3D U-Net for Brain Tumour Segmentation

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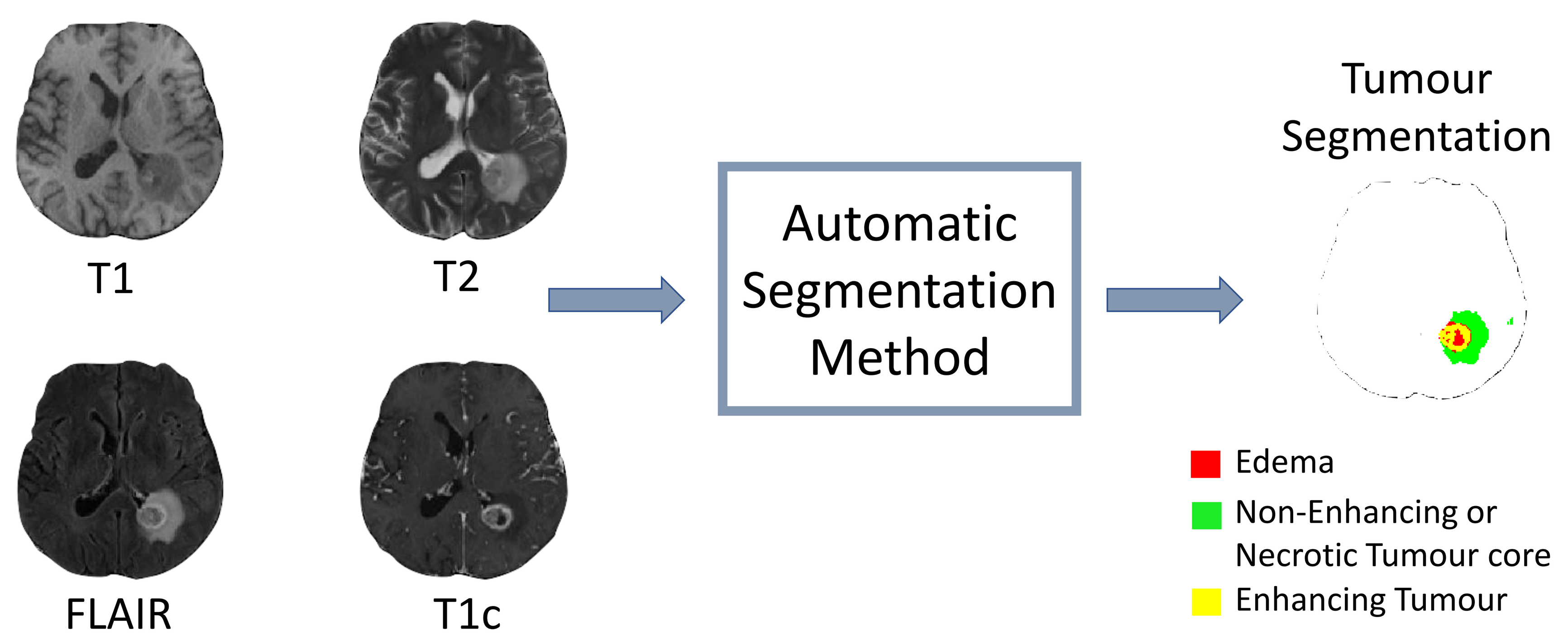
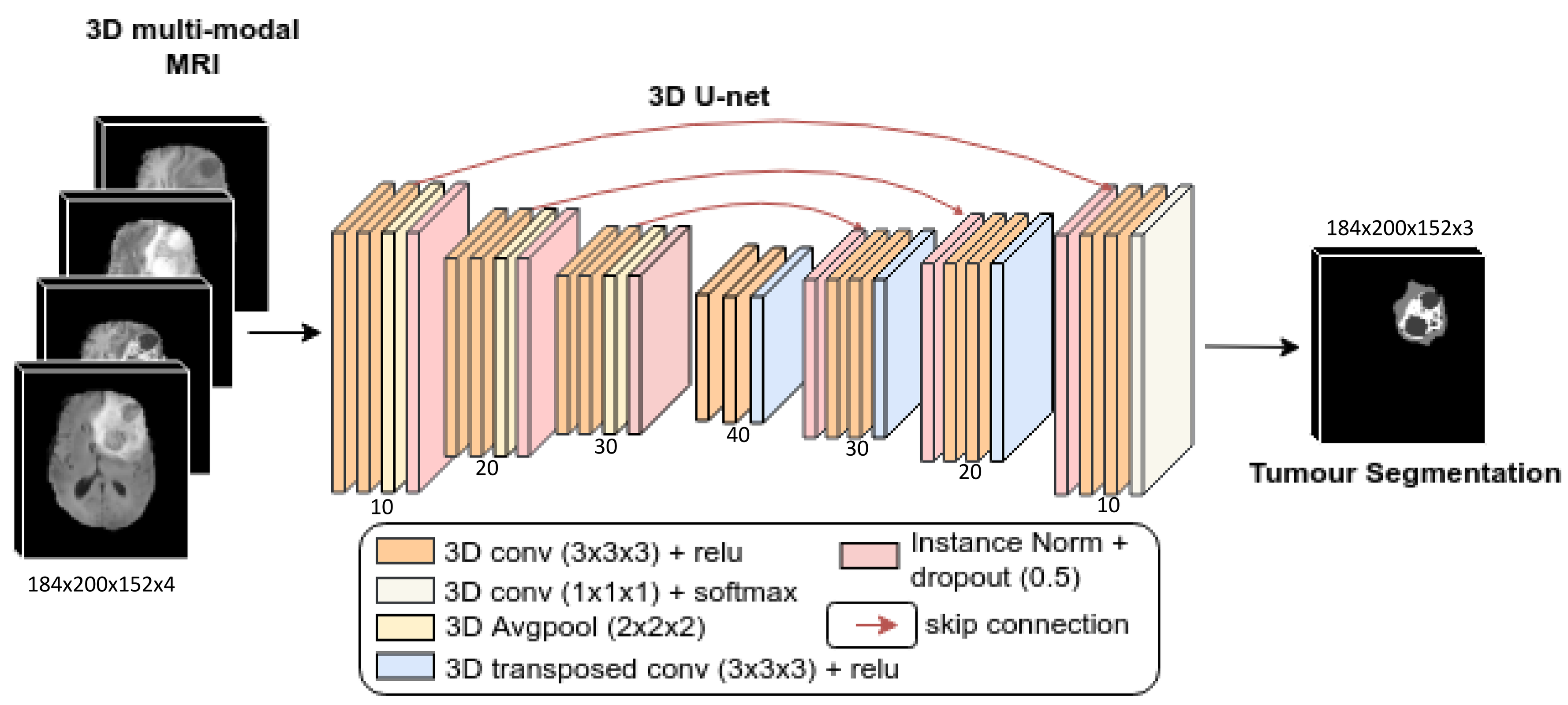
Introduction



- Automatic segmentation algorithms can be useful for faster and reliable tumour delineation.
- Automatic brain tumor segmentation is a challenging task due to the wide variety of tumor locations, sizes, and shapes
- Various machine learning approaches for automatic tumour segmentation
  - Context-sensitive Random Forrest [1]
  - Multilevel Markov Random Field [2]
  - Multi-scale 3D CNN with Conditional Random Field [3]
  - Boundary Aware Fully Convolutional Neural Network [4]

Method



Architecture Details:

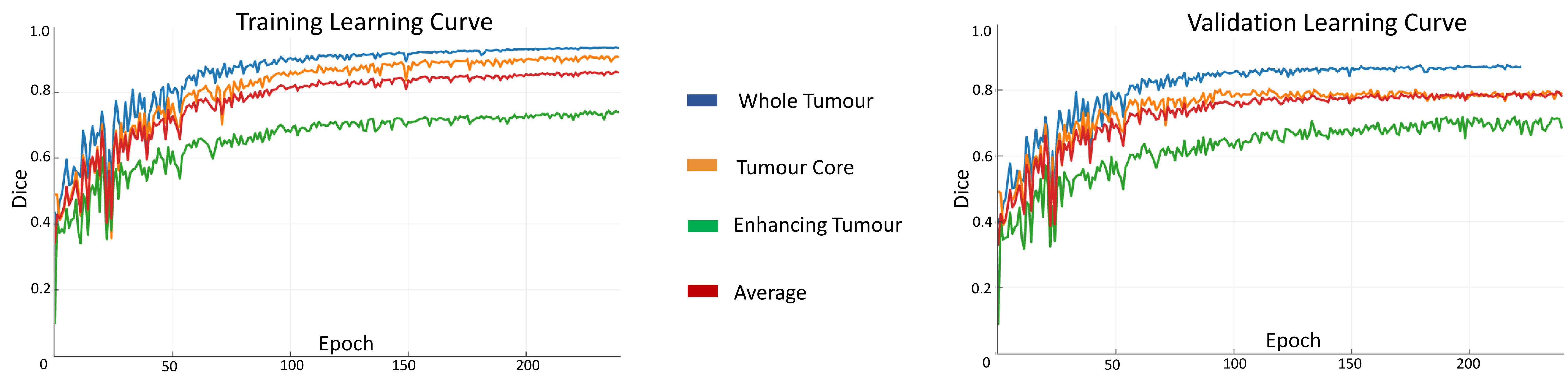
- 4 resolution step 3D U-net [5]
- Use of AvgPooling instead of MaxPooling for downsampling.
- Use of Transposed convolution for upsampling.
- Use of Instance-Norm and Dropout after each step
- Categorical Cross-Entropy (CCE) with curriculum class weight as loss function
- Pre-processing: Intensity Standardization using the mean and standard deviation over the masked region of a given MR image

Quantitative Results

	Dice			Sensitivity			Specificity			Hausdorff-95		
	ET	WT	TC	ET	WT	TC	ET	WT	TC	ET	WT	TC
Mean	0.690	0.888	0.793	0.774	0.880	0.802	0.998	0.995	0.996	7.251	6.600	7.941
StdDev	0.294	0.094	0.206	0.245	0.118	0.210	0.004	0.006	0.007	13.318	11.215	11.805
Median	0.817	0.918	0.876	0.861	0.913	0.879	0.999	0.996	0.999	2.237	3.606	4.062
25quantile	0.641	0.878	0.748	0.709	0.850	0.723	0.997	0.994	0.996	1.414	2.236	2.236
75quantile	0.878	0.941	0.926	0.935	0.958	0.942	0.999	0.998	0.999	5.385	6.557	9.327

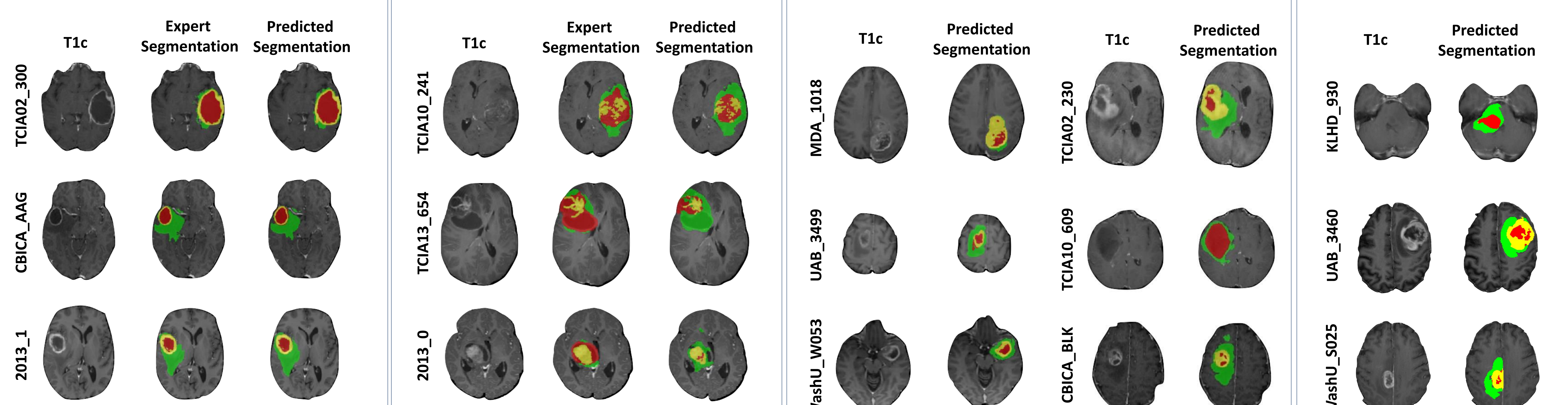
	Dice			Sensitivity			Specificity			Hausdorff-95		
	ET	WT	TC	ET	WT	TC	ET	WT	TC	ET	WT	TC
Mean	0.788	0.909	0.825	0.824	0.911	0.811	0.998	0.995	0.998	3.520	4.923	8.316
StdDev	0.233	0.059	0.179	0.222	0.082	0.212	0.004	0.004	0.002	4.992	8.154	13.521
Median	0.869	0.921	0.902	0.893	0.933	0.901	0.999	0.996	0.999	1.732	2.914	3.240
25quantile	0.809	0.894	0.773	0.824	0.880	0.711	0.998	0.994	0.998	1.414	2.000	2.000
75quantile	0.911	0.951	0.945	0.942	0.964	0.958	0.999	0.998	0.999	3.000	4.970	8.658

Challenge Metric Statistics: 5-Fold Cross-Validation on BraTS 2018 Training Set (Left) and BraTS 2018 Validation Set (Right). Results are specified for enhancing tumor (ET), whole tumor (WT), and tumor core (TC)



Training (Left) and Validation (Right) Dice Scores as a function of number of epochs for one of the five cross-validation fold.

Qualitative Results



BraTS 2018 Training Dataset HGG case

BraTS 2018 Training Dataset LGG case

BraTS 2018 Validation Dataset

BraTS 2018 Test Dataset

Reference:
[1] Zikic et al. "Context-sensitive classication forests for segmentation of brain tumor issues." Proc MICCAI-BraTS (2012): 1-9.
[2] Subbanna et al. "Iterative multilevel MRF leveraging context and voxel information for brain tumour segmentation in MRI." In Proceedings of the IEEE CVPR, pp. 400-405. 2014.
[3] Kamnitsas et al. "Ecient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation." Medical image analysis 36 (2017): 61-78.
[4] Shen et al. "Boundary-aware fully convolutional network for brain tumor segmentation." In MICCAI, pp. 433-441. Springer, Cham, 2017.
[5] Cicek et al. "3D U-Net: learning dense volumetric segmentation from sparse annotation." In MICCAI, pp. 424-432. Springer, Cham, 2016.
[6] Menze et al. "The multimodal brain tumor image segmentation benchmark (BRATS)." IEEE TMI 34, no. 10 (2015): 1993.

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