



Editorial

Future directions on the merge of quantitative imaging and artificial intelligence in radiation oncology



Radiation oncology has for several decades been a field with constantly evolving technological developments. Technology has contributed to form our evidence-based scientific discipline determining the most favorable strategies for delivering radiotherapy with optimal radiation doses at the right time and place to achieve the optimal outcome [1].

Technological developments in medical image acquisition and analysis have increasingly provided faster and more detailed anatomical imaging and are today central for contouring of both targets and organs at risk (OARs), treatment planning, response prediction and evaluation, and quality assurance. On the other side, errors in image acquisition and quantification impact directly on the accuracy of radiotherapy delivery. Two papers exploiting technological advancements in imaging to develop new and more automated strategies for OAR and metastatic lymph node contouring have recently been published in our journal [2,3].

Computed tomography (CT) scanning has been pivotal in the development of radiotherapy planning. CT, now often acquired daily during the course of treatment, provides the geometric fidelity required to assess the position of the tumor, surrounding tissues and OARs. However, with the increasing availability and integration of magnetic resonance imaging (MRI) into the radiotherapy planning process, additional opportunities are emerging. MRI offers a superior soft-tissue contrast compared to CT, and also provides possibilities for a multitude of different acquisition protocols enabling both detailed anatomical imaging and assessment of a range of functional tissue properties using the more advanced protocols such as diffusion-weighted MRI and dynamic contrast-based MRI. These functional sequences can together with post-processing tools provide quantitative measures of radiobiological tissue characteristics, which can be exploited to deliver more tailored radiotherapy to each patient and also with the possibility for adjustments during the course of treatment [4]. The use of MRI may therefore result in a more optimized treatment where the tumor response is increased and normal tissue damage is decreased.

With the recent developments of novel MR-guided radiotherapy systems, including the integration of MRI scanners and linear accelerators, MRI is now becoming a reality also for daily monitoring of geometric accuracy, dose accumulation and of radiotherapy response measures [5,6]. Although MRI has been a more resource and time-demanding acquisition than CT, new technological developments with for instance parallel acquisition are now providing faster, high-resolution, 4-dimensional acquisitions providing both anatomical and functional information during radiotherapy delivery [7,8]. This opens new avenues for quantitative assessment of longitudinal changes during the course of radiotherapy.

A key challenge for daily quantitative imaging is contouring of the target and OARs. Currently, expert clinicians perform the contouring manually. Such a process is labor-intensive and also associated with considerable variations between experts. Contouring accuracy is regarded a particularly important task in radiation oncology, as sub-optimal tumor coverage and poor quality radiotherapy plans are major factors for disease relapse and inferior survival [9].

Automation of the contouring process has the potential to substantially decrease the workload while possibly increasing contour consistency [10]. The need for automated contouring of the target and OARs has been a major reason for why artificial intelligence (AI) has become attractive for our discipline [11]. AI and machine learning are terms used to describe computerized approaches to identify complex mathematical relationships within data. While AI is not a new concept, recent advances in computing power, algorithms, data collection and data sharing have enabled an explosion in the capabilities and utilization of AI. This is also facilitated by an increase in parallel computing capabilities through graphics processing unit (GPU) architectures and other frameworks such as cloud-based computing.

Krizhevsky et al. presented the breakthrough study in 2012 using a convolutional neural network (CNN) model, AlexNet, to reduce the error rate for object (i.e. target and OAR) recognition [12]. This model showed impressive results and became important for further developments of organ segmentation in radiotherapy. Later, Tong et al. used CNN models to perform automatic multi-organ segmentation in patients with head and neck cancer [13]. However, for clinical use in radiotherapy planning, automated target and OAR segmentation needs to be robust and accurate. Recent studies investigated the use of different networks to reach maximum accuracy for automatic segmentation [14]. Efficient translation of the methods to other centers has to be guaranteed. In this issue, Brunenberg et al. performed an independent validation of a deep learning-based CT contouring method for OARs in the head-and-neck region [2]. The study demonstrated that AI-based automatic contouring which had been trained in one institution could safely and efficiently be transferred to another institution for subsequent clinical use. Such independent validation is of crucial importance to ensure freedom from dependencies on institutional image acquisition settings. Further in this issue, Gurney-Champion et al. combined 3D CNN models with quantitative information from diffusion-weighted MR images to achieve automatic contouring of metastatic lymph nodes in patients with head and neck cancer [3]. This study aimed at developing a highly reproducible method for lymph node segmentation in order to objectively analyze sequential information from quantitative information assessed during each fraction of radiotherapy delivery. With this visionary approach, the study paves

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the way for future online radiotherapy adaptation with respect to quantitative imaging information. Similarly, Kuisma et al. recently reported on a study validating automated MRI segmentation in prostate cancer patients using comparison to manually created structures [15], Elguindi et al. presented a deep learning-based method for automatic segmentation of both targets and OARs to expedite MRI-based radiotherapy in prostate cancer [14], and Jong et al showed a method using CT images for automatic segmentation of cardiac substructures for breast cancer radiotherapy [16].

These studies also focus on the central role of quantitative image data for developing high-accuracy AI models, and oppositely, the detrimental effects of uncertainties in image acquisition and quantification. To reduce errors in the imaging data it is crucial to standardize image acquisition protocols, post-processing analysis methodology and other tools used to integrate the image information into the treatment planning and delivery process, as well as the AI models.

Target and OAR segmentation is not the only application of AI in radiation oncology. Other emerging applications include automated planning and dose optimization, decision support, and quality assurance. Although there still is an ongoing debate about the increasing number of machines in our institutions and in part replacement of human jobs, it is clear that developments in AI have the potential to streamline several areas in radiation oncology.

Personalized patient care is often regarded as the way forward [1], with AI being key to its further progression. While AI is introducing a dramatic change to the way therapy can be approached, it is also important to appreciate that the manual role of radiation oncologists, physicists and radiotherapists will still be critical. At the present stage the development is also associated with some challenges. The algorithms and results from the small studies need to be validated in independent multicenter studies, larger patient cohorts and through demonstrated clinical feasibility before they can be routinely implemented. Challenges related to standardization in image acquisition, image analysis and software need to be addressed. New data-sharing paradigms are required between institutions and vendors, and should be embraced for faster development and comprehensive clinical validation. Beyond the obvious benefit of automating labor-intensive tasks, such as contouring, AI has an enormous potential to guide personalized radiotherapy to new horizons. These might take into account input variables from various time-dependent sources, as e.g. sequential quantitative imaging or genetic markers, and may also change current paradigms of classical radiotherapy by altering dose prescriptions, fractionation schedules or other treatment parameters.

In conclusion, there is no doubt that the merge between quantitative imaging and AI in radiation oncology has the potential to improve the radiotherapy delivery process and reduce error rates. Looking ahead, the trend of AI will become central in future radiation oncology due to the precision and efficiency the radiation oncology discipline is demanding.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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