# Brain Tumor Segmentation using MRI Image

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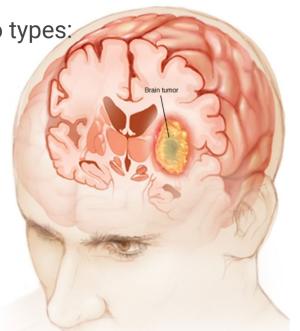
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### Introduction

- Brain tumor is of two types:
  - Primary brain tumor
  - Secondary brain tumor

Gliomas are primary brain tumors and they are of two types:

- HGG = High Grade Glioma
  - Malignant brain tumor
  - Requires surgery and radiotherapy
- LGG = Low Grade Glioma



### Introduction

- Deep learning models have been used for segmentation task
- Each MRI image contains 3 types of tumor:
  - Enhancing Tumor
  - Non-Enhancing Tumor
  - Edema Tumor

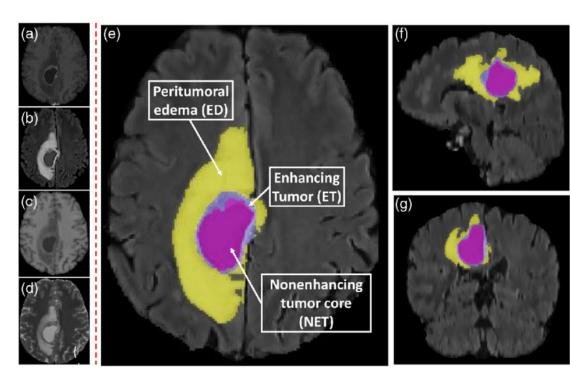
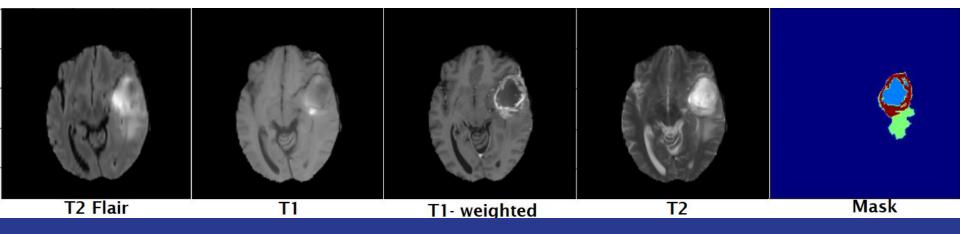


Fig: (a)T1 (b) T1-weighted (c) T2 Flair (d) T2 (e) axial view of Segmented Brain Tumor MRI Image (f) sagittal view (g) coronal view

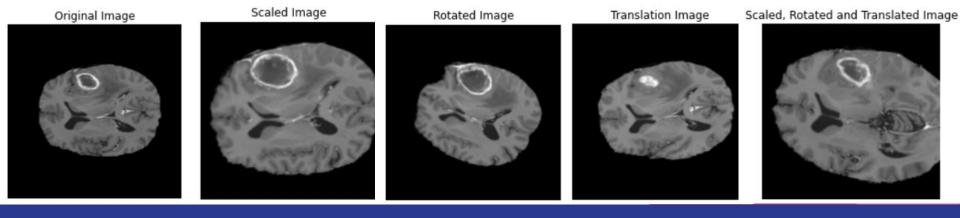
### BraTS'19 Dataset

- The dataset contains 259 MRI scans of patients with high-grade gliomas (HGG).
- Each MRI image is of size 240x240x155.
- The dataset contains MRI image of 4 different modalities.
- Each image contains three types of tumor: Non-enhancing Necrotic tumor (NET), enhancing tumor (ET), and edema (ED) tumor.



# Preprocessing data

- In biomedical field, the dataset is not freely available
  - Images can only be annotated by experts.
- BraTS'19 dataset contains only 259 MRI images along with their labelled mask.
- For data augmentation, the 3D MRI image is scaled, rotated and translated.

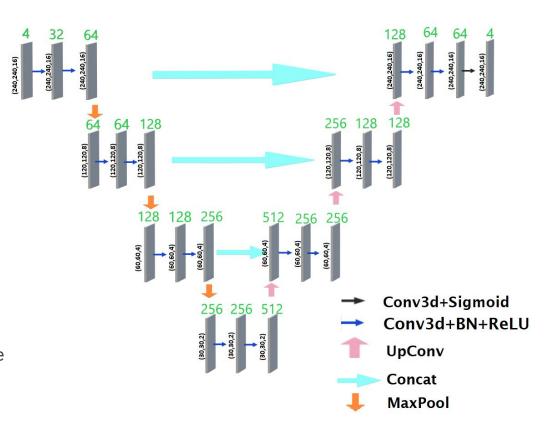


# Segmentation Models

### **UNet 3D**

#### Two parts

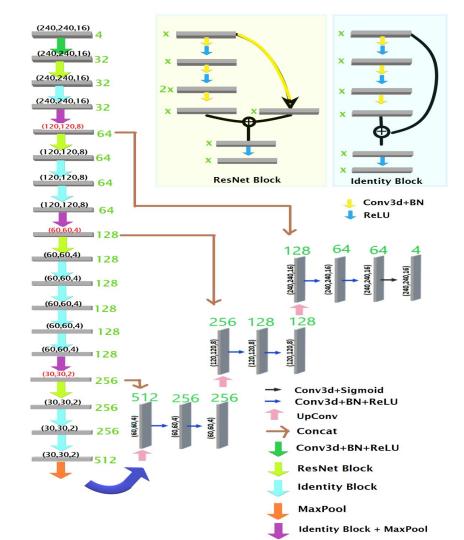
- Downsampling part
  - Feature channels doubled
  - Decreasing the Image size
- Upsampling part
  - Upconvolution of image
  - Concatenation of feature maps
    - Localizing information
  - Final layer: 1x1 convolution
    - 64-feature maps -> 4-feature maps



### ResUnet

#### Two parts

- Downsampling path => ResNet
  - Skip connections used
    - Overcome vanishing gradient problem
  - Max Pooling done for concatenation
  - 3x3x3 Convolutional layer + BN + ReLU
- Upsampling path => Unet 3D
  - Upconvolution of image
  - Concatenation of feature maps
    - Localizing information
  - Final layer: 1x1 convolution
    - 64-feature maps -> 4-feature maps

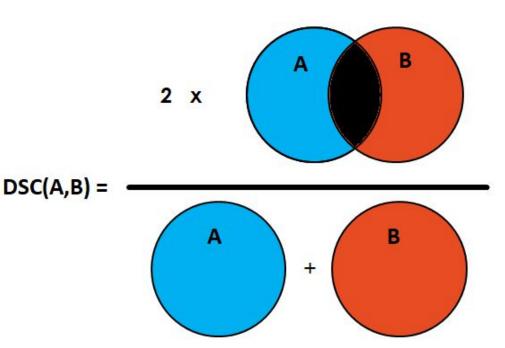


### **Loss Function**

#### **Dice Coefficient**

- Measures similarity between 2 images
- Range of dice coefficient => [0,1]
  - 1 => completely similar
  - 0 => completely different
- Loss = (1- Dice Coefficient)

$$DSC(f, x, y) = \frac{2 \times \sum_{i,j} f(x)_{ij} \times y_{ij} + \epsilon}{\sum_{i,j} f(x)_{ij} + \sum_{i,j} y_{ij} + \epsilon}$$



where,

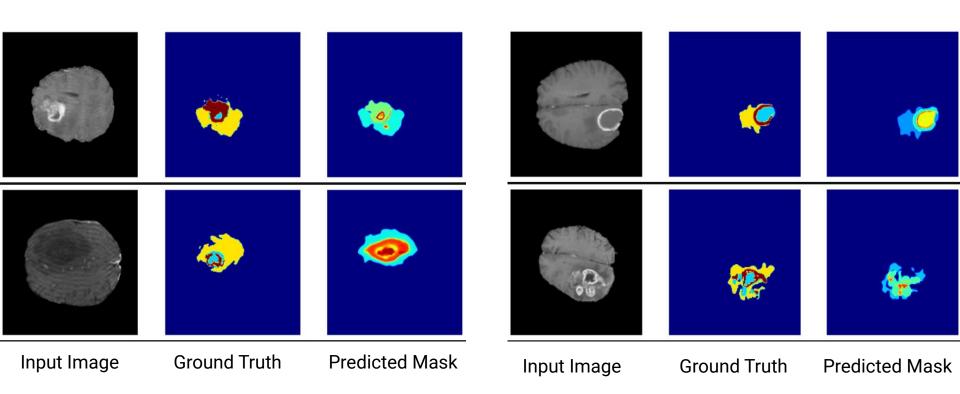
x = input image

f(x) = predicted image

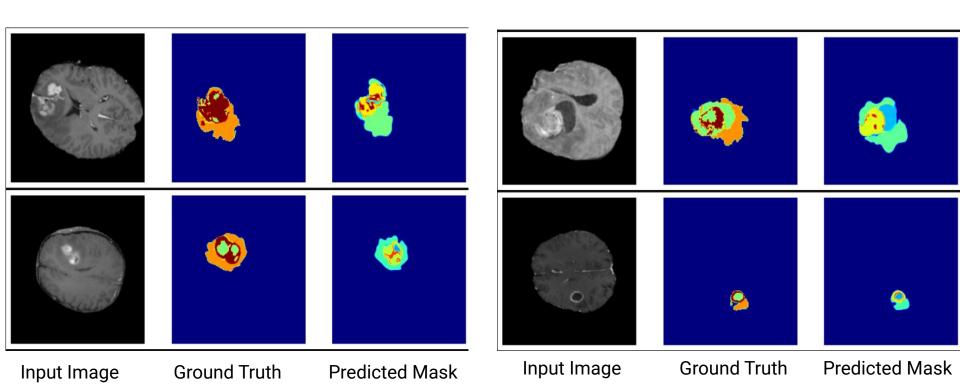
y = ground truth

 $\epsilon$  = small number added to avoid division by zero error

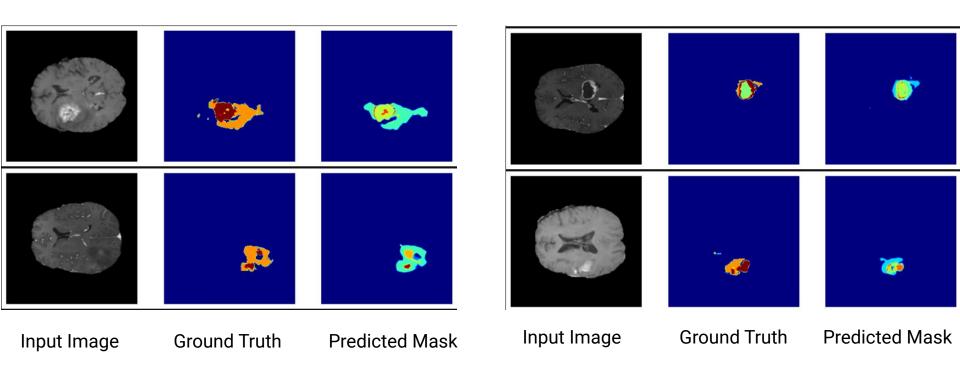
# Result: For Unet-3D



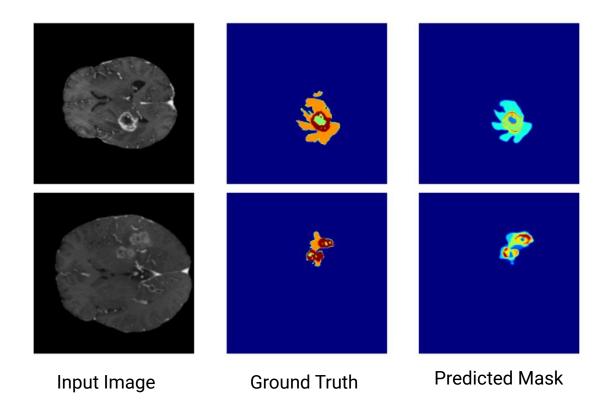
## Result: For ResUnet-3D



## Result: For Unet-2D



# Result: For ResUnet-2D



# Result: Quantitative

- Dice Tumor Core(TC)
  - $\circ$  Dice TC = (NET + ET)/2
- Dice Enhancing Tumor(ET)
  - Dice ET
- Dice Whole Tumor
  - Dice WT = (NET +ET + ED)/3

| Model      | Epochs | Dice TC | Dice ET | Dice WT |
|------------|--------|---------|---------|---------|
| UNet-3D    | 15     | 0.35395 | 0.4332  | 0.3940  |
| ResUnet-3D | 10     | 0.37995 | 0.4729  | 0.4300  |
| Unet-2D    | 40     | 0.7510  | 0.7201  | 0.7466  |
| ResUnet-2D | 30     | 0.6663  | 0.6781  | 0.6815  |

Table 1: Dice Coefficient on Training Set

| Model      | Epochs | Dice TC | Dice ET | Dice WT |
|------------|--------|---------|---------|---------|
| UNet-3D    | 15     | 0.37485 | 0.457   | 0.4089  |
| ResUnet-3D | 10     | 0.30785 | 0.3881  | 0.3614  |
| Unet-2D    | 40     | 0.7212  | 0.7090  | 0.7166  |
| ResUnet-2D | 30     | 0.6443  | 0.6981  | 0.6622  |

Table 2: Dice Coefficient on Test Set

# Thank You!!

Github Link: <a href="mailto:swapnilmalviya-git/BrainTumorSegmentationUsingBratsDataset">swapnilmalviya-git/BrainTumorSegmentationUsingBratsDataset</a> (github.com)