Brain Tumor Segmentation on FLAIR Images Using SegNet and GANs

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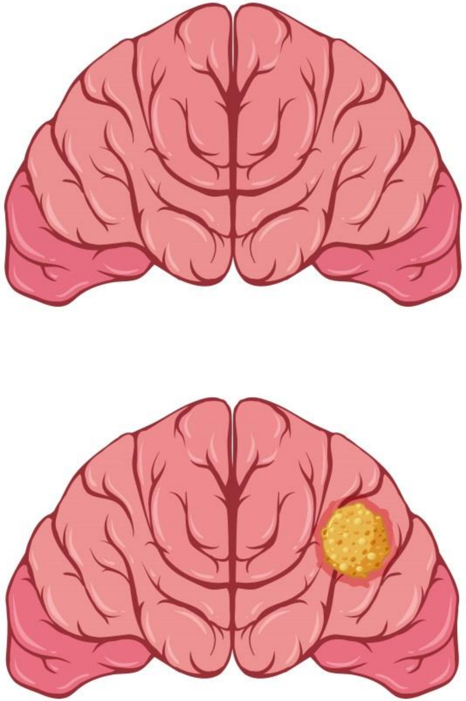
Contents

Motivation

- Brain tumor affecting thousands every year regardless of age, gender, and geographic differences
- Complexity to categorize tumors urges researchers to devise an algorithm that:
  - Identify core and different parts of tumor in MRIs
  - Segment those identified tumor regions efficiently and automatically
- Scarcity of standardized annotated MRI data:
  - Hinders the usage of data-driven approaches (DL/CNN)



[1]

Problem Statement

- Questions this project addresses:
  - Is it possible to synthesize tumor labels and relative MRIs?
  - Is synthesized data compatible with BraTS dataset?
  - Can the addition of synthesize data improve segmentation performance?

[2]

- Our Aim is to:
  - Generation of compatible data to address the problem of data scarcity
  - Combine synthesize data to BraTS to improve segmentation efficiency

Project Overview

Generation of synthetic labels

Generation of synthetic MRIs

Evaluation of the synthetic dataset

Technical Background

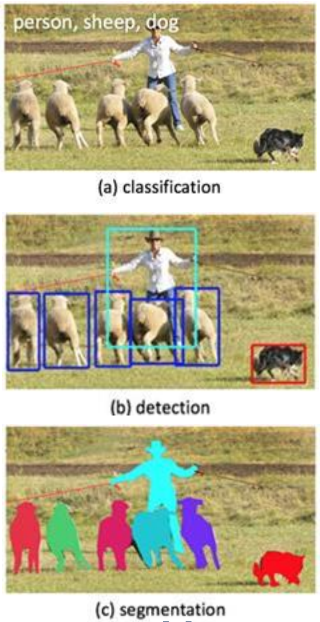
Image Segmentation

- Three levels of Image Analysis

Classification
- Categorizing image into classes
- e.g., human, cat, dog, tree etc.

Detection
- Detecting object within image

Segmentation
- Pixel level mask for different objects in Image

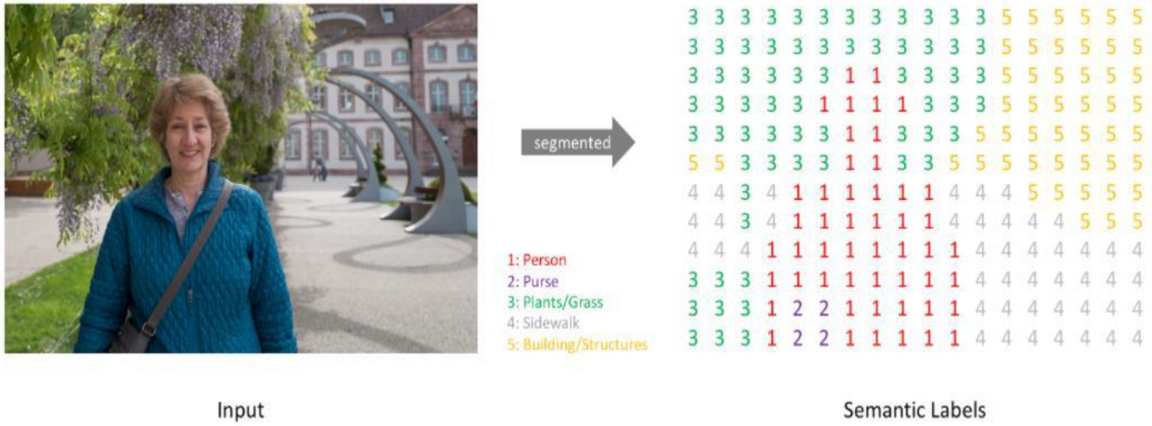


[3]

- Image Segmentation: a task of finding group of pixels that "go together"

Semantic Segmentation

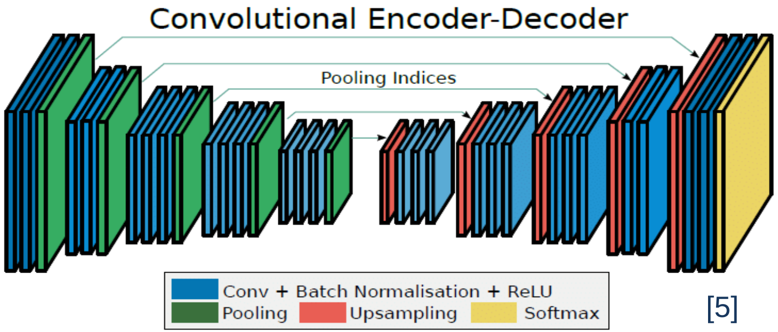
- Classifying and localization of pixels into predefined classes



[4]

SegNet

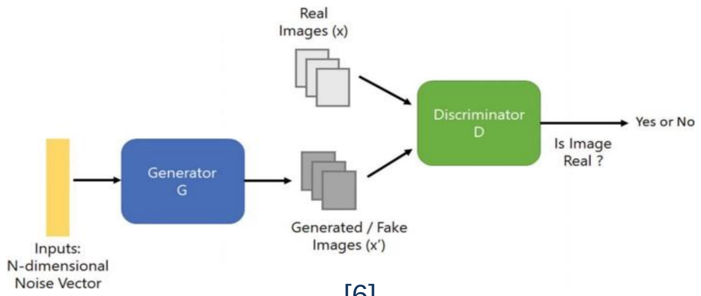
- A deep learning model to perform semantic segmentation:
  - Composed of 13-layer convolutional architecture, an encoder, a decoder followed by pixelwise classification layer
    - Encoder uses maxpooling to forward feature maps
    - Decoder has up sampling with convolutional filter
- Used for class-wise segmentation of:
  - Original BraTS dataset
  - Various ratios of original added with synthetic datasets



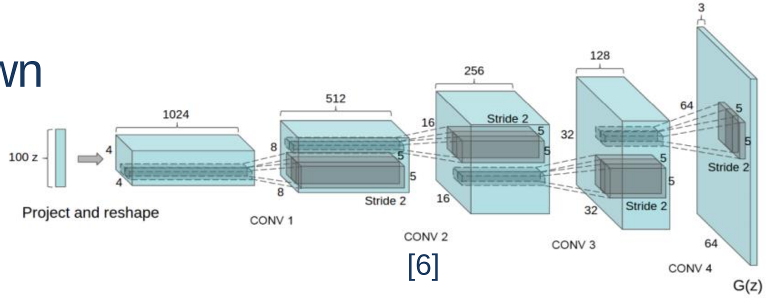
[5]

Deep Convolutional GANs

- A network comprises of a Generator and a Discriminator:
  - Unlike conventional Generative Adversarial Networks:
    - Substitutes fully connected layers with stride Conv layers
    - Uses learnable up sampling and down sampling instead of maxpooling
- Being used to generate compatible MRI labels



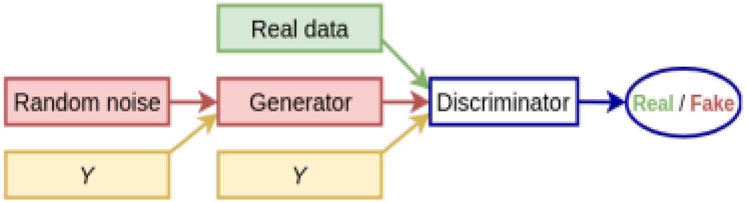
[6]

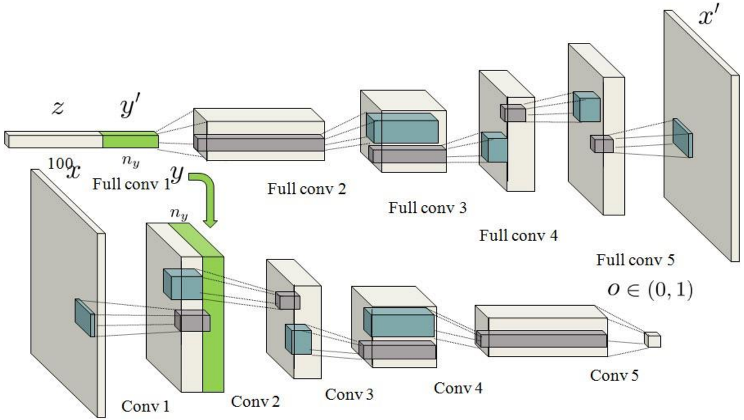


[6]

Conditional GANs

- Also, a network comprises of a Generator and a Discriminator:
  - DCGAN won’t help if we need to classify what we are generating
  - To control what we generate, we need to condition the output
    - Labels or data containing attributes relative to input
- In our case, it does image-to-image translation





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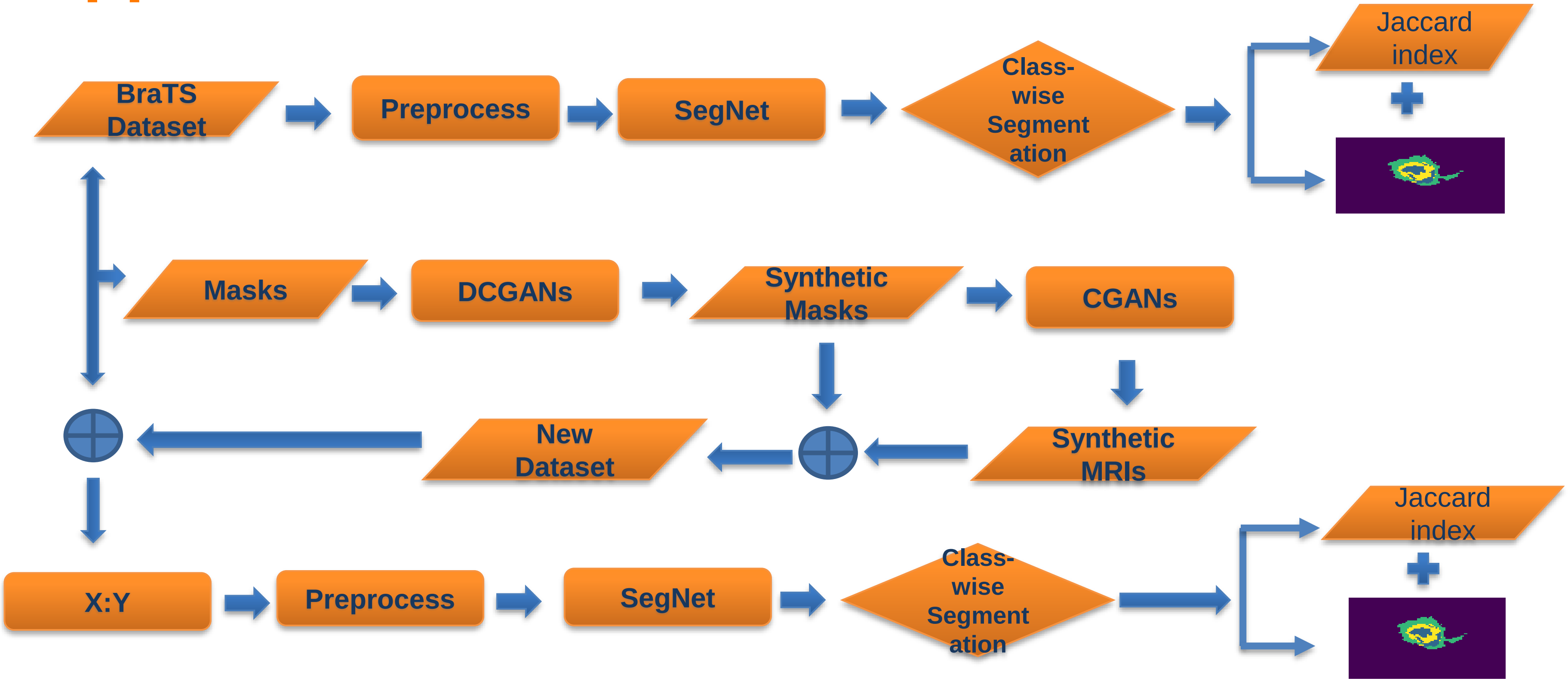
Methodology

Approach

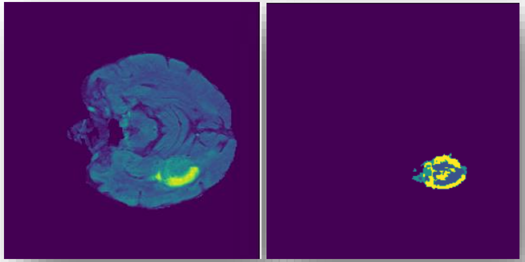


BraTS Dataset
Preprocess
SegNet
Class-wise Segmentation
Jaccard index
Masks
DCGANs
Synthetic Masks
CGANs
Synthetic MRIs
New Dataset
X:Y
Preprocess
SegNet
Class-wise Segmentation
Jaccard index

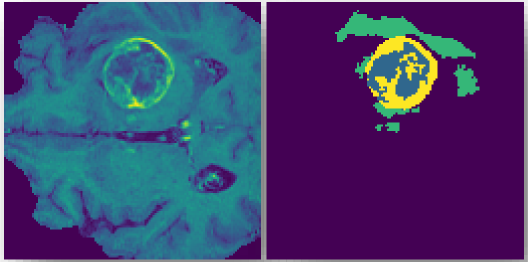
Preprocessing

- Original BraTS image and label shape → 240*240*155
  - Total data of 210 subjects, 4 modalities and a label
  - Large label area with no useful information, so,
    - Labels with min 1% useful info selected (195)
    - image and label resized to 195*(128*128*128)
    - Normalized using min-max scalar
    - Converted from 3D to 2D,so, 24960*128*128
    - Hence, reduced computational complexity

Before Preprocess

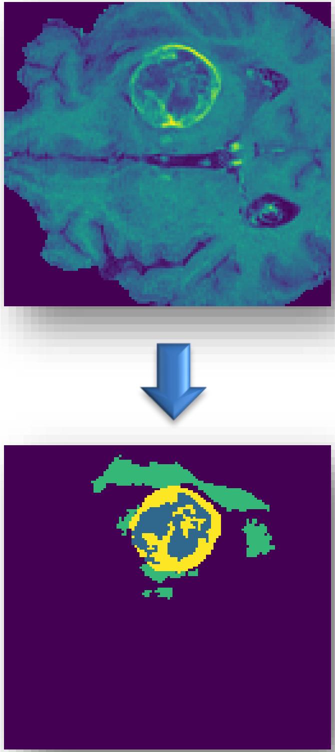


After Preprocess



Class-wise Segmentation of BraTS dataset

- Preprocessed image and label shape:
  - Image ➞ 24960*128*128*1 and Mask ➞ 24960*128*128*4
    - Last dimension shows no. of channels or classes
  - Learning Parameters and loss functions:
    - Optimizer ➞ Adam with learning rate = 0.0004
    - Loss function ➞ categorical cross entropy
    - Epochs ➞ 40 on batch size of 10



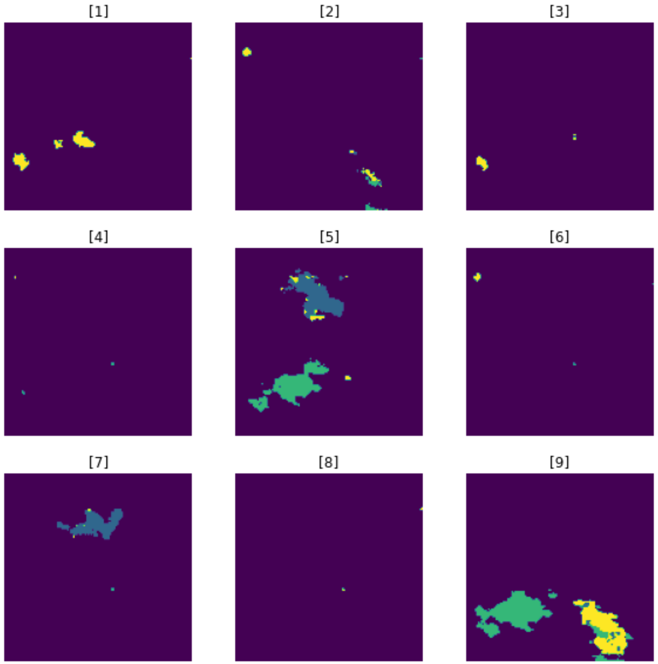
DC-GANS

- Original BraTS masks given as input
  - Optimizer = Adam, lr = 0.0001
  - Activation Function = Leaky ReLU
  - Epochs = 60
  - Training time = 17 hours
- Generates compatible MRI labels

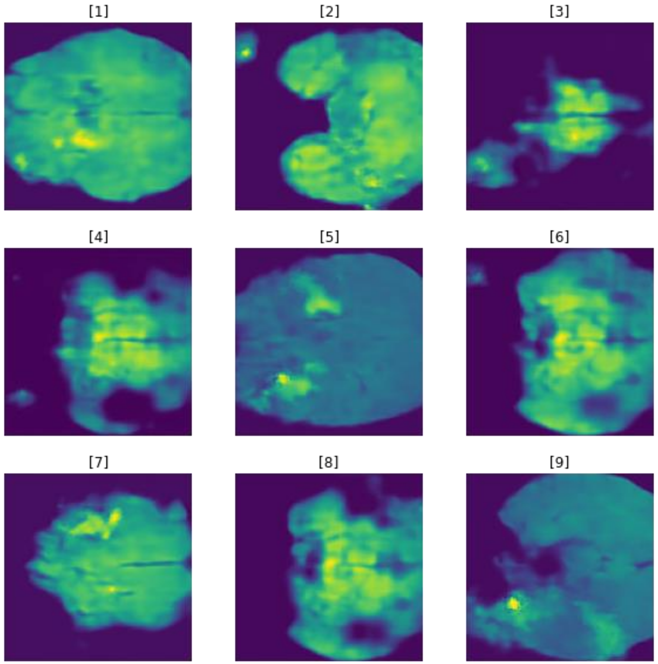
C-GANs

- Synthetic masks from DCGAN given as input
  - Optimizer = Adam with lr = 0.0002
  - Activation Function = tanh
  - Epochs = 100
  - Training time = 7 hours
- Generates compatible MRI Images

DC-GANS



C-GANs



Frame Work

- Limited MRI Dataset Generation
  - Generated synthetic dataset in different ratios realtive to Original BraTS dataset

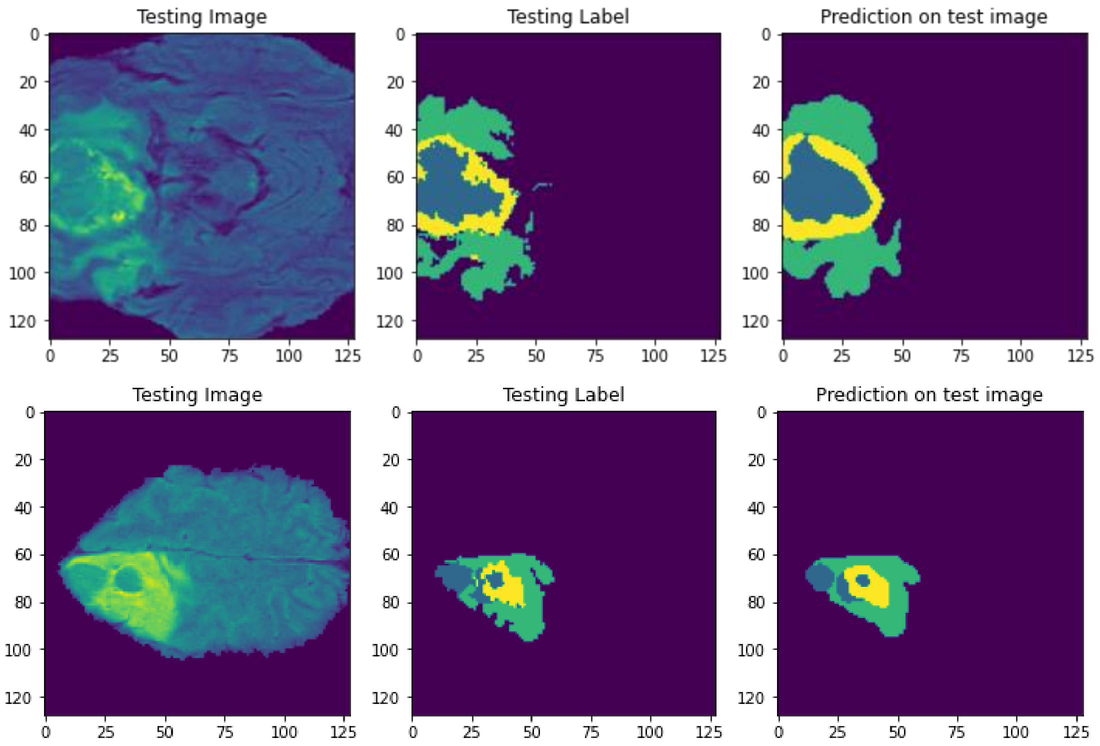
- 5:1
  - For each 5 original MRI and label,1 MRI and label generated
  - Generated 4800 MRI and Labels

- 4:1
  - For each 4 original MRI and label,1 MRI and label generated
  - Generated 1200 more and added to make total of 6000 synthetic

- 3:1
  - For each 3 original MRI and label,1 MRI and label generated
  - 2000 more, added to previous making total of 8000 synthetic data

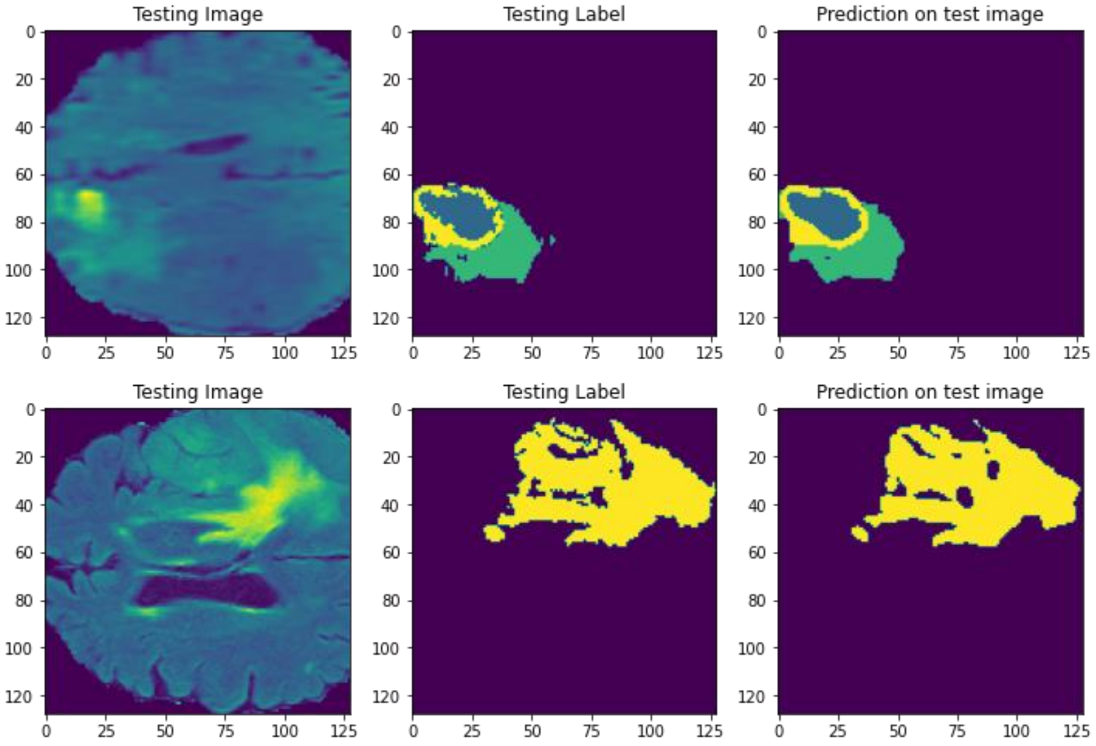
Results and Evaluation

Segmentation Results for BraTS dataset



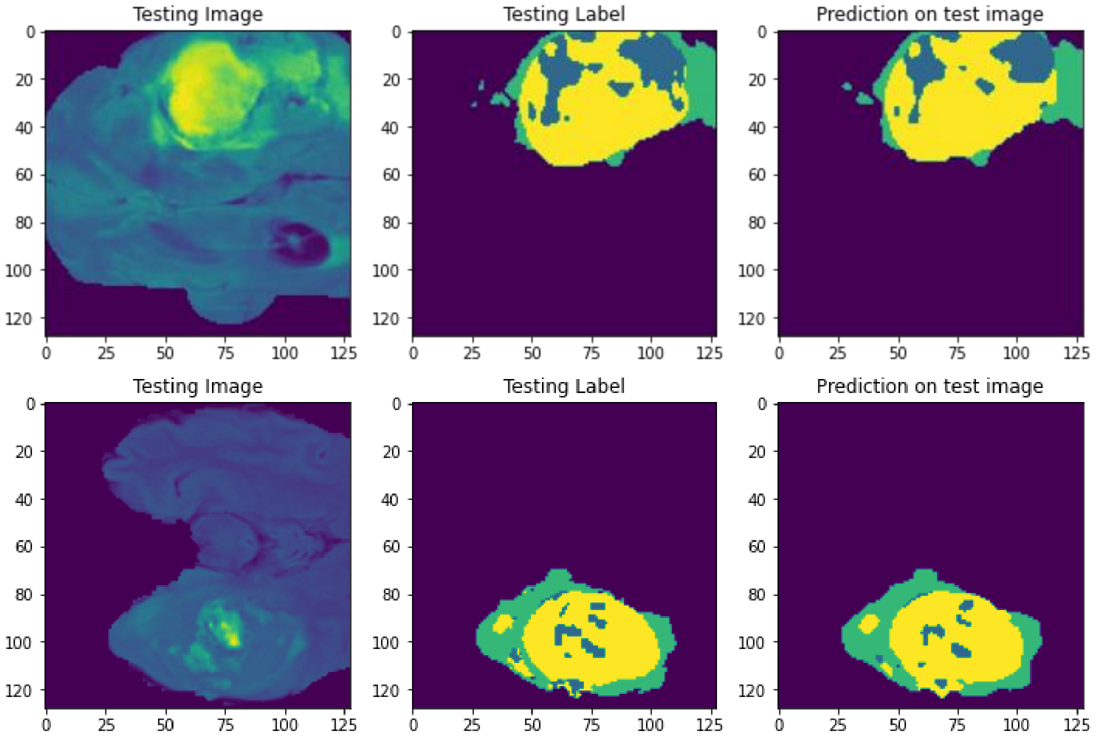
Class	Jaccard Coefficient in %
Class 0	99.5%
Class 1	69.1%
Class 2	82.5%
Class 3	74.7%

Segmentation Results for 5:1



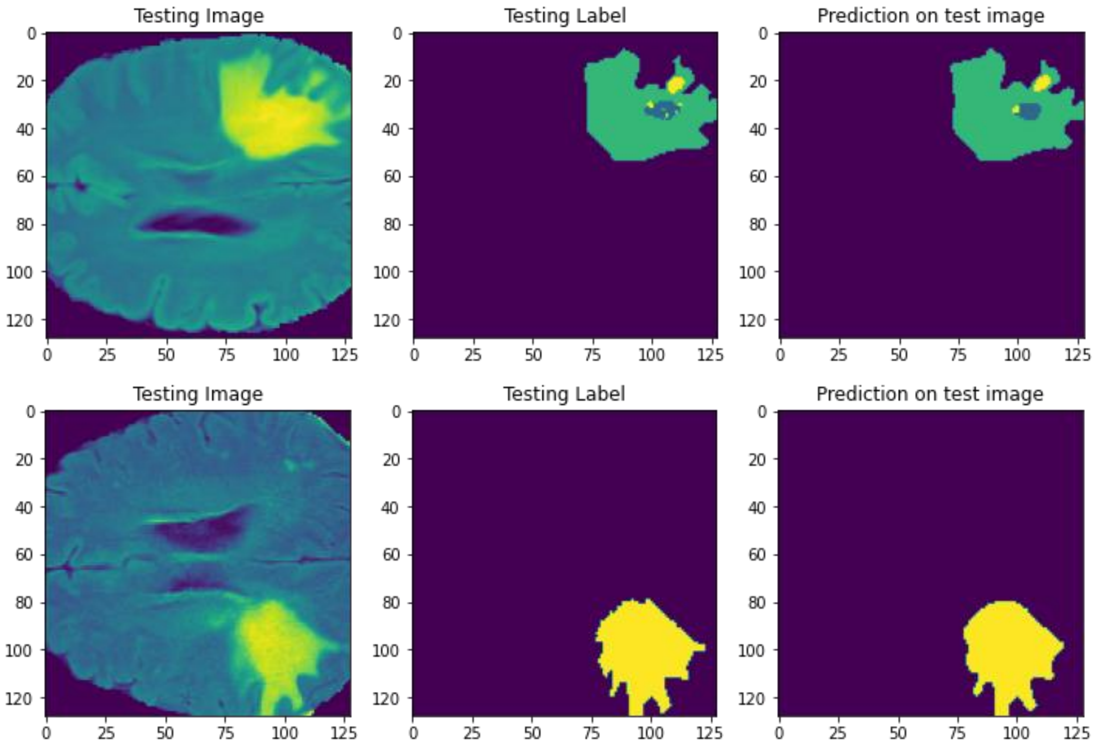
Class	Jaccard Coefficient in %
Class 0	99.5%
Class 1	69.1%
Class 2	82.4%
Class 3	73.4%

Segmentation Results for 4:1



Class	Jaccard Coefficient in %
Class 0	99.5%
Class 1	70.2%
Class 2	83.8%
Class 3	75.2%

Segmentation Results for 3:1



Class	Jaccard Coefficient in %
Class 0	99.5%
Class 1	65.8%
Class 2	82.5%
Class 3	74.3%

Summary

	Original Dataset	5:1	4:1	3:1
Class 0	99.5%	99.5%	99.5%	99.5%
Class 1	69.1%	69.1%	70.2%	65.8%
Class 2	82.5%	82.4%	83.8%	82.5%
Class 3	74.7%	73.4%	75.2%	74.3%

Discussion and Future Work

- Did we answer our problem statement?
  - MRI data generated
    - Has acceptable compatibility
  - Up to certain ratio, addition of synthetic data
    - Improved segmentation accuracies
  - Though there is space for improvements including:
    - Fine tuning hyperparameters and more training for GANs
    - Use more sophisticated/latest GAN architectures

[10]

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