MEDICAL IMAGE SEGMENTATION USING DEEP LEARNING

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BTP-1
Presentation
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BACKGROUND

- Brain tumor is a cancerous or non-cancerous mass or growth of abnormal cells in the brain.
- Brain tumors can be deadly, significantly impact the quality of life, and change everything for a patient and their loved ones.
- The International Association of Cancer Registries (IARC) reported that there are over 28,000 cases of brain tumors reported in India each year.
- 308,102 people were diagnosed with a primary brain or spinal cord tumor in 2020.
- A cancerous or non-cancerous mass or growth of abnormal cells in the brain.
- Treatment options for brain tumors depend on the type, size, and location of the tumor and may include surgery, radiation therapy, and chemotherapy.

PROBLEM STATEMENT
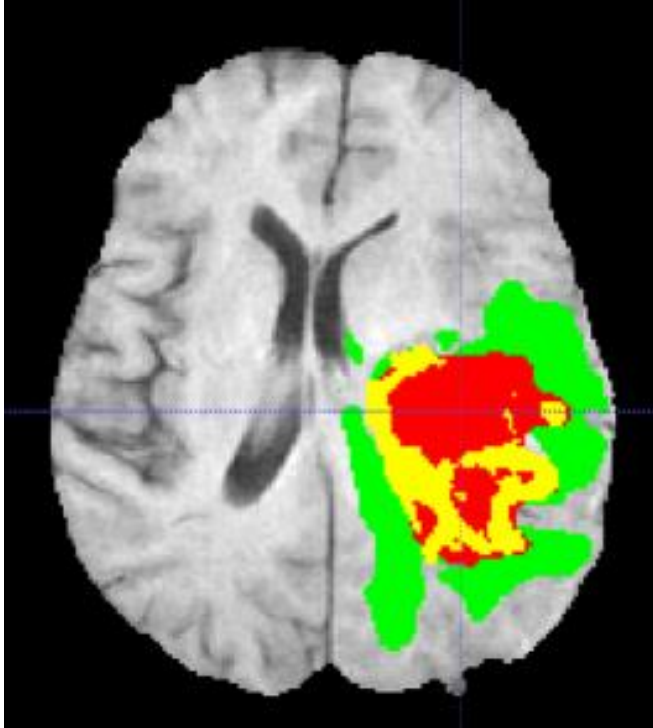
Source: nvidia research

- Brain tumor segmentation in MRI is considered a complex procedure because of the variability of tumor shapes and the complexity of determining the tumor location, size, and texture.
- Manual tumor segmentation is a time-consuming task and highly prone to human error.
- We need an automated method that can identify tumor slices and segment the tumor across all image slices in volumetric MRI brain scans.
- These accurate results would be of enormous potential value for improved diagnosis, treatment planning, and follow-up of individual patients.
- Gliomas are most common brain tumors with different degrees of aggressiveness, shape and size and segmentation is difficult.
- open datasets for designing and testing such segmentation algorithms are limited.

DATASET DESCRIPTION

- The Dataset that has been used is BraTS2020 challenge data with 369 sample MRI Scans of Brain.
- Each sample comprises of 4 modalities each of which is a 3D image with 240x240x155 dimensions.
- All images were acquired with different clinical protocols and various scanners from multiple (n=19) institutions and have been segmented manually by experienced neuroradiologists.
- Annotations comprise the GD-enhancing tumor (ET — label 4), the peritumoral edema (ED — label 2), and the necrotic and non-enhancing tumor core (NCR/NET — label 1) and label 0 is unlabeled.

DATASET DESCRIPTION
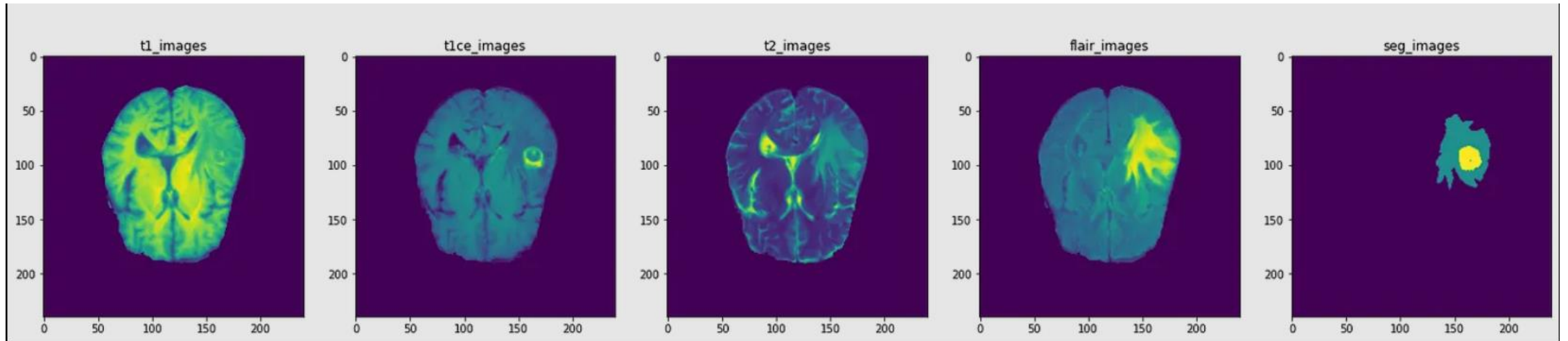
DATASET DESCRIPTION
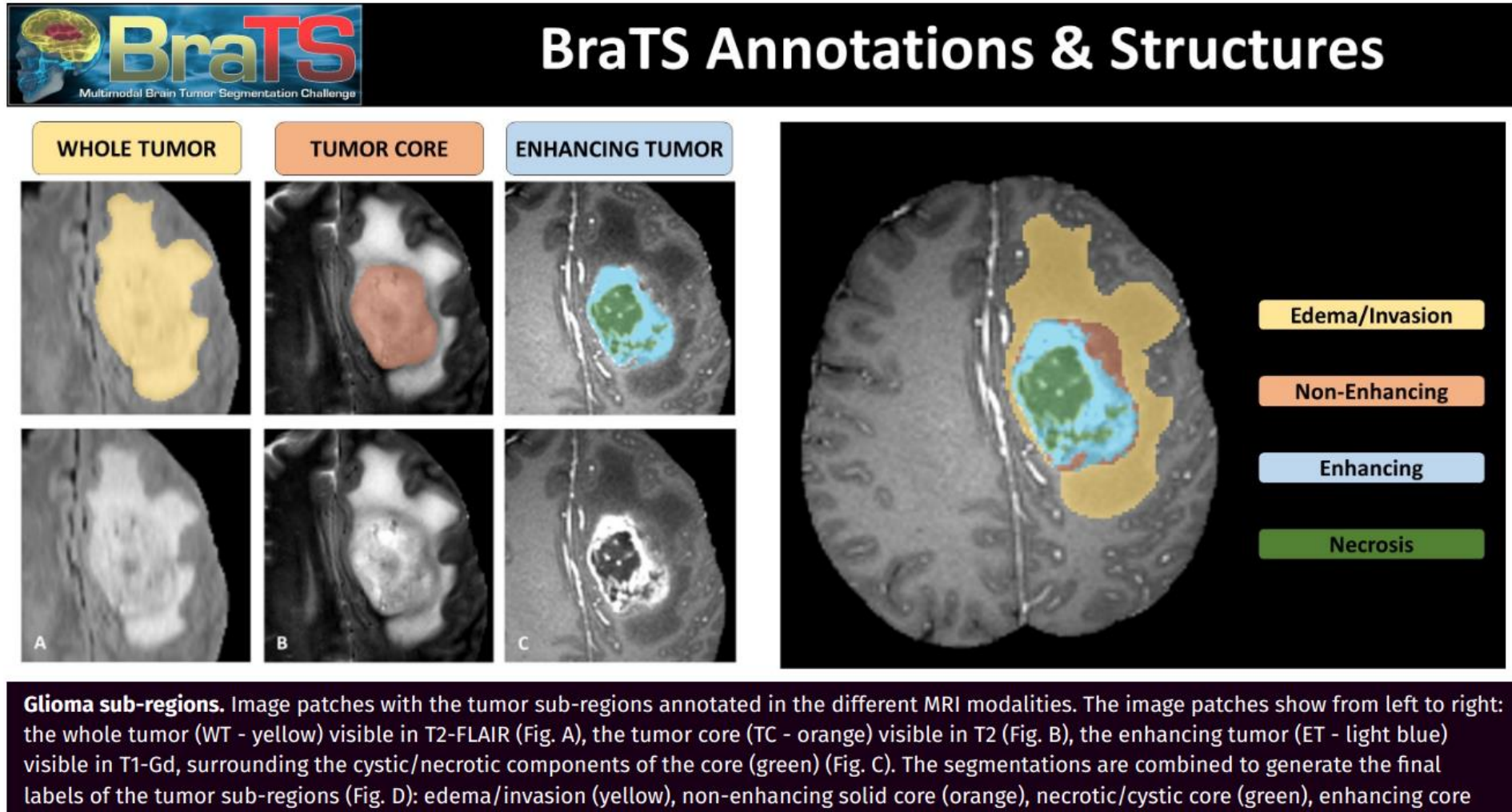
DATA PRE-PROCESSING

- Each image of brain has 4 modalities and the size of them is approximately 80MB, which is very large for a single Image of brain.
- Now among those 4, T1CE is just contrast enhanced image of T1 and hence we don't use T1 and use the rest.
- Since MRI intensities vary depending on manufacturers, acquisition parameters, and sequences, input images need to be standardized to values between 0 and 1 by dividing by maximum value.
- We crop each of the volume to 128x128x128. The cropping is carried from 56 to 184 co-ordinates for both X and Y dimensions and from 13 to 141 for the Z dimension(channels). This removes extra voxels around brain.
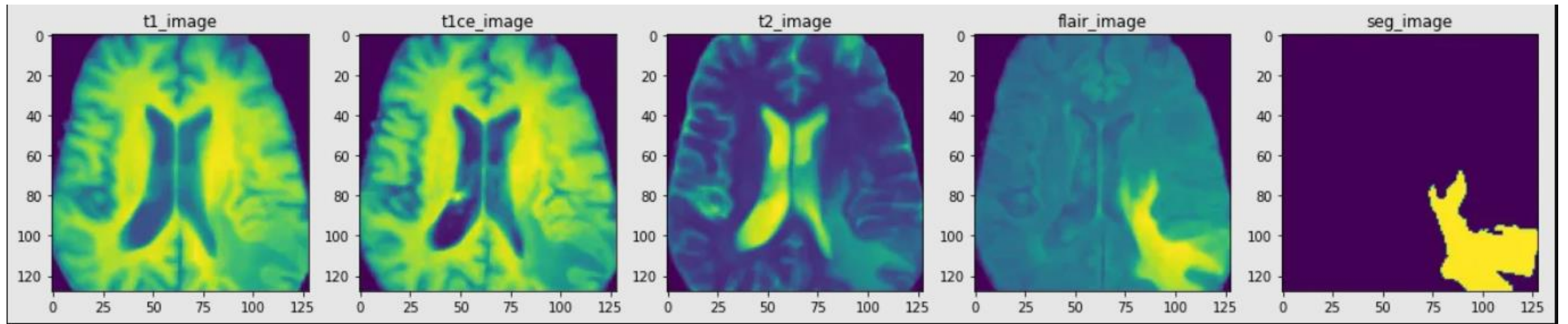
CROPPED IMAGE

MODEL USED

- Model used is 3D U-Net and U-Net was originally developed for Medical Image segmentation tasks.
- Has two main parts, Contraction path (encoder) and Expansion path (Decoder).
- Contraction path down samples the input and try to extract the features in the input image. Max pooling is mainly used.
- Expansion path up samples the output from last section of contraction path and tries to generate high-resolution feature maps that correspond to the segmentation mask. Transposed convolutions is mainly used.
- ReLU is used as activation in both paths and sigmoid for the output layer. Then using softmax gives us the voxel-wise classification probabilities.
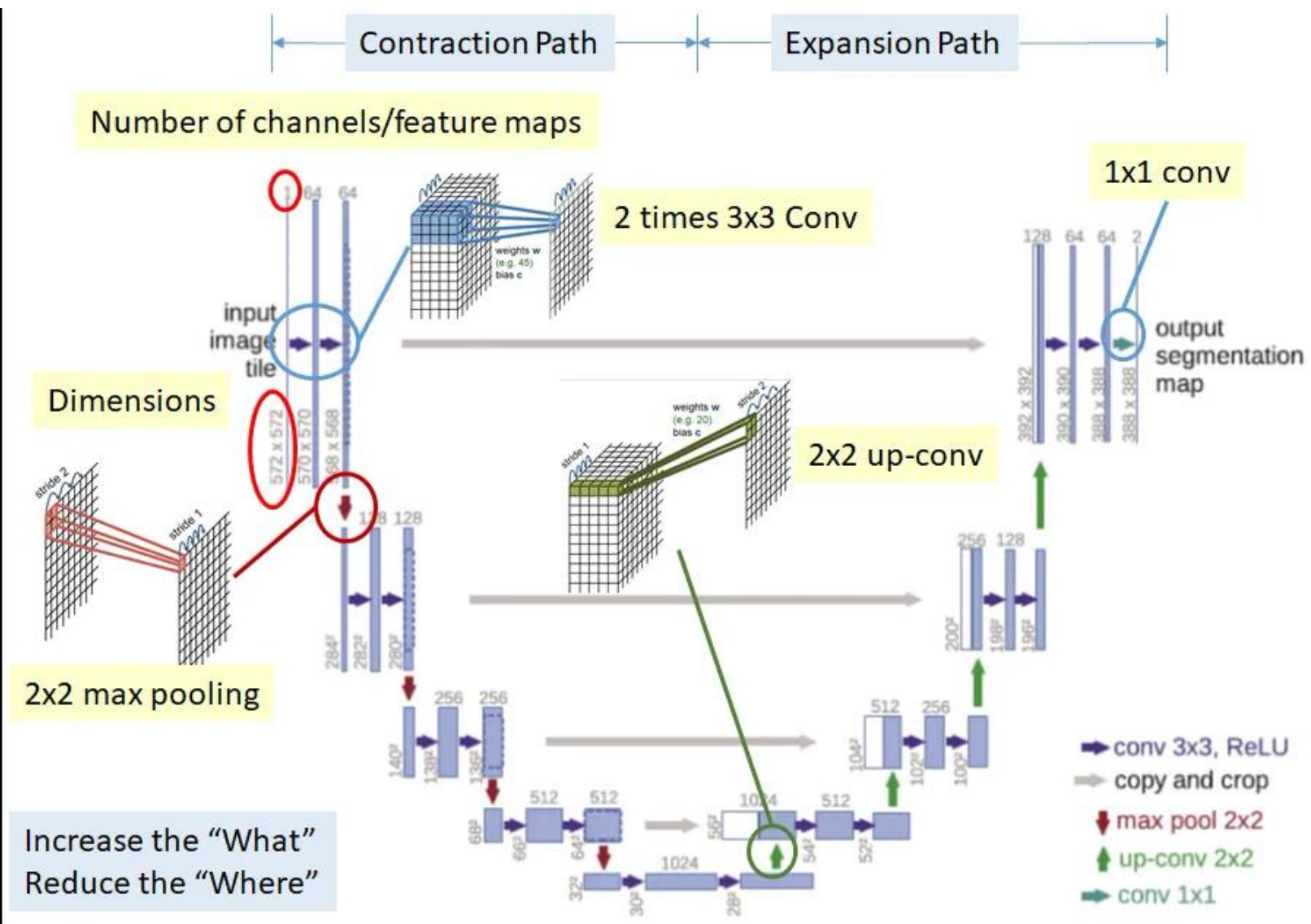
LOSS FUNCTOIN

$$DSC = 1 - \frac{1}{N} \sum_n \frac{S_n * R_n + \varepsilon}{S_n^2 + R_n^2 + \varepsilon}$$

- The model is trained using Dice Loss as Loss function. The loss L is computed batch-wise and channel-wise.
- n the number of output channels, S the output of the neural network after sigmoid activation, R the ground truth label and ϵ a smoothing factor (set to 1 in our experiment)

METRICS USED

- Intersection over union (IoU) is known to be a good metric for measuring overlap between two bounding boxes or masks
- Dice Similarity Coefficient (DSC) is used for evaluation in the BraTS challenge by CBICA. With TP the true positives (number of correctly classified voxels), FP the false positives and FN the false negatives, the DSC is given by
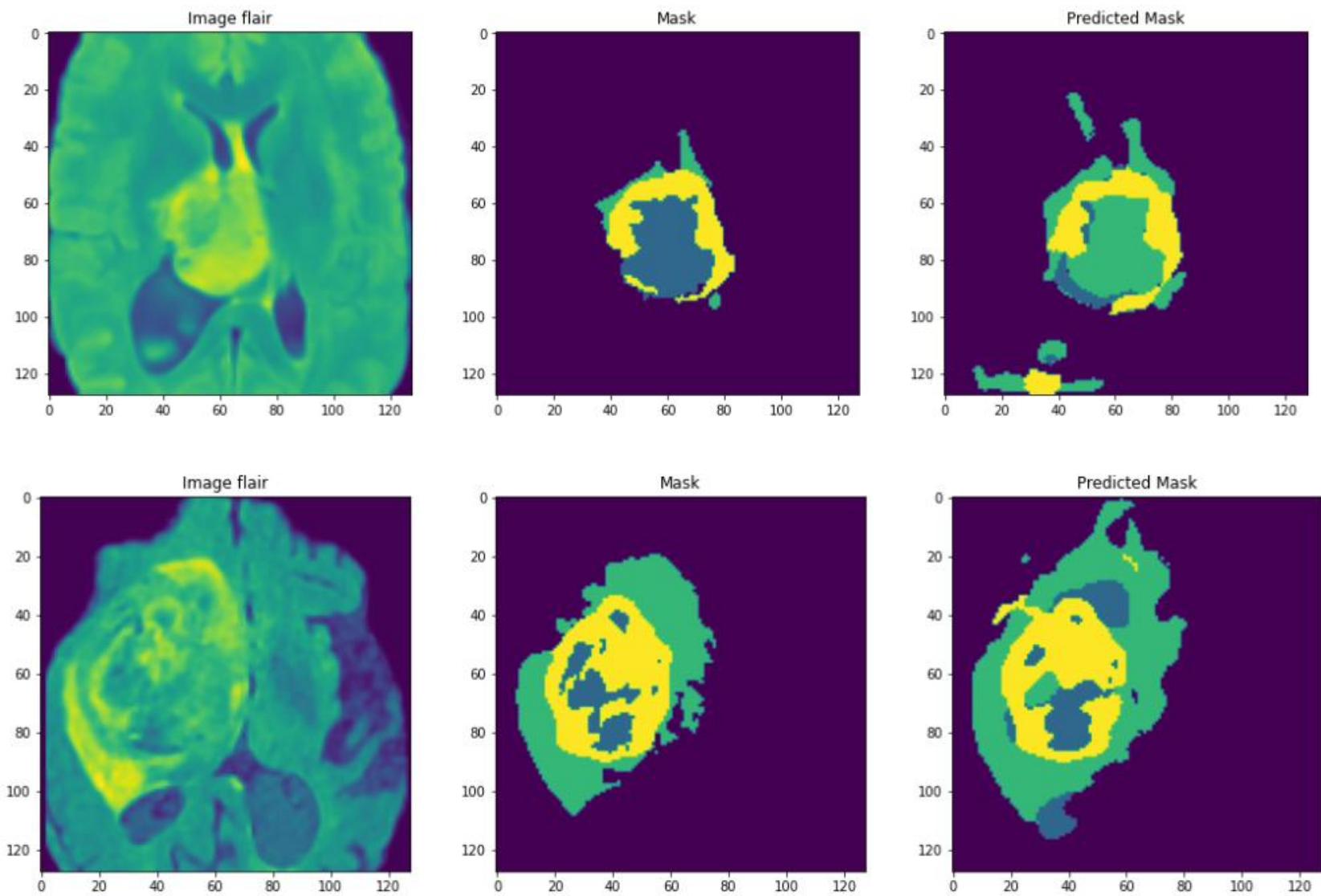
$$DSC = \frac{2TP}{2TP + FN + FP}$$

- Hausdorff distance is another used measure which greatly penalizes outliers: a prediction could exhibits almost voxel-perfect overlap, but if a single voxel is far away from the reference segmentation, the Hausdorff distance will be high.

GENERATED RESULTS

Image flair — Mask — Predicted Mask
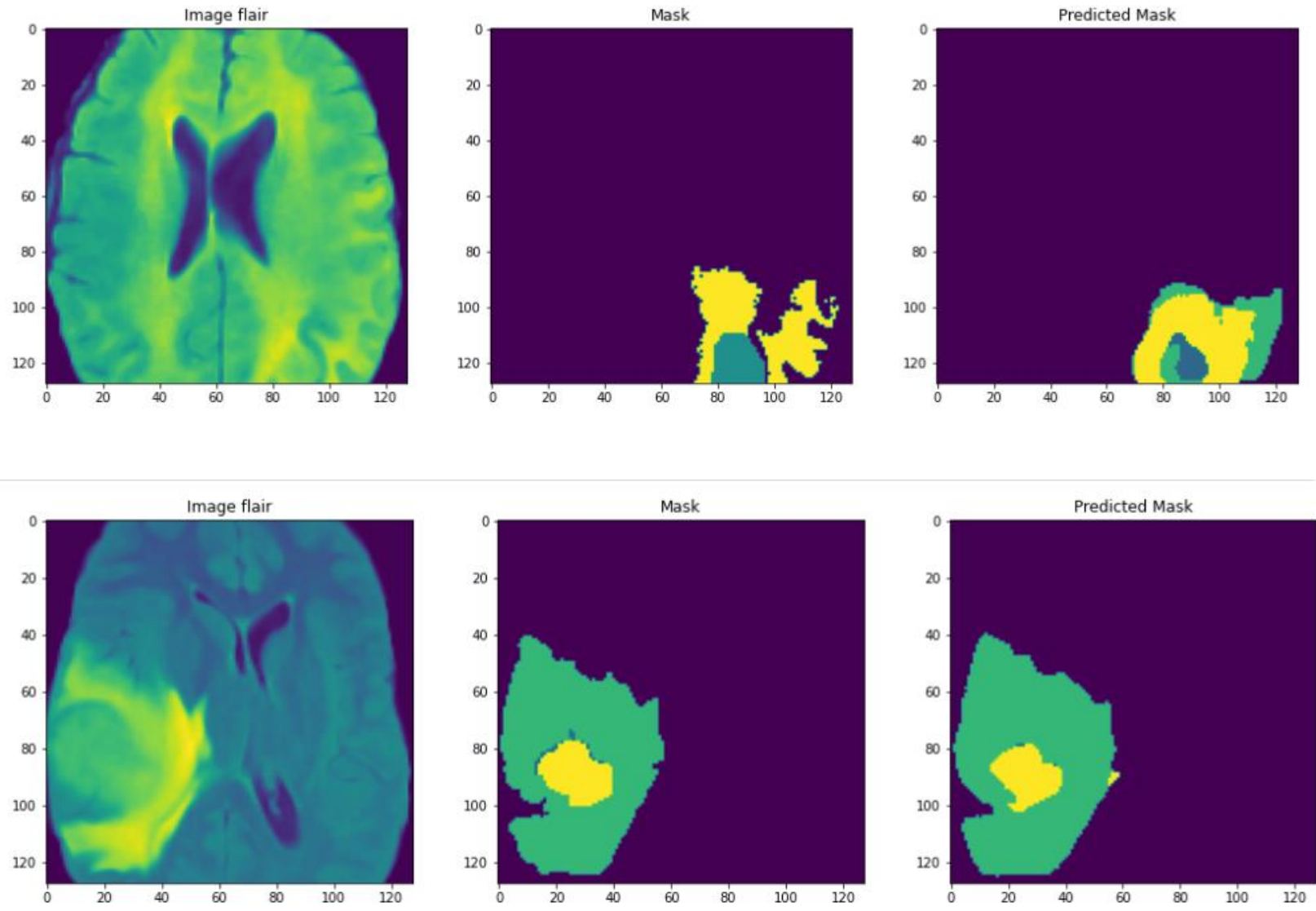
GENERATED RESULTS

SCORES

- After training the 3D-UNET model on MRI images for 30 epochs, the achieved IoU score of 0.6880.
- Upon training for more epochs and hyper-parameter tuning of the same code, the Dice ET score is expected to reach around 0.65

Metric	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
Mean	0.341	0.364	0.548	0.440	0.458	0.579	0.999	0.998	0.999	80.968	20.700	31.640
StdDev	0.201	0.252	0.254	0.349	0.309	0.350	0.004	0.007	0.005	104.5	23.28	28.8
Median	0.456	0.409	0.270	0.457	0.470	0.502	0.994	0.993	0.995	65.01	47.71	55.22

In the below table, Lables L1,L2..are Dice_ET, Dice_WT, Dice_TC, Sensitivity_ET ,Sensitivity_WT, Sensitivity_TC, Specificity_ET, Specificity_WT, Specificity_TC, Hausdorff95_ET, Hausdorff95_WT and Hausdorff95_TC

FUTURE WORKS

- Need to train for more epochs and hypertune the parameters to achieve better Dice scores.
- Need to explore some more architectures like nn-Unet to achieve state-of-the-art results and improve the Dice Scores.
- Due to the model complexity and resources limitation, we have trained with image of size (128,128,128) only. We can try with the larger input image as well for better performance of model.
- A new loss function called Reuse of Established CNN Classifier Apropos Unsupervised Learning (RECAL) should be tested

Pitch Deck

THANK YOU