Active learning for glioma segmentation with deep learning

Low-grade glioma are a type of brain tumor that is unpredictable in its evolution. Some patients may live many years in a relatively stable situation, while other glioma progress quickly to a more malignant type. They are commonly treated through resection, chemotherapy and radiation therapy. However, there is currently no known treatment that can completely remove the tumor and despite treatment the tumor will eventually return. MR imaging plays an important role in the treatment process as it gives a means of monitoring the disease without harming the patient.

We are interested in the evolution of glioma and would like to predict the malignant evolution or recurrence of low-grade glioma. Imaging provides valuable information for this research, but we need to extract some quantititave measurements from the images in order to compare them effectively. This can be done through segmentation of the tumor: the delineation of (specific parts of) the tumor in the 3D image (see Fig. 1). Currently this is performed manually, but for large patient groups with multiple scans per patients this becomes an untractable task. Therefore, convolutional neural networks (CNNs) are being developed to perform automatic segmentation.

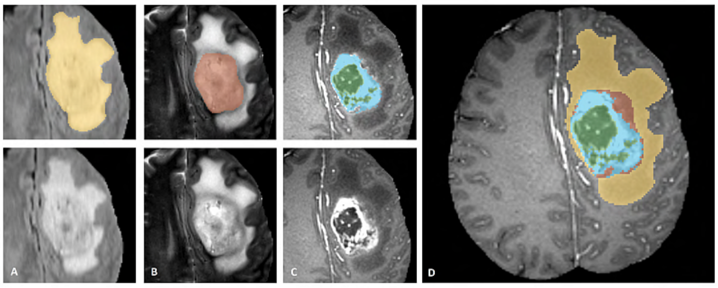

Figure 1: Example of a glioma segmentation into multiple sub-structures. A: the whole tumor (yellow). B: the tumor core (red). C: The enhancing tumor structures (blue) and necrotic core (red). D: the combined segmentation. This image is part of the BraTS multi-modal brain tumor segmentation benchmark. [1]

Though the deep learning approach to segmentation provides decent results, it is still not as accurate as the work of a radiologist. The results need to be checked and corrected before they are used in a research setting, especially because some results will be much worse than others. However, each corrected segmentation can be used to improve the model. With this in mind, it would be interesting to know if we can implement a smart protocol for checking the images.

First, we would like to predict beforehand when the model provides inaccurate results, so that we can check those images first. Then, we would like to know if adding these more difficult cases to the model will also improve the model faster. Perhaps the most difficult cases are not the most informative, but we can find some other criterion to select new data. There is a field of machine learning research aimed at solving these questions, called 'active learning'. The deep learning models provide an additional challenge in this case, because they are expensive to train. Re-training the entire model whenever a new image is added is untractable, so how can we add the data effectively? To answer these questions we have access to datasets from multiple sources with segmentations, as well as a working deep learning segmentation model and GPU facilities to experiment with different protocols and scenarios.

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References

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