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Performance Analysis of Segmentor Adversarial Network (SegAN) in Bio-Medical Images for Image Segmentation

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Agenda

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- Novelty
- Methodology
  - Dataset Description
  - SegAN (Architecture)
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Introduction

- **Image Segmentation** is the process of **partitioning an image** into multiple segments into much more **easier analysis able form**. (Example MRI images, road images for autonomous driving etc.)
- Cancer refers to **abnormal growth of cells**, it can either be benign or malignant.
- Cancer can **cured easily**, if it is found at earlier stages.
- With the **help of segmentation**, it is easy in **finding shape, volume of cancer region and plan the radiation treatment** for it accordingly
- Since, **manual annotation** of tumor region is **very time consuming** and is prone to **human errors** because of tumor different sizes, shapes, contrast and locations[2].
- Thus, requires an **accurate and reliable automated segmentation techniques**, that can be useful to both clinical and research purposes.

Figure 1: Example for Image Segmentation

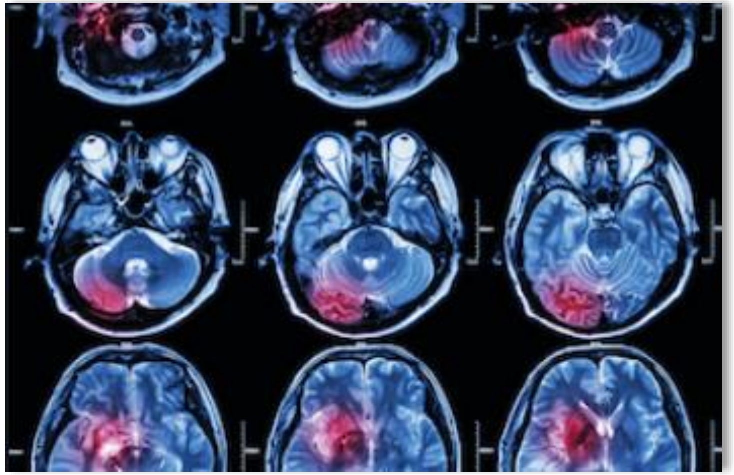


Figure 2: Example for Cancer in Brain

- **Generative adversarial network (GAN)** is a type of architecture which is used for **generative modelling**(Which involves in generating new samples/data that comes from an existing distribution of samples which will be different from the dataset which we give for training.
- GAN was developed by **Ian Goodfellow in 2014** and recently gaining popularity in various task of **computer vision**.
- Some of the **applications of GAN** is **Generating new images**, **Face Aging**, **Super resolution**, **Generate new human poses**, **generating realistic photograph**.
- In this GAN family, **SegAN** is new architecture, published in **2018**, which is been used in **very areas**. So we proposed to use this architecture for the task **of bio-medical image segmentation** of two data sets **brain tumor** and **skin cancer**.

Figure 4: Generating new images from exiting images

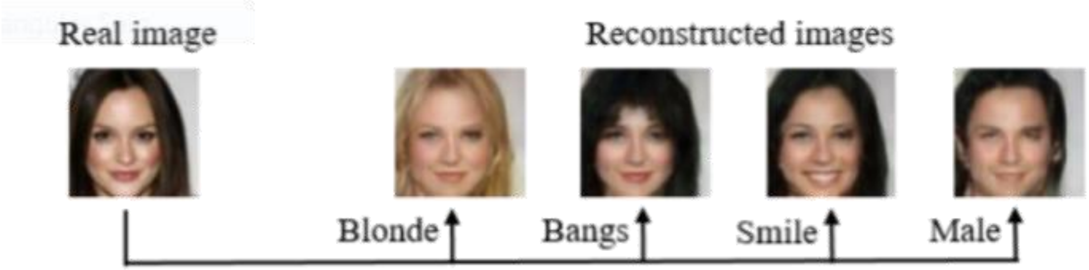


Figure 5: Generating new edited images from a given image

Objective

- To do performance analysis of **Segmentor Adversarial Network (SegAN)** on Bio-Medical images for **Image Segmentation task.**

Survey

A Conditional Adversarial Network for Semantic Segmentation of Brain Tumor [1].

1

- For fully automatic brain tumor segmentation they have proposed **conditional GAN (cGAN)** with **Brats 2017** dataset.
- They considered three subsections of tumors: **whole, core and enhancing**
- The evaluation parameters considered was **dice score** (similarity score) and they achieved about **0.80, 0.54, 0.59** for whole, core and enhancing tumor respectively

SegAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation [2].

2

- They proposed Segmentor Adversarial Network **(SegAN)** for bio-medical image segmentation with **brats 2015** dataset
- They have considered three subsections of tumors: **whole, core and enhancing**
- The architecture out performed all existing methods and achieved **dice score** of **0.85, 0.70, 0.66** for whole, core and enhancing tumor respectively.

Adversarial Learning with Multi-scale Loss for Skin Lesion segmentation [3].

3

- They have considered Segmentor Adversarial Network **(SegAN)** for bio-medical image segmentation with **ISIC 2017** skin lesion dataset
- The skin cancer in ISIC is **melanoma**
- SegAN architecture successfully out performed all other existing methods with a **dice score** of **0.86.**

Methodology/Block Diagram

Figure 3: Flow Chart

Dataset Description

Datasets

BraTS 2017 Brain Tumor Dataset

- **135** Subjects **High-Grade Glioma** & **108** subjects of **Low-Grade Glioma** [5][6]
- Each subject, consist **4 scans**: a) **T1-Weighted**, b) **T1-Gd, c) T2-Weighted** and d) **T2-FLAIR** and **two segmentation labels**: **manual** and **computer-aided**
- 3 **ground truth labels**: a) **Whole Tumor**, b) **Core Tumor**, c) **Enhancing Tumor**
- Each scan is **3D brain volume** (240x240x155)

ISIC 2018 Skin Lesion

- **2594 images of Skin Cancer** with corresponding ground truth labels [4]

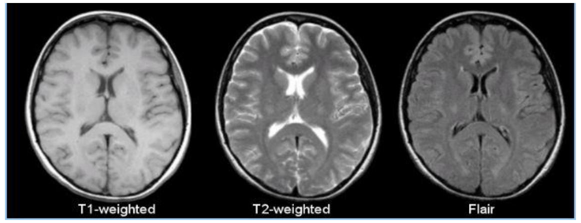


Figure 5:Different types of scans; T1-weighted, T2-weighted and FLAIR [1]

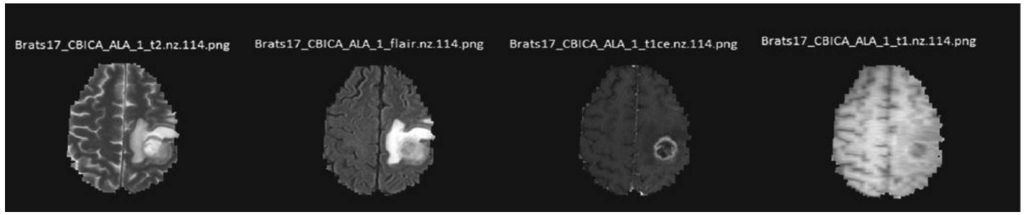


Figure 6:Different appearance of tumor in 4 different types of scans [1]

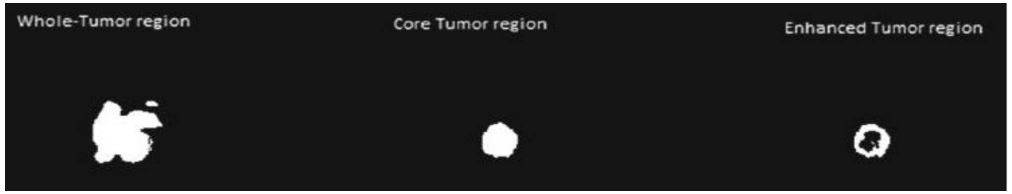


Figure 7:three types of tumor ; whole tumor, core tumor, enhancing tumor [1]

Figure 8:Example of Skin Cancer Dataset [4]

Segmentor Adversarial Network (SegAN)

- **SeGAN architecture** consists of two parts: **Segmentor and Critic**.
- The **Segmentor** is used to **generate label map** corresponding to the input which is given .
- The **Critic** is used to **distinguish between types of inputs:** original image masked by ground truth label and original image masked by predicted label from segmentor. [2]
- The training of **Segmentor** aims at **minimizing** the multi-scale loss function and training of **Critic** aims at **maximizing** the multi-scale loss function. [2]

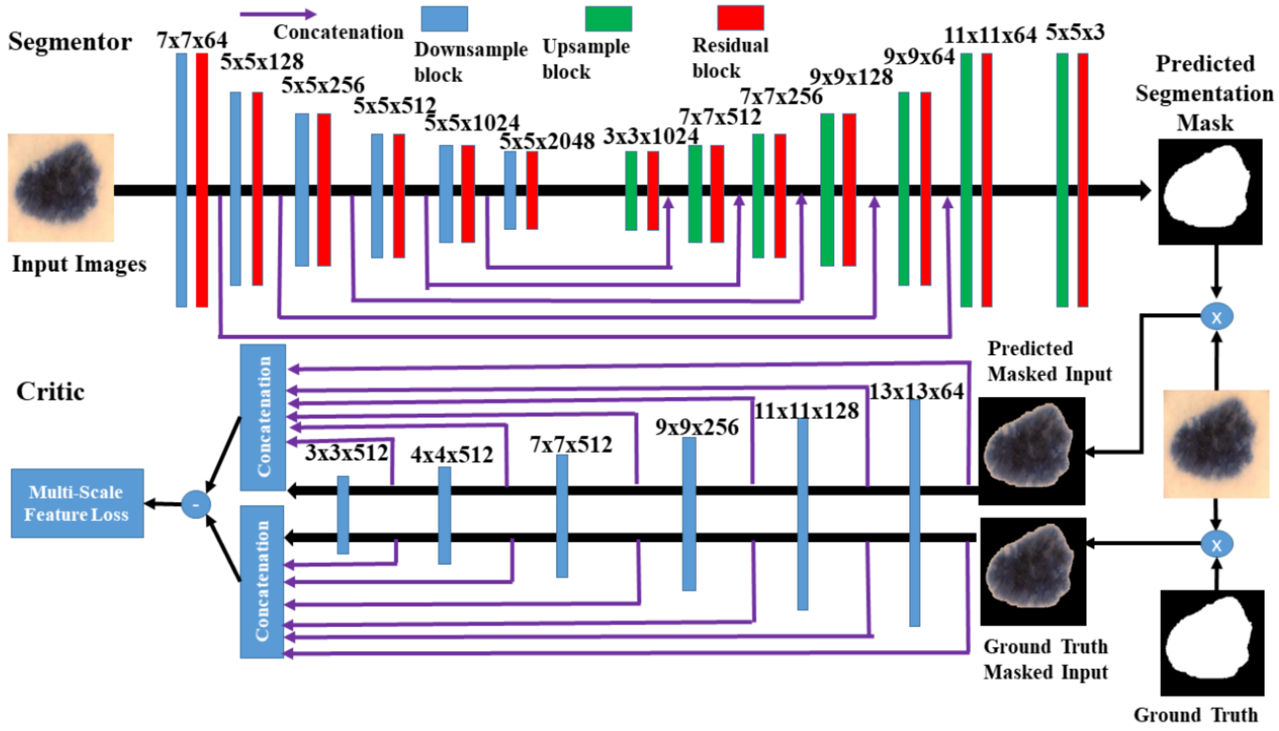


Figure 9:SegAN Architecture [2]

Results: Image Segmentation of **Skin Cancer(ISIC 2018)** Using **SegAN**

Dice Score:

- It is measure, which is used to find the similarity between the labels such as Predicted label by SegAN and ground truth label.
- It is also defined as twice the number of pixels common to both samples divided by the sum of the number of pixels in each sample

$$DSC = \frac{2|P \cap T|}{|P| + |T|}$$

Jaccard Index:

- It is defined as the intersection of pixels of two samples predicted and ground truth labels, divided by union of pixels of predicted and ground truth labels.

$$JaccardIndex = \frac{|P \cap T|}{|P \cup T|}$$

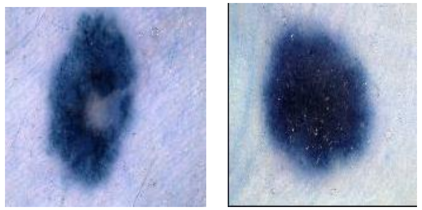
Assume, |P intersection T| = 12800,
|P| = 160*160 = 25600,
|T| = 160*160 = 25600,
DSC = (2*12800)/(25600+25600) = 0.50

Number of Images	Data Split	Epochs	Dice	Jaccard
1000	90:10	500	0.6804	0.5689
		750	0.6804	0.5689
		1000	0.6804	0.5689
		1500	0.6933	0.5821
		2000	0.6945	0.5846
		2500	**0.6945**	**0.5846**

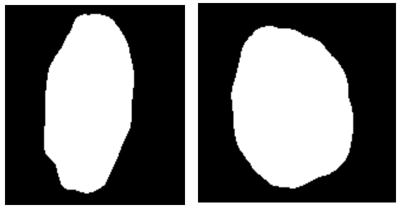
Table 1: Image Segmentation results by using SegAN architecture on ISIC 2018

Output

Input Image



Predicted Label by SegAN



Ground Truth Label

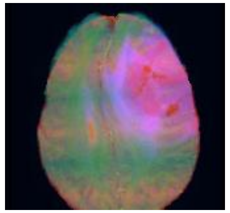
Results: Image Segmentation of **Brain Tumor (BraTS 2017)** using **SegAN**

Number of Images	Data Split	Epochs	Whole		Core		Active	
			Dice	Jaccard	Dice	Jaccard	Dice	Jaccard
1000	90:10	500	0.2094	0.1599	0.2096	0.1592	0.1050	0.05
		750	0.2326	0.1746	0.2198	0.1711	0.1050	0.05
		1000	0.2450	0.1830	0.2356	0.1746	0.1152	0.06
		1500	0.2591	0.1919	0.2496	0.1836	0.1300	0.07
		2000	0.2629	0.1946	0.2512	0.1862	0.1300	0.07
		2500	**0.2656**	**0.1946**	**0.2512**	**0.1862**	**0.1350**	**0.07**

Table 2: Image Segmentation results by using SegAN architecture on BraTS 2017

Output

Input Image



Predicted Label by SegAN
(at 200 and 2500 epochs respectively *(best sample among all the samples given)*

Ground Truth Label

Conclusion

- Performance analysis of Segmentor Adversarial Network on bio-medical images for image segmentation task is done with two different type of tumor data such as BraTs 2017 brain tumor and ISIC skin lesion dataset. SegAN showed a comparable performance with both the dataset for image segmentation task.
- Their performance were compared and found that SegAN architecture performed better with ISIC 2018 skin lesion dataset when compared with BraTS 2017 brain tumor data.

Future Scope

- To do **Image segmentation** task for **same two datasets** with other architectures such as **U-Net, SegNet** and improve the segmentation performance.

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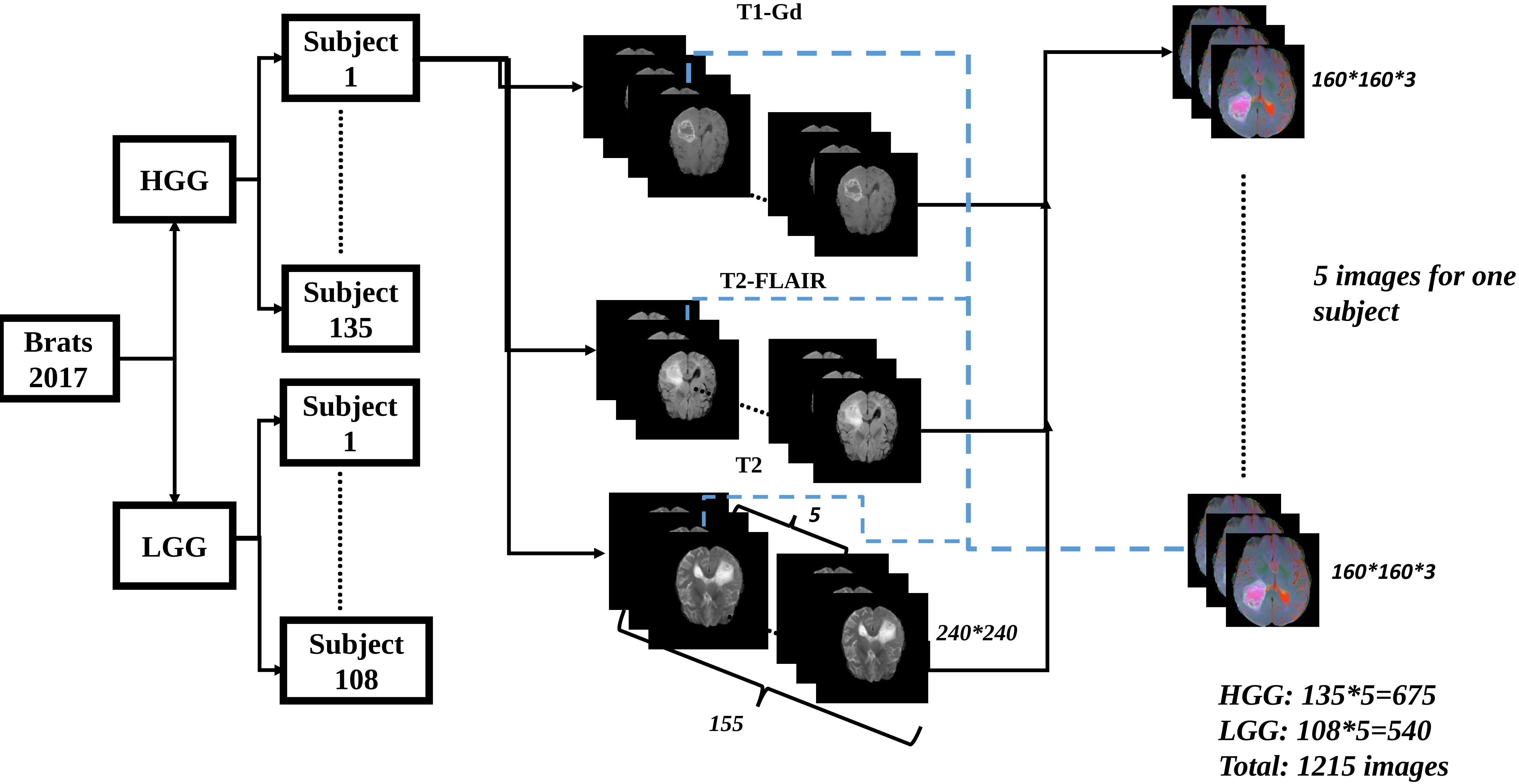
Thank you

Back Up

Results

- **Preprocessing – Brats 2017**
  - According to paper [4] [*SegAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation*], they considered only 3 scans out of 4 scans : T1-Gd, T2-weighted, T2-Flair.
  - Considered 5 slices from 155 slices of 3D brain volume from each scan in each subject .
  - The images should be central cropped to dimension 160x160 from 240x240.
  - Then they concatenated each slice of different scan together (3 scans) to form a image of dimension 160x160x3, shown in figure 8.
  - Label Extraction: Extracting the information of different tumors from the given segmentation label, show in figure 9.
  - Data Split 90:10, 90% for training and 10% for testing.
  - Data Augmentation: Scale, Horizontal Flip, Vertical Flip, Color Jitter
- **Preprocessing – ISIC 2018**
  - First resize the image into 180x135 from 4092x4892 [5].
  - Then resize the image into 128x128 during training
  - Data Split 80:20, 80% for training and 20% for testing.
  - Data Augmentation: Scale, Horizontal Flip, Vertical Flip, Color Jitter


Brats 2017
HGG
LGG
Subject 1
Subject 135
Subject 1
Subject 108
T1-Gd
T2-FLAIR
T2
5
155
240*240
160*160*3
160*160*3
5 images for one subject
HGG: 135*5=675
LGG: 108*5=540
Total: 1215 images

Label Extraction

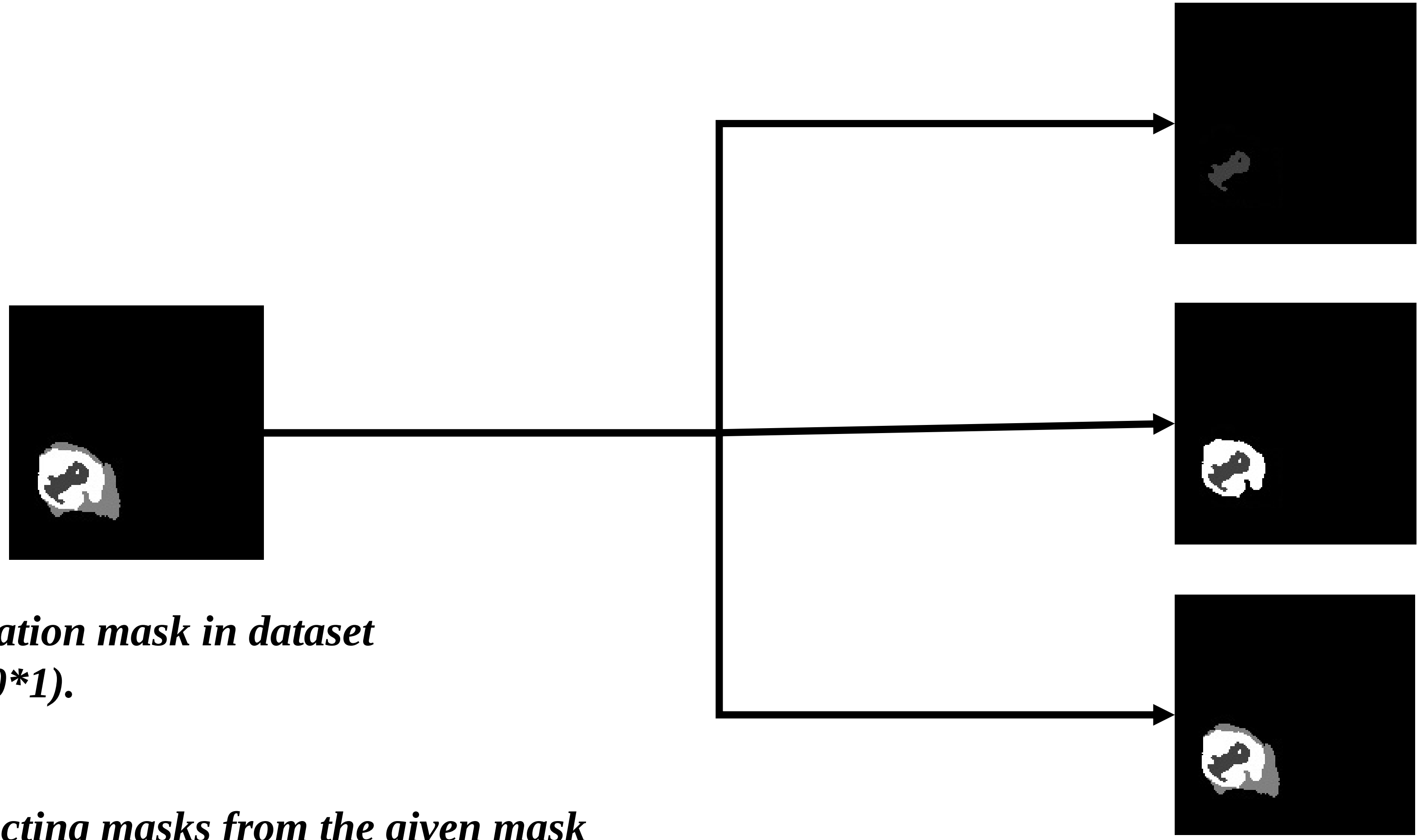


Fig : Extracting masks from the given mask