Multimodal Brain Tumor Segmentation Challenge

Reliance Industries Limited

www.ril.com

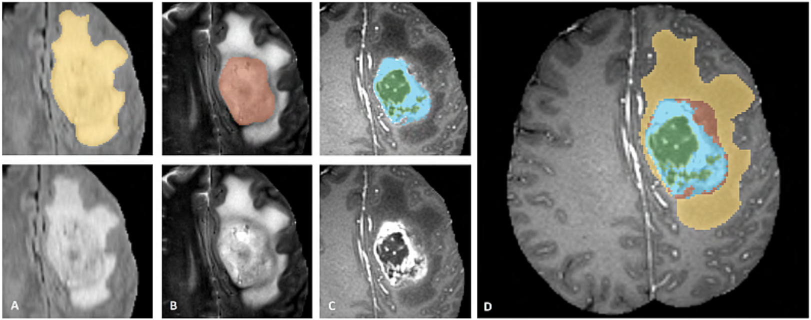
March 28, 2019

Overview

Scope

- BraTS has been focusing on the evaluation of methods for the segmentation of brain tumors in multimodal magnetic resonance imaging (MRI) scans.
- BraTS 2018 utilizes multi-institutional pre-operative MRI scans and focuses on the segmentation of intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, namely gliomas.
- Furthemore, BraTS18 also focuses on the prediction of patient overall survival, via integrative analyses of radiomic features and machine learning algorithms.

Glioma sub-regions



From Left to Right: The whole tumor (yellow) visible in T2-FLAIR (Fig.A), the tumor core (red) visible in T2 (Fig.B), the enhancing tumor (light blue), The cystic/necrotic components of the core (green) (Fig. C). The final labels of the tumor sub-regions (Fig.D): edema (yellow), non-enhancing solid core (red), necrotic/cystic core (green), enhancing core (blue).

Tasks

Task 1: Segmentation of gliomas in MRI scans.

Produce segmentation labels of the different glioma sub-regions.
The sub-regions considered for evaluation Will be: 1) the "enhancing tumor" (ET), 2) the "tumor core" (TC), and 3) the "whole tumor" (WT). The labels in the provided data are: 1 for NCR NET, 2 for ED, 4 for ET, and 0 for everything else.

Task 2: Prediction of patient overall survival (OS) from MRI scans.

After producing segmentation labels from the MRI scans, use machine learning algorithms in an attempt to predict patient overall survival (OS).

Dataset

Data description:

All BraTS scans are available as NIfTI files. MRI scans of:
High grade glioma (HGG) - 210 patients
Lower grade glioma (LGG) - 75 patients

For each patient:

Following manually annotated files by clinical experts are present:

1. Flair
2. T1
3. T1ce
4. T2
5. Segmentation

Survival Data Description:

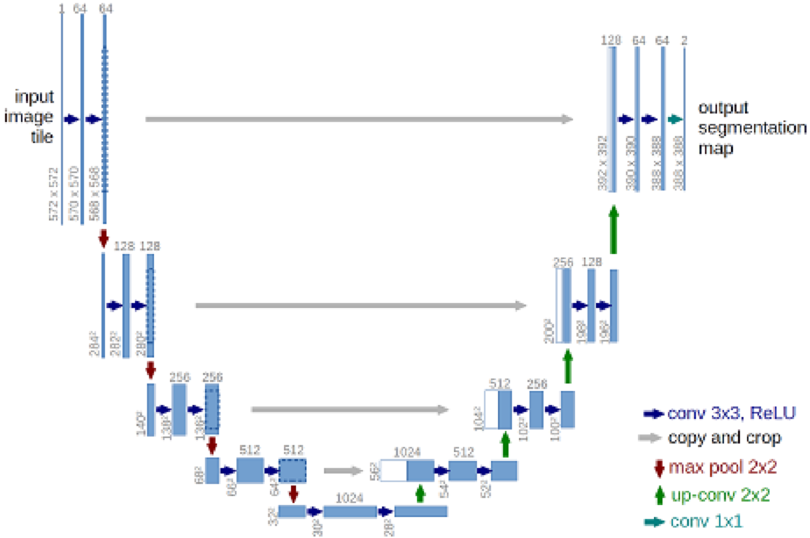
The overall survival (OS) data includes age of patients and the survival of the patients in days.

Approaches

U-Net

- Symmetrical up sampling and convolution layers are used to bring the pixel-wise prediction of the input image.
- It performs extremely well for medical image segmentation challenges
- Generally the dataset of the medical images are small, but U-Net has capability to learn from small annotated dataset.

U-Net : Architecture

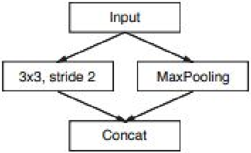


ENet

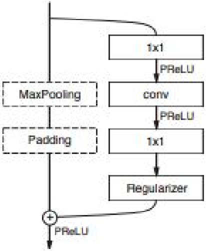
- ENet (Efficient Neural Network) has the ability to perform pixel-wise segmentation in real-time
- 18x Faster, 75x less FLOPs, 79x less parameters and provides similar or better accuracy when compared with existing models (such as SegNet)
- Inspired by encoder-decoder network architecture
- Compared to SegNet, which is a symmetric architecture, ENet consists of a larger encoder and a small decoder
- ENet has few parameters and space required is only 0.7 MB

ENet

ENet: Real-Time Semantic Segmentation



(a)



(b)

ENet Architecture

Table 1: ENet architecture. Output sizes are given for an example input of 512×512.

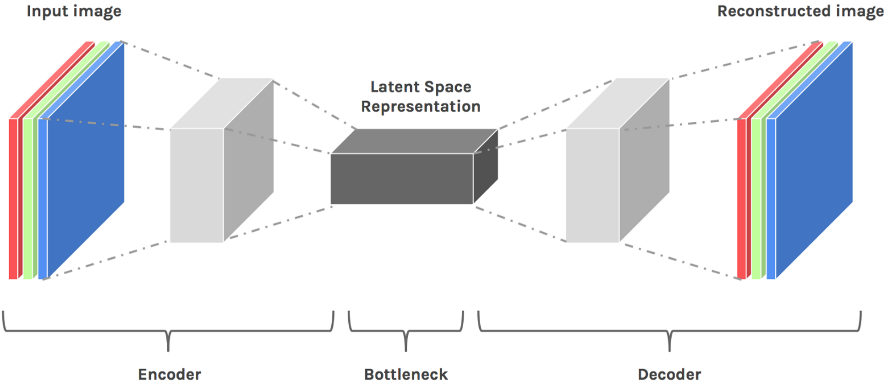
Name	Type	Output size
initial		$16 \times 256 \times 256$
bottleneck1.0	downsampling	$64 \times 128 \times 128$
$4\times$ bottleneck1.x		$64 \times 128 \times 128$
bottleneck2.0	downsampling	$128 \times 64 \times 64$
bottleneck2.1		$128 \times 64 \times 64$
bottleneck2.2	dilated 2	$128 \times 64 \times 64$
bottleneck2.3	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.4	dilated 4	$128 \times 64 \times 64$
bottleneck2.5		$128 \times 64 \times 64$
bottleneck2.6	dilated 8	$128 \times 64 \times 64$
bottleneck2.7	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.8	dilated 16	$128 \times 64 \times 64$
Repeat section 2, without bottleneck2.0		
bottleneck4.0	upsampling	$64 \times 128 \times 128$
bottleneck4.1		$64 \times 128 \times 128$
bottleneck4.2		$64 \times 128 \times 128$
bottleneck5.0	upsampling	$16 \times 256 \times 256$
bottleneck5.1		$16 \times 256 \times 256$
fullconv		$C \times 512 \times 512$

DCGANs : Deep Convolutional Generative Adversarial Networks

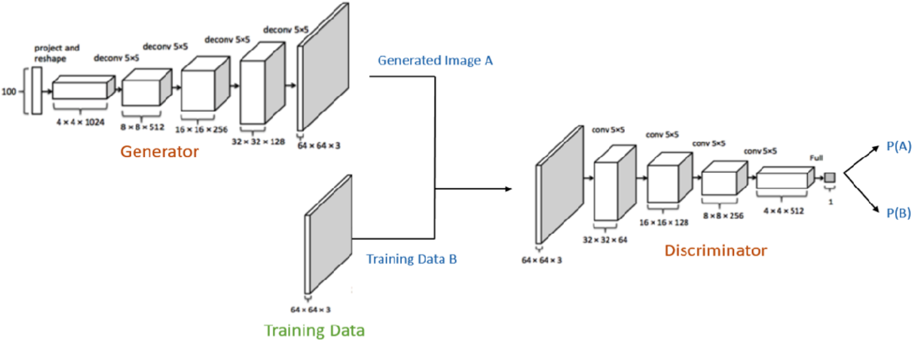
- Adversarial models are used to test the model with the worst possible input.
- No need to define the loss function
- Generator Generates data
- Discriminator decides if the data belongs to original training data or is generated by the generator.
- Generator learns to fool discriminator by generating as good replica as possible
- Discriminator learns to become a good distinguisher of real and fake data.
- Deep Convolutional GAN can be trained to produce Image segmentation from images

DCGAN

Autoencoders



Architecture : DCGAN

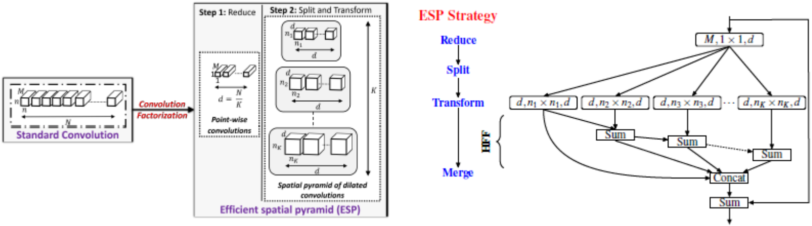


Architecture of DCGAN

ESPNET (EFFICIENT SPATIAL PYRAMID)

- Semantic Segmentation of high resolution RGB images at the rate of 112 frames per second on high-end GPU, 21 FPS on a laptop
- New Convolution module ==> Efficient Spatial Pyramid(ESP) based on Convolution factorization principal
- ESPNet is fast, small, low power and low latency
- Outperforms all current CNN networks such as MobileNet, ShuffleNet, Enet, PSPNet
- Decomposes a standard convolution into 2 step:
    - Point-wise convolutions
    - Spatial pyramid of dilated convolution
- Reduces parameter and allow network to learn the representation from a large Receptive field
- ESP Strategy:
  Standard Convolution → *Reduce* → *Split* → *Transform* → *Merge*

ESPNET



ESPNET Architecture

Timeline

Data Pre-proceesing:	Completed
Model Training	March, First week
Model Evaluation and Submission	End of March

End