Alessia De Biase

Short Biography:

Currently she is a PhD candidate in Deep Learning in Medical Imaging at the Department of Radiation Oncology of the University Medical Centre Groningen (UMCG), with a research focus on personalized adaptive radiotherapy. Her primary focus lies in implementing deep learning modelling techniques to tackle crucial tasks such as tumour segmentation and treatment outcome prediction. To achieve this, she leverages multi-modal imaging data acquired before and during treatment. Along with her research, she is a board member of the Machine Learning Lab Community at the UMCG.

Abstract:

The advent of image-guided therapy represented a milestone in medical innovation, revolutionizing the precision and effectiveness of various medical procedures. In modern cancer treatments, such as radiation therapy, three-dimensional images are created that help find the exact location of tumor lesions. The preferred imaging modality for radiotherapy is computed tomography (CT), as it enables the calculation of the dose that will be delivered to the target volumes and organs at risk. However, stand-alone CT images did not prove to be sufficient for tumor delineation in all cases. Recent studies showed that FDG-PET imaging is crucial in detecting some types of cancer, such as head and neck, lung, esophageal, lymphoma, etc. Some of the benefits of combined PET/CT imaging for radiotherapy planning are 1) visually enhancing the differences between tumor and soft tissue, and 2) reducing intra- and inter-observer variability in tumor delineation [1]. However, while the use of complementary image modalities increases the likelihood of detecting tumor boundaries, it simultaneously introduces an additional layer of complexity for the contouring expert. Semi-automated and automated tumor segmentation methods were then introduced to speed up radiotherapy treatment planning.

After demonstrating its immense capabilities in modeling natural images, artificial intelligence's impact extended to the field of medical imaging as well. The added value of deep learning models is being able to integrate and process information from different imaging modalities simultaneously and rapidly. If relying only on anatomic data from CT and MRI scans proved not to be enough for radiation oncologists to perform accurate tumor segmentations, a similar limitation emerged with AI-driven tumor segmentation models. Recent studies showed that using PET only or PET/CT, compared to using CT only, as input for deep learning tumor segmentation methods achieves higher performance in lung [2] [3] [4] [5], head and neck [6] [7] [8], and esophageal cancer [9]. The high uptake regions, in fact, indicate active tumor regions in PET images, facilitating tumor detection. Problems arise when tumor cells are not active or the standardized uptake value (SUV), used as a semi-quantitative measurement for PET pixel values, is influenced by biological factors. Can AI overcome those PET imaging limitations? The use of PET in conjunction with other imaging modalities, such as CT or MRI, helped reduce false positives, for example. Nonetheless, there are still significant barriers to clinical implementation, which are not solely attributed to the nature and quality of the input data employed for these models but also to the limitations of AI algorithms. One such obstacle is the inability of traditional AI models to convey their level of confidence when providing specific answers to the end user [10].

The role that AI can play now is to assist radiation oncologists in performing tumor contouring for radiotherapy treatment planning. Thus, it is necessary for future research to be oriented towards uncertainty-aware deep learning models. Yet, it is equally important that the next generation of imaging work towards the development of high-sensitivity and high-resolution scanners, resulting in a concurrent mitigation of artifacts [1] [11].