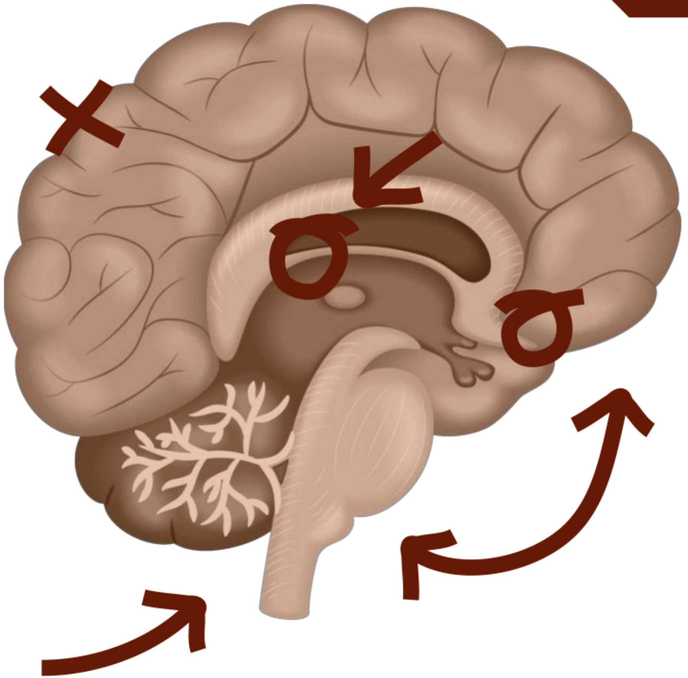
Creating the new dataset

5 rows ⌄ 5 rows × 4 columns

	patient_id	image_path	mask_path	diagnosis
0	TCGA_DU_7010_19860307	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	0
1	TCGA_DU_7010_19860307	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	0
2	TCGA_DU_7010_19860307	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	0
3	TCGA_DU_7010_19860307	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	0
4	TCGA_DU_7010_19860307	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	/kaggle/input/lgg-mri-segmentation/kaggle_3m/T...	0

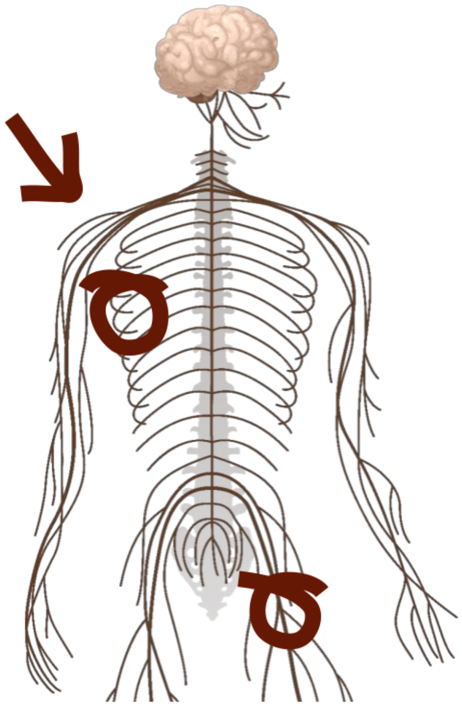
04

Data Visualization

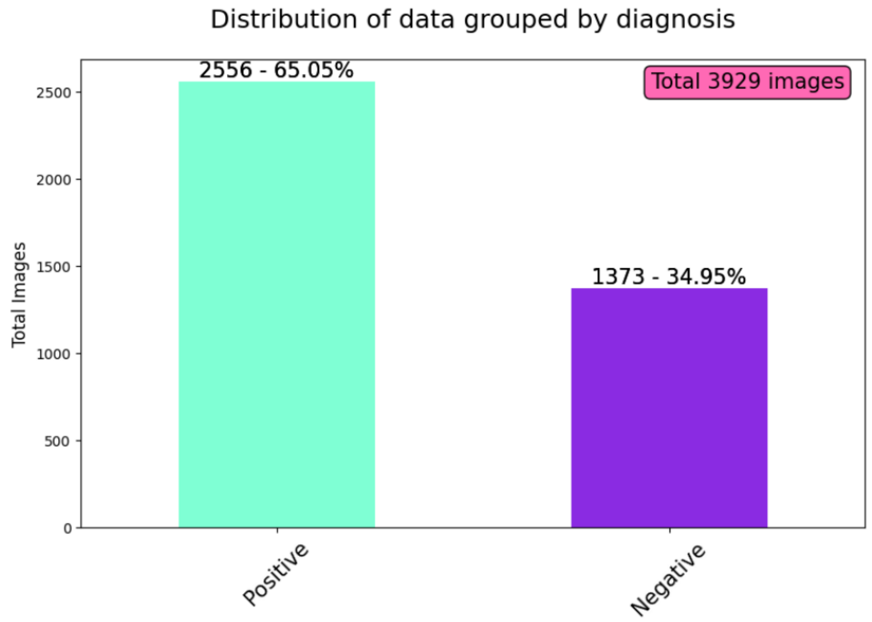


04.1

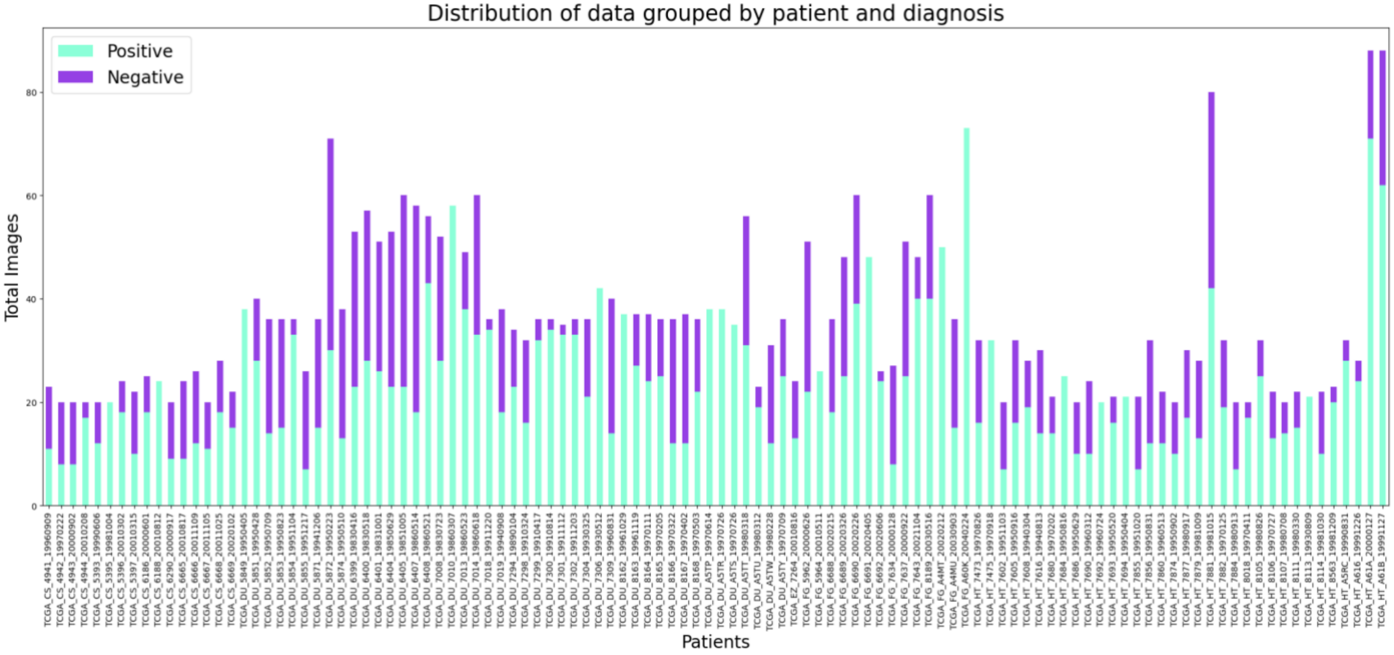
Distribution



Distribution

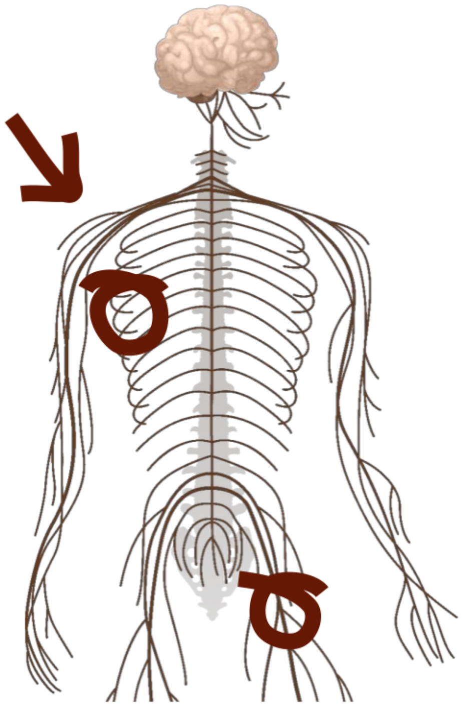


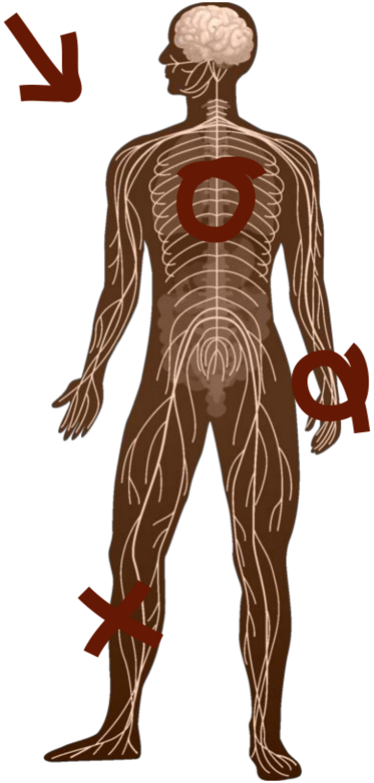
Distribution of data grouped by patient and diagnosis



04.2

Visualization of Brain MRI Images

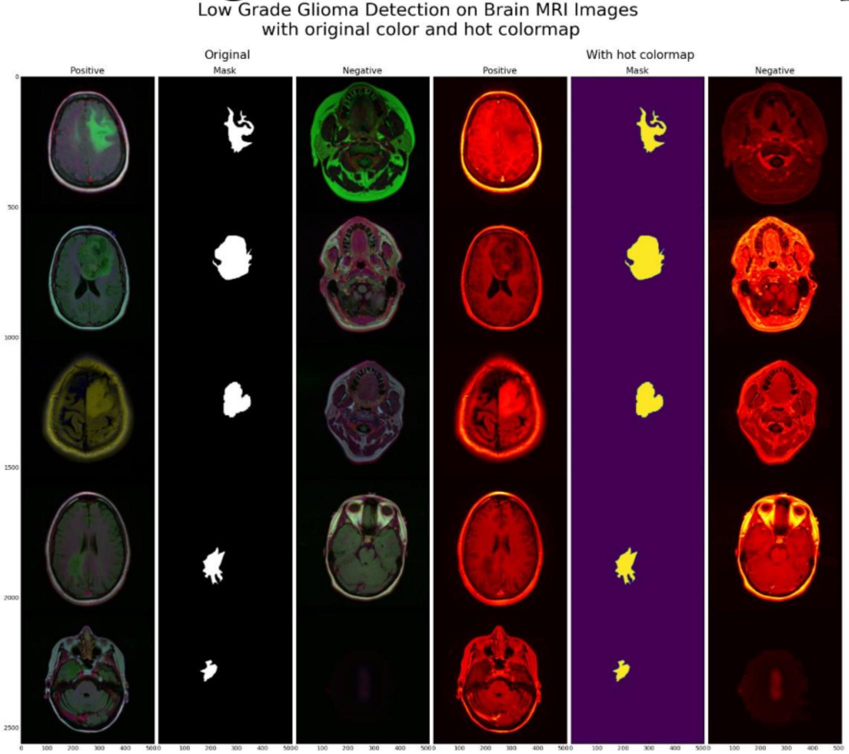




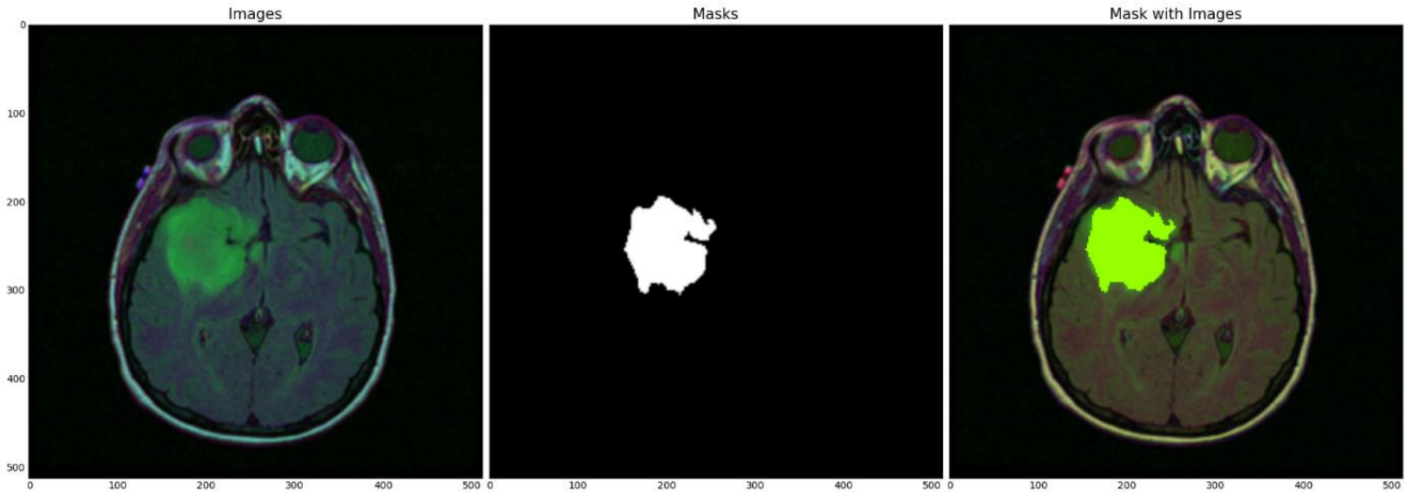
Why is the hot-colormap important?

- Highlight different tissue types in the brain based on their MRI intensities
- Low-intesity values to dark colors (black)
- High-intensity values to bright colors (red, yellow, and white)
- Distinguish different structures in the brain such as grey matter, and white matter.
- Differentiating between healthy and abnormal tissue, such as tumors.

Low-Grade Glioma on Brain MRI Images with original color and hot colormap

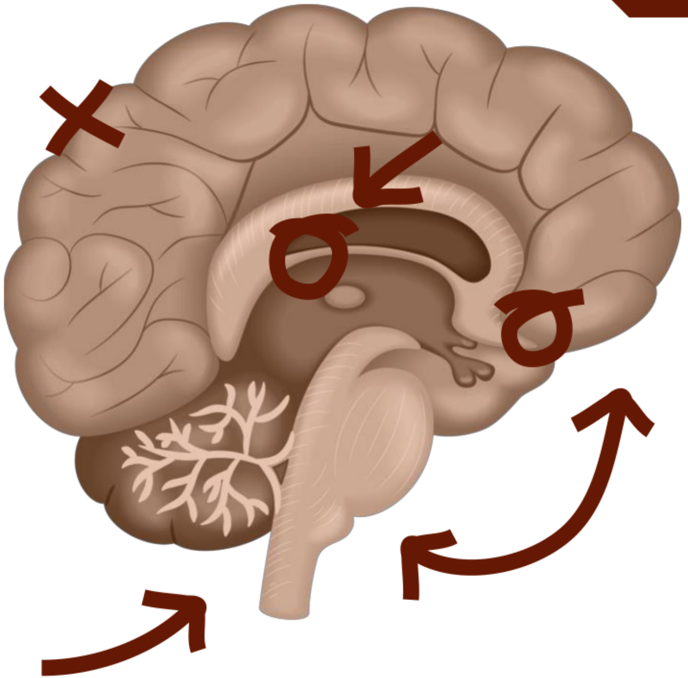


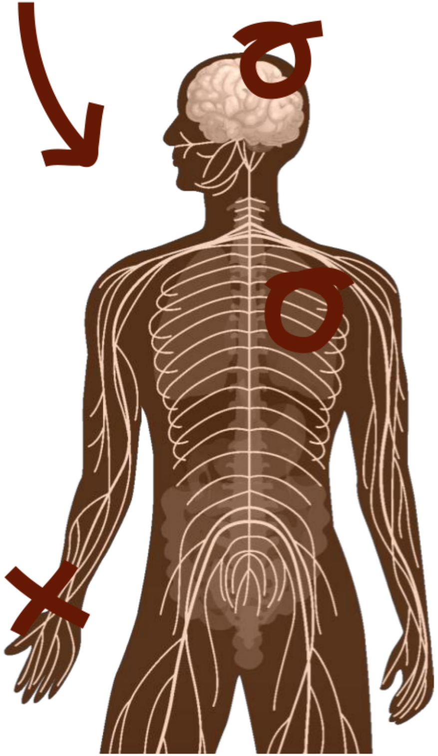
Tumor location is shown as segmented on a Brain MRI Images



05

Data Augmentation

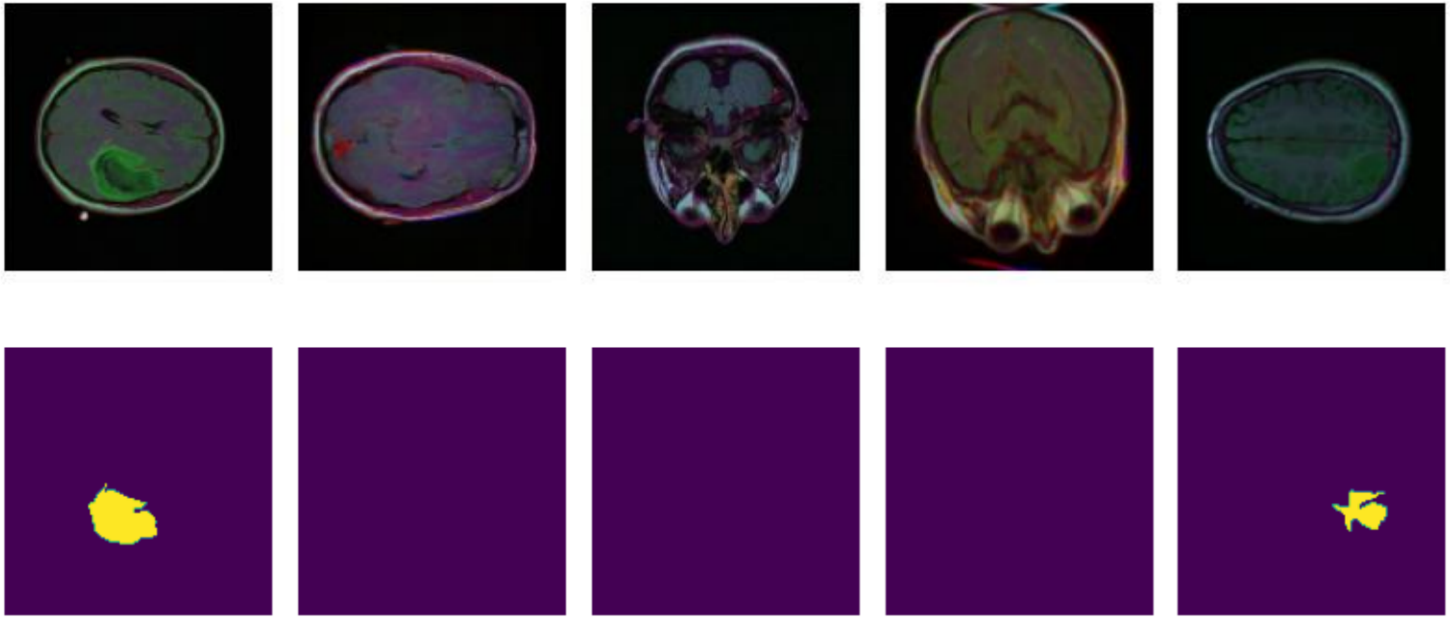




Why the Albumentations library is important?

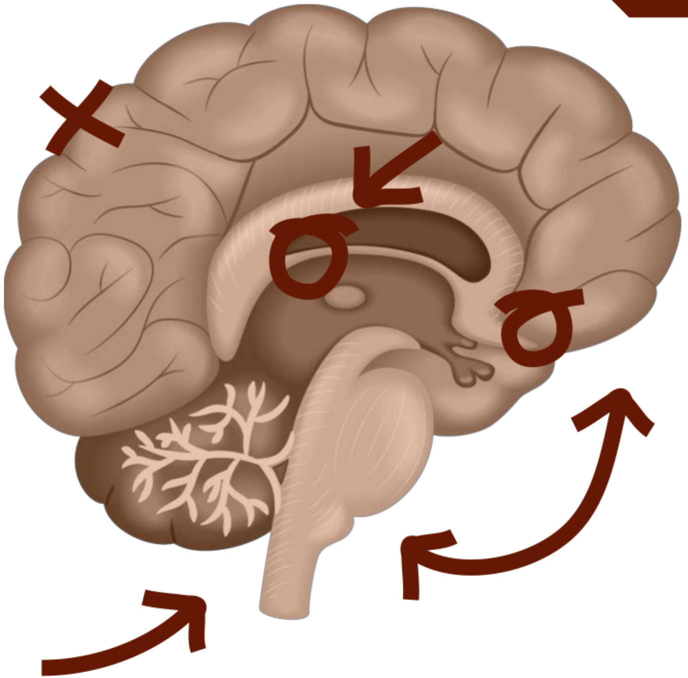
- Wide range of image segmentation techniques that can be applied to medical images
- Easy composition of multiple augmentations together
- Techniques
    - Elastic information | Grid - Optical Distortion
    - Brightness,
    - Constrant changes
    - Random rotation

Augmented Brain MRI and Mask Images



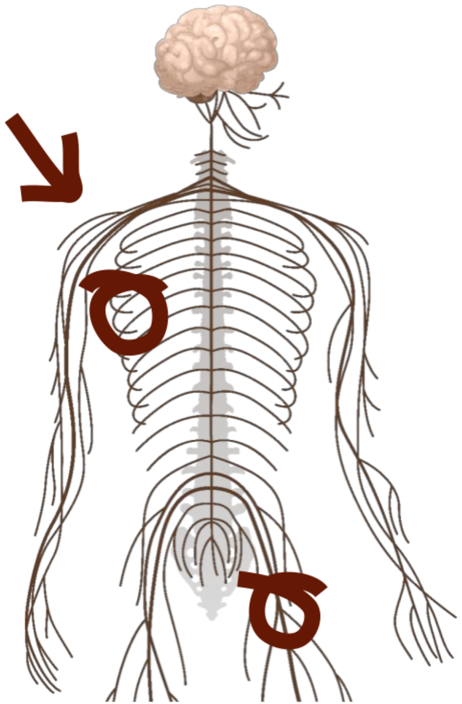
06

Modeling



Why PyTorch instead of TensorFlow?

- Easier to work with the Albumentation library and for complex tasks such as segmentation
- Dynamic computational graphs
- Models need to adapt to different input shapes and sizes.



Model Information and Decision

U-Net

A specific type of FCN that is designed for biomedical image Segmentation
Composed of an encoder and a decoder
Widely used in brain tumor segmentation

Feature Pyramid Network (FPN)

A type of deep neural network architecture that is designed for object detection and semantic segmentation
Top of CNN
Pyramid of feature maps

ResUNet

A type of CNN that used residual connections between layers to allow the network
UNet + ResNet

Models Architecture

U-Net

15 convolutional
14 rectified linear units (ReLU)
3 max-pooling layers
3 up-sampling layer

Feature Pyramid Network (FPN)

18 convolutional
10 rectified linear units (ReLU)
5 max-pooling layers
1 top-down layer
3 sampling addition layers
3 smooth layers
1 up-sampling layer

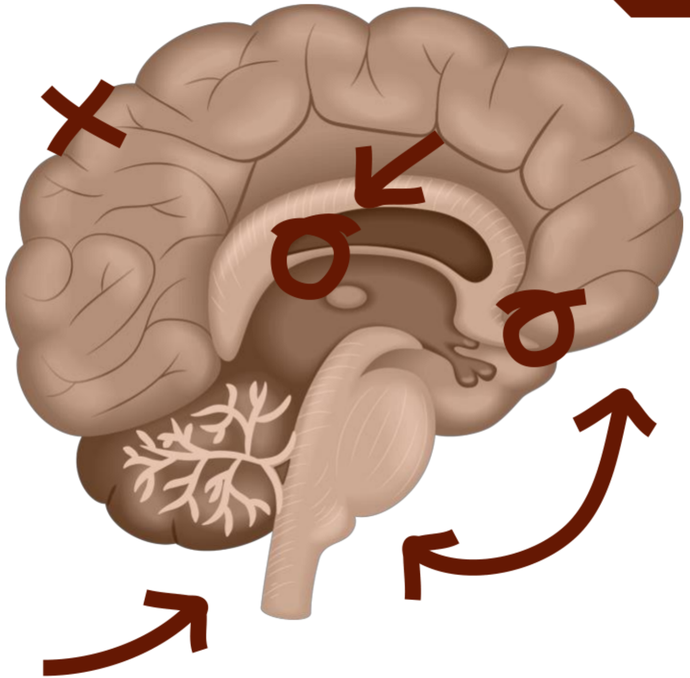
ResUNet

Pretrained model (ResNet50-32x4d model)
5 down-sampling layers
4 up-sampling layers
2 convolutional
1 rectified linear unit (ReLU)

Note: Dice Coefficient Metric is used as the Segmentation quality metric.
Dice Coefficient Loss is used as the Segmentation loss.

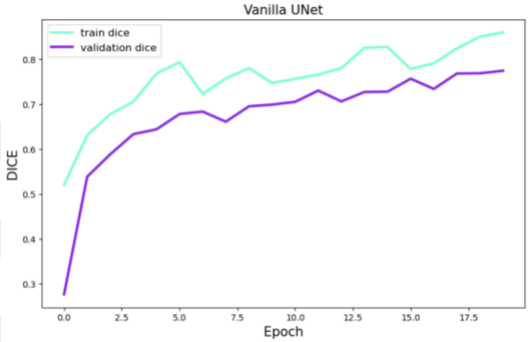
07

Evaluation

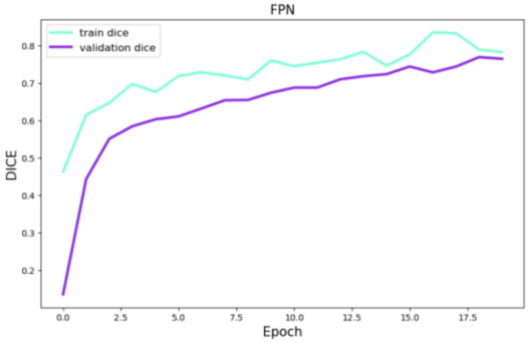


Evaluation of the Model Architectures on Training and Validation Data

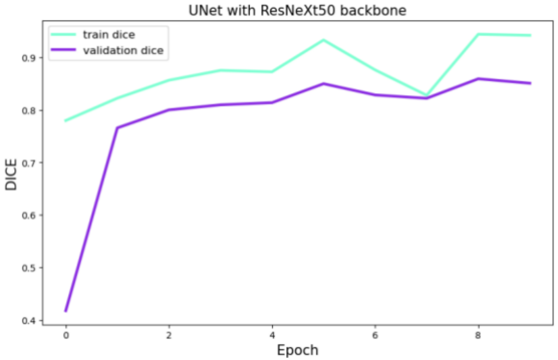
U-Net



Feature Pyramid Network (FPN)



ResUNet



Evaluation of the Model Architecture on Test Data

U-Net

```
Vanilla UNet
Mean IoU of the test images - 83.0%
```

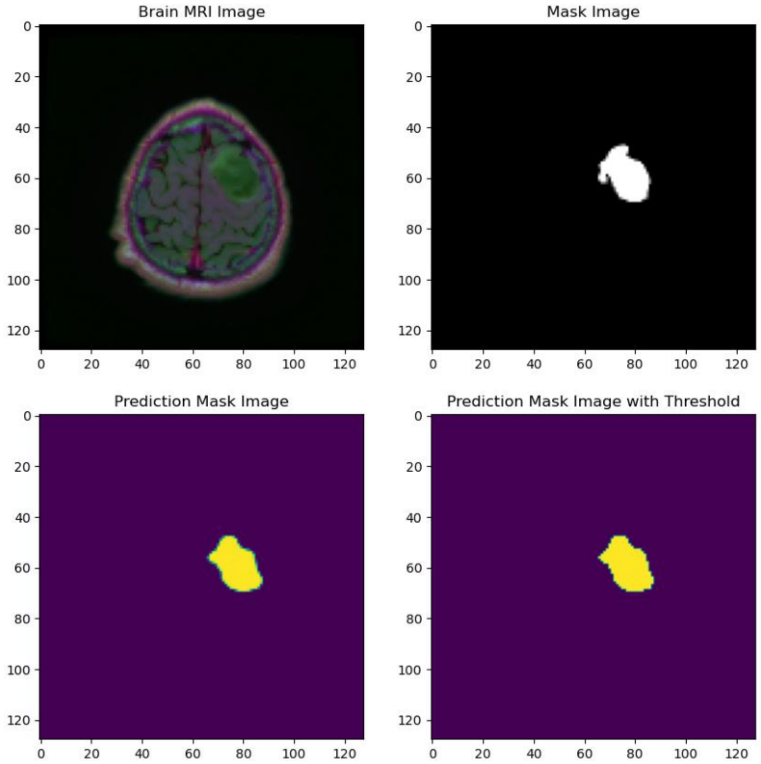
Feature Pyramid Network (FPN)

```
FPN
Mean IoU of the test images - 78.0%
```

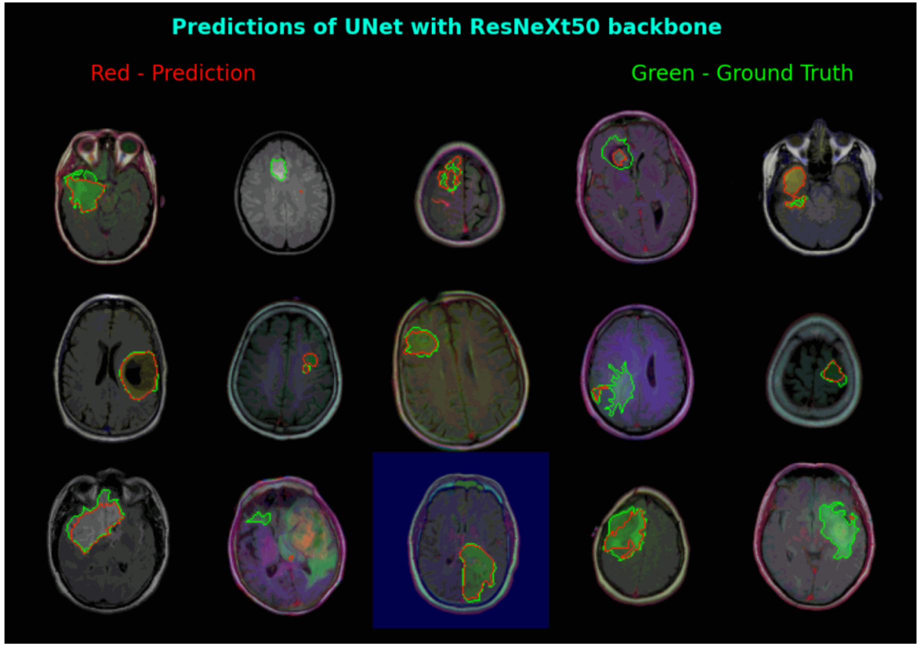
ResUNet

```
UNet with ResNeXt50 backbone
Mean IoU of the test images - 89.0%
```

Evaluation of the Random Test Sample

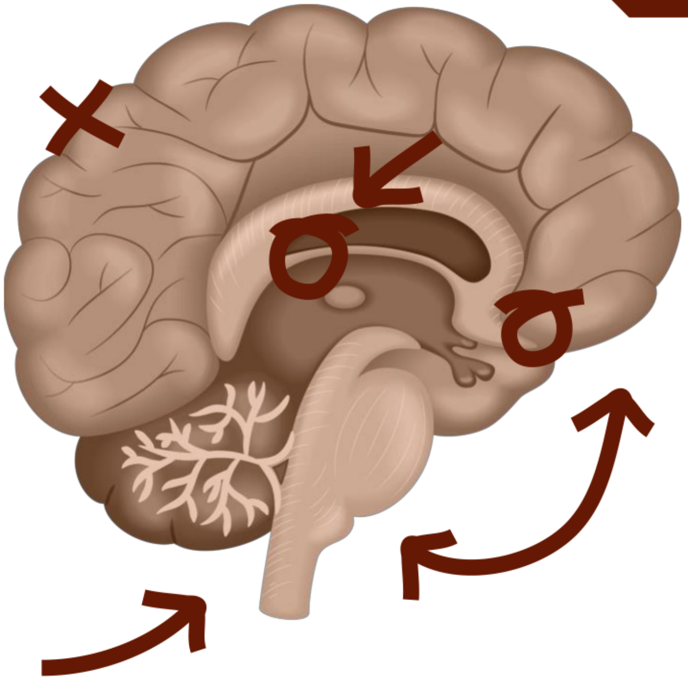


Evaluation of the Prediction and Ground Truth Masks on the Brain MRI Images



08

Core Skills



Core Skills

Soft Skills I gained

- Resillience
- Self-compassion
- Time Management

Soft Skills we gained as a group

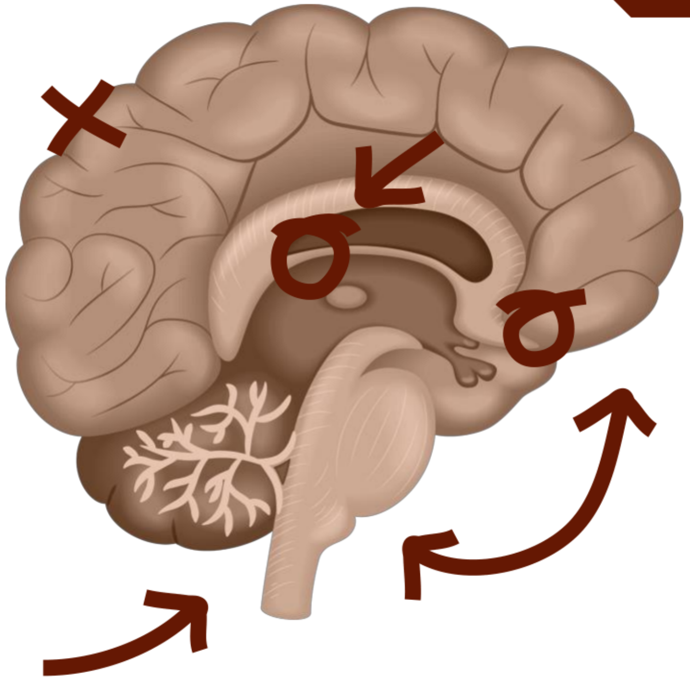
- Teamwork
- Sisterhood
- Communication

Love yourself, appreciate yourself, see the good in you and respect yourself.

BETTY SHABAZZ

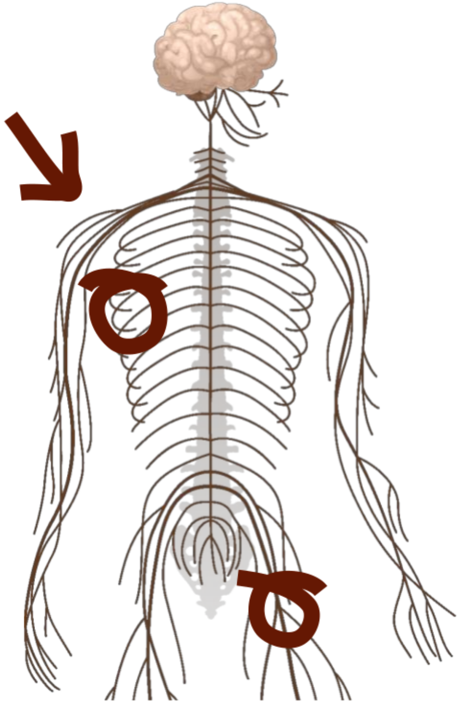
09

Resources



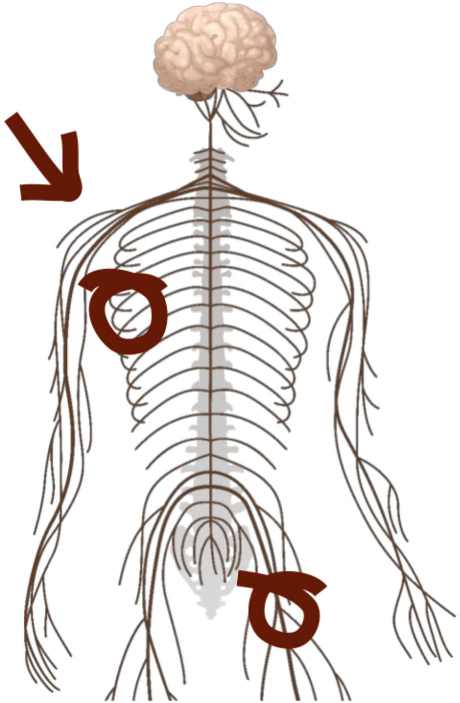
Articles

- Automatic Segmentation and Shape, Texture-based Analysis of Glioma Using a Fully Convolutional Network
- Low-grade gliomas
- Fluid-Attenuated Inversion Recovery Magnetic Resonance Imaging Detects Cortical and Juxtacortical Multiple Sclerosis Lesions
- Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm
- Data Augmentation for Brain-Tumor Segmentation
- Brain tumor image segmentation using Deep learning
- Comparison of Jaccard, Dice, and Cosine Similarity Coefficient To Find Best Fitness Value
- Albumentations: Fast and Flexible Image Augmentations



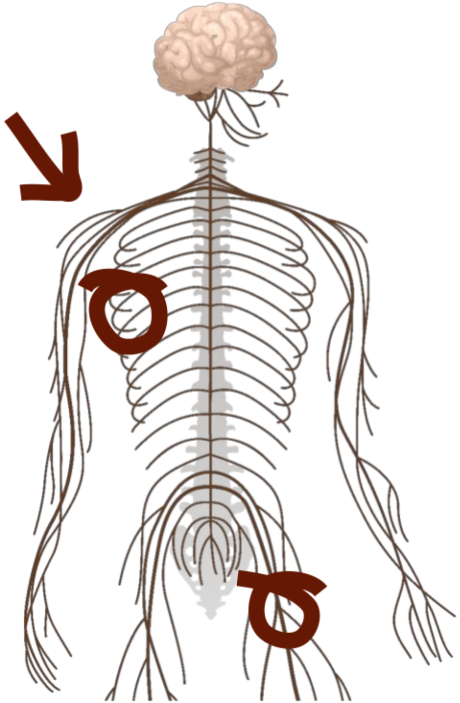
Blog Posts - Slides

- Feature Pyramid Network (Object Detection)
- A Unified Architecture for Instance and Semantic Segmentation
- Understanding Feature Pyramid Networks for object detection (FPN)
- Carvana Image Masking Challenge–1st Place Winner's Interview



Websites

- LGG-1p19qDeletion - The Cancer Imaging Archive (TCIA) Public Access
- Albumentations Documentation
- Papers with Code - U-Net Explained
- Papers with Code - Brain Tumor Segmentation
- Deep learning-based skull stripping and FLAIR abnormality segmentation in brain MRI using U-Net
- Brain MRI | Data Visualization | UNet | FPN
- BrainMRI|UNet|FPN|ResNeXt50
- Brain MRI Detection | Segmentation | ResUNet
- Brain MRI Segmentation



Thank you!