The re-evaluation of Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Network

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Background Information

Gliomas, a type of brain tumor, has two main basic grades: low-grade gliomas(LGG) and high-grade gliomas(HGG). The BraTS 2017 dataset [1] contains MRI images of both LGG and HGG in four modalities: T1, T1Gd, T2 and FLAIR, which provides the look of gliomas in different views. With the enriched information provided by the dataset, the dataset also contains three tasks for people to encounter: segment the whole tumor (WT), enhanced tumor (ET) and tumor core (TC). We choose improve the model introduced in the paper by Wang [2, 3], which scores second place in the competition.

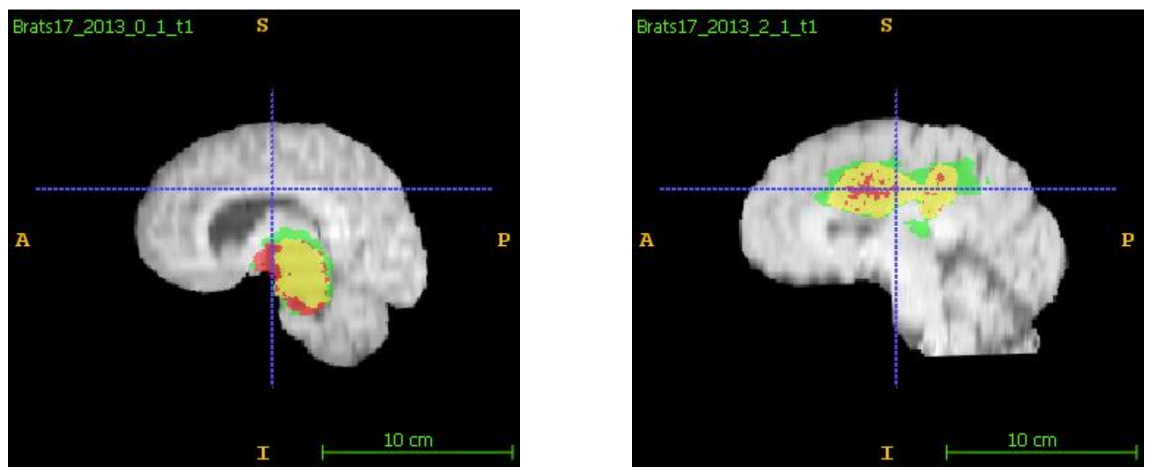

Fig 1. . Sample LGG(left) and HGG(right) images [1]

Individual Contribution and Workflow

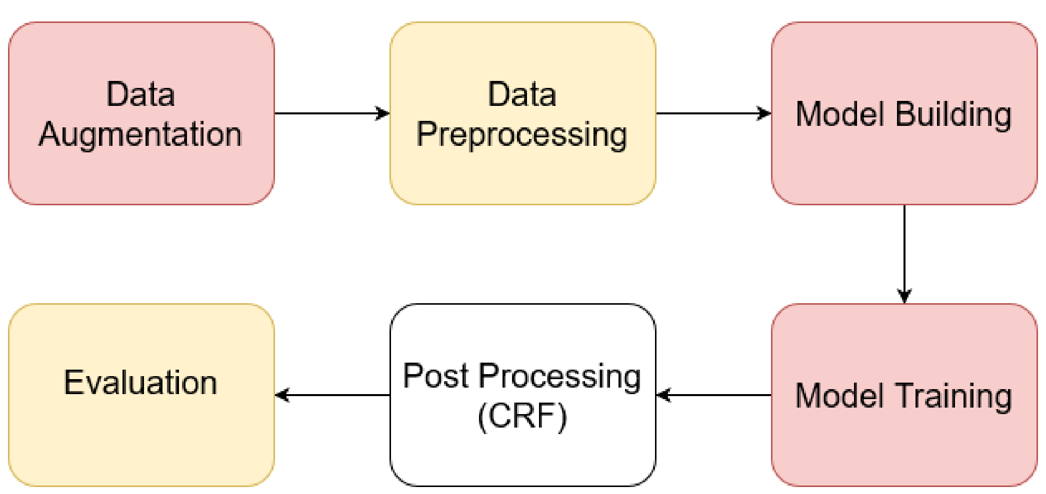

Fig 2. Work Flow(red indicates parts I have majorly participated in, yellow indicates parts I have minorly participated in, star means this part is new from original model)

Data Augmentation

- Observed the lack of LGG in the dataset
- Performed elastic deformation to the LGG dataset to help to resolve the issue

Model Building:

- Reimplement the model from scratch in PyTorch to support better extensibility for the model.
- Minor update to model architecture: changed convolution size and layer order to ensure the performance of the model could approach the original.

Training & Testing:

- Discovered better performance with different loss function.
- Major debug with several crucial issue in the first draft.

Model Building

Model Building

Original model was built on Niftynet with Tensorflow V1, which is not maintained by any organization anymore. Consider the massive extension and higher readability supported by PyTorch, we decided to migrate the model to PyTorch. During the reimplementation, I made two minor changes: the changed down sample and prediction layer from 3 to 2, which allows the model to maintain the original size introduced by the author, meanwhile capture more high-level information from previous layer.

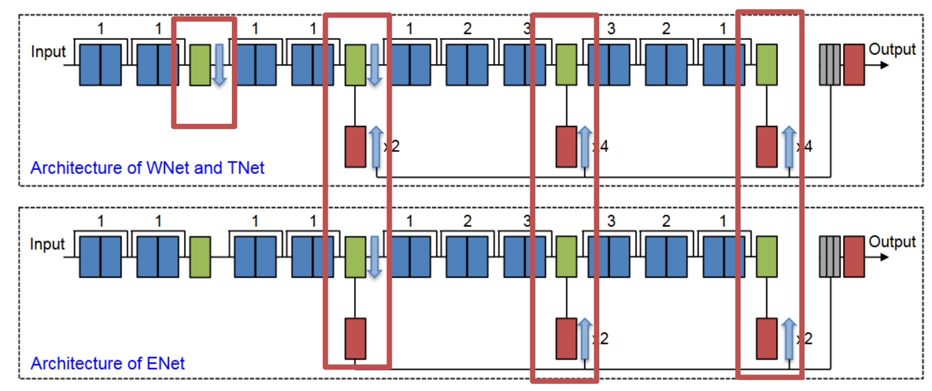

Fig 3. Modified Layer(in red block) in Original Architecture [2,3]

Model Training

Besides the modification on the model architecture, we also did some changes on the training settings. I used Cross Entropy Loss instead of Dice Loss, as we observed better performance on CE over Dice in our scenarios.

By applying changes, we could get a reasonable accuracy in a 20 images test set. (Note: the test images are actually in the training set of the author's model, so we also compare the performance indicated in the paper)

	WT	TC	ET
Base	91.7	80.6	63.9
Author	92.9	91.9	88.7
Paper	87.4	77.4	78.3

Table 1. Base Model Performance Compare to Author's Final Model [2, 3]

References

- [1] https://www.med.upenn.edu/sbia/brats2017.htm
- [2] Guotai Wang, Wenqi Li, S´ebastien Ourselin, and Tom Vercauteren (2018) *Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks*
- [3] Eli Gibson*, Wenqi Li*, Carole Sudre, Lucas Fidon, Dzhoshkun I. Shakir, Guotai Wang, Zach Eaton-Rosen, Robert Gray, Tom Doel, Yipeng Hu, Tom Whyntie, Parashkev Nachev, Marc Modat, Dean C. Barratt, Sébastien Ourselin, M. Jorge Cardoso^, Tom Vercauteren^. "NiftyNet: a deep-learning platform for medical imaging." Computer Methods and Programs in Biomedicine, 158 (2018): 113-122. https://arxiv.org/pdf/1709.03485
- [4] F. Pérez-García, R. Sparks, and S. Ourselin. TorchIO : a Python library for efficient loading, preprocessing, augmentation and patch-based sampling of medical images in deep learning. Computer Methods and Programs in Biomedicine (June 2021), p. 106236. ISSN: 0169 2607.doi:10.1016/j.cmpb.2021.106236.
- [5] https://torchio.readthedocs.io/transforms/augmentation.html

Data Augmentation

Originally, the dataset only contains 210 HGG images and 75 LGG images, which the is imbalance. HGG and LGG has significantly patterns on MRI scans, we believe that enhancing the data set would have gain on the final performance.

On top of the observation, I introduced potential data augmentation to the project. We finally decided on three data augmentation method: RandomElasticDeformation and RandomAnisotropy.

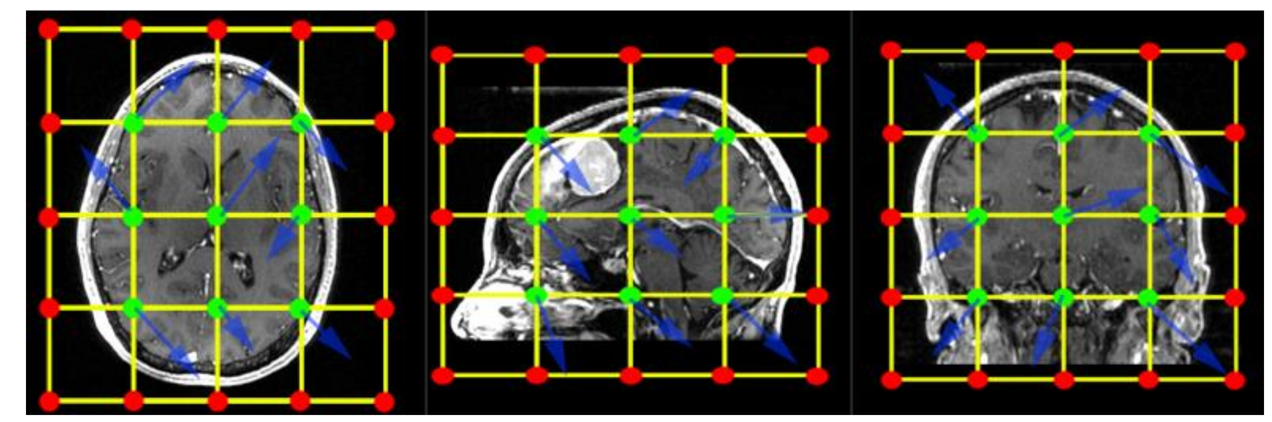

Fig 4. Elastic Deformation Method with 5 Control Points[5]

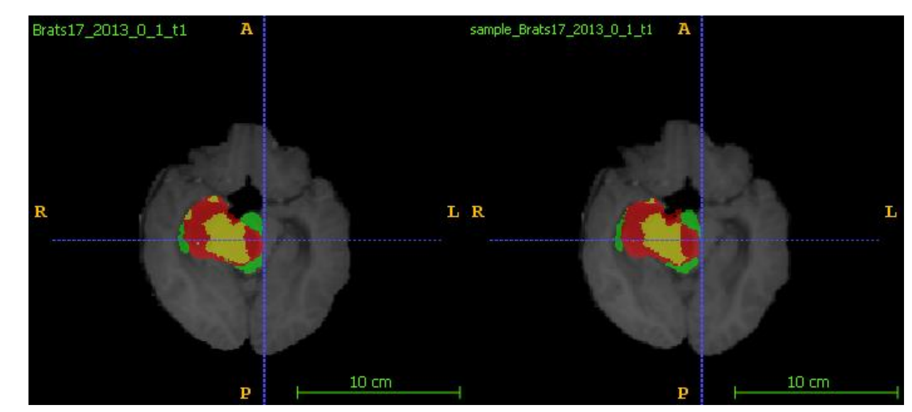

Fig 5 Before Elastic Deformation(left) and After Elastic Deformation(right)

By performing two random data augmentation for each LGG image, we will have 225 LGG images (75 original and 150 augmented) and 210 HGG images. We prepared a testing set with 10 original LGG and 10 HGG images to compare the performance of model before and after data augmentation. We tested the performance of the model before and after data augmentation with CRF included. We found that data augmentation could significantly improve (~5) performance in tumor core segmentation with small loss (<1.5) in WT and ET segmentation.

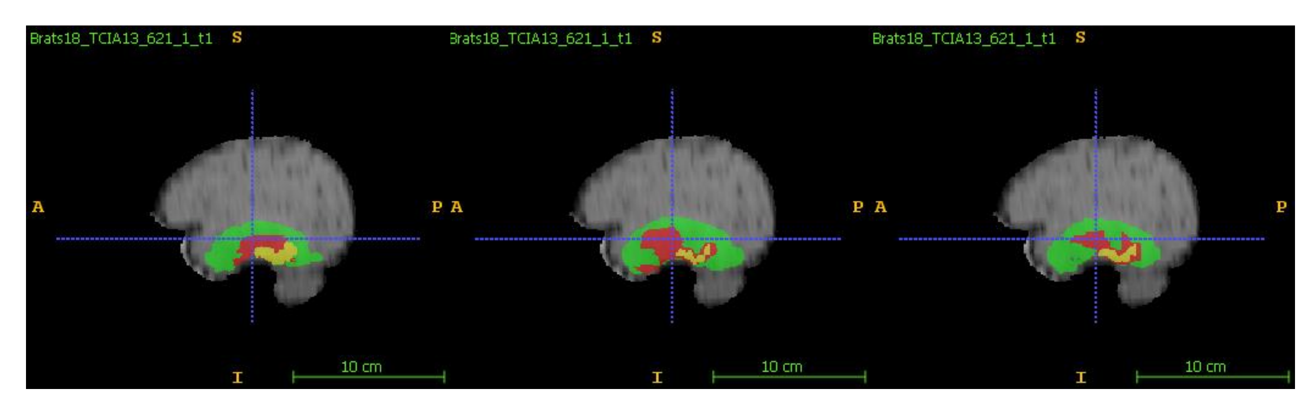

Fig 6. Segmentation Result on LGG for GT(left), Baseline(middle) and Data Augmented (right)