

MRI-based 3D brain tumor image segmentation using deep learning method

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Brain tumor

- A mass or growth of abnormal cells in your brain
- Can be benign or malignant
- Primary and metastatic brain tumors
- Glioma is a main type of brain tumor originate from glial cells
- Low-grade and high-grade





Brain tumor treatment

- Treatment: surgery, chemotherapy, radiotherapy
- Early diagnosis using medical imaging:
 - Computed Tomography (CT)
 - Single-Photon Emission Computed Tomography (SPECT)
 - Positron Emission Tomography (PET)
 - Magnetic Resonance Spectroscopy (MRS)
 - Magnetic Resonance Imaging (MRI)



Magnetic Resonance Imaging (MRI)

150 2D images -> a 3D volume

- Non-invasive technique that uses radio frequency signals to excite target tissues to produce their internal images under the influence of a very powerful magnetic field
- Provide valuable structural information and enabling diagnosis and segmentation of tumors
- Four standard MRI modalities

Source https://www.sciencedirect.com/science/article/pii/S187705091632587X



Fig. 1. Four different MRI modalities showing a high grade glioma, each enhancing different subregions of the tumor. From left; T1, T1-Gd, T2, and FLAIR. Images are generated by using BRATS 2013 data⁵.

Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels



Source http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture11.pdf

Image segmentation

Image segmentation is the process of partitioning a digital image into multiple segments

Semantic vs Instance Segmentation

Brain tumor image segmentation

- We want to protect healthy tissues while destroying tumor cells during the therapy
- Manual annotation takes a lot of time

A deep-learning based solution for brain tumor segmentation



Methods for brain tumor segmentation

- Manual: 100% human iteration
- Semi-automatic: human + algorithms
- Fully-automatic: no human interaction

Challenges

- Tumor vary greatly from patient to patient
- Tumor boundaries are unclear and irregular
- MRI images also vary dramatically from scan to scan
- Different modalities needed

2012	2013	
35 Training	35 Training	
15 Testing	15 Testing	

"BRATS 2012			
The Multimodal Revis Tumor Image Segmentation Renchmark (BRATS)			
Band Davie, John Sall and Jack Sall and Sall			

"BRATS 2016

ECANCER IMAGING ARCHIVE

2014	2015	2016
214 Training	214 Training	214 Training
38 Testing	53 Testing	191 Testing

2017	2018	2019	2020	"BRATS 2020
284 Training	286 Training	335 Training	369 Training	current
46 Validation	66 Validation	125 Validation	125 Validation	dataset
146 Testing	191 Testing	166 Testing	166 Testing	



Classes: edema (yellow), core (red), enhancing (blue), necrotic/fluid filled (green) Regions: "whole tumor", "tumor core", "active tumor"



Dataset

Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)

U-Net & 3D U-Net



Source https://arxiv.org/pdf/1505.04597.pdf

Methods

2 X Area of Overlap IoU = Area of Union + loU Dice Coefficient/F1 Score

1 - Perfect overlap

0 – No overlap

Accuracy measurement

Expected outputs

Author	Method	Level of user interaction	Performance (Dice Scores)		
			Whole Tumor	Core Tumor	Active Tumor
Human	Medical training and experience	Manual	0.88	0.93	0.74
Rater					
Pereira et al. ³¹	CNN with small (3x3) filters for deeper architecture	Fully automatic	0.88	0.83	0.77
Kwon et al. ¹⁵	Generative model that performs joint segmentation and registration	Semi-automatic	0.88	0.83	0.72
Havaei et al. ²⁹	Cascaded Two-pathway CNNs for simultaneous local and global processing	Fully automatic	0.88	0.79	0.73
Tustison et al. ¹⁹	Concatenated RFs, trained using asymmetry and first order statistical features	Fully automatic	0.87	0.78	0.74
Urban et al. ²⁷	3D CNN architecture using 3D convolutional filters	Fully automatic	0.87	0.77	0.73
Havaei et al. ¹⁰	Uses SVM; training and segmentation implemented within the same brain	Semi-automatic	0.86	0.77	0.73
Dvorak and Menze ³²	Local structured prediction with CNN and k-means	Fully automatic	0.83	0.75	0.77
Davy et al. ³⁰	Two-pathway CNN for simultaneous local and global processing	Fully automatic	0.85	0.74	0.68
Zikic et al. 28	3D input patches are interpreted into 2D input patches to train a CNN	Fully automatic	0.837	0.736	0.69
Hamamci et al. ⁹	Generative model, uses cellular automata to obtain tumor probability map	Semi-automatic	0.72	0.57	0.59
Rao et al. ³³	Four CNNs, one for each modality, with their outputs concatenated as an input into a RF	Fully automatic	Not reported	Not reported	Not reported

Thank you!