Chapter 8
Machine Learning in Radiation Oncology

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ABSTRACT

Machine learning (ML) is transforming radiation oncology by enhancing precision, efficiency, and personalization. Key applications include: (1) Treatment planning—U-Net and nnU-Net achieve >85% Dice scores for tumor segmentation, while GANs optimize dose distribution; (2) Predictive modeling—Radiomics and genomics predict treatment response/toxicity, though data heterogeneity challenges reproducibility; (3) Personalized therapy—Biomarker-driven adaptation and digital twins enable dynamic adjustments. Challenges include data scarcity, model validation, and interdisciplinary collaboration, with federated learning proposed for privacy-preserving data sharing. ML automates workflows, improves outcomes, and addresses resource disparities, but requires standardized protocols, robust validation, and ethical frameworks for equitable adoption. Future directions include federated learning advances, multi-center trials, and prospective studies to translate research into practice.

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BACKGROUND AND LITERATURE REVIEW

The rising cancer burden, estimated to hit 28.4 million fresh cases every year by 2040 (Grahovac, 2023), has further increased the need to find more accurate, effective, and tailored treatment options. Radiation oncology, which is one of the pillars of cancer treatment, is especially pressed to move beyond the conventional protocols. The major issue is to get the best possible control over tumours and least possible toxicity to the neighbouring healthy tissues, which is naturally complex and differs positively in individual patients.

The artificial intelligence (AI) and clinical medicine have joined forces creating an opportunity to tackle this challenge. Initial computational work in radiation oncology was on the rule-based systems and simple statistical models of processes such as dose calculation. Nevertheless, with the development of machine learning (ML) and deep learning in particular, the shift in approach to automation to intelligent assistance has become possible. It was shown that convolutional neural networks (CNNs), including U-Net, can be used to automate the labour-intensive task of tumour and organ-at-risk segmentation, with Dice coefficients comparable to human experts (Seminal work by (Giraud et al., 2019) and others). At the same time, the so-called radiomics appeared, to which researchers, including (Dercle et al., 2021), attributed quantitative characteristics of medical images as a potential predictor of treatment response and toxicity.

Irrespective of this positive trend, there are some gaps evident in the literature. To start with, the reproducibility crisis affects most ML applications, particularly in the field of radiomics, frequently because of the absence of standardised protocols of image acquisition, preprocessing, and validation (Zhovannik, 2022; Dercle et al., 2021). Second, it has a high level of translational disparity; many of the models are highly accurate in retrospective research, but a minimal number are subject to rigorous prospective clinical verification [Citation: Dercle et al., 2021]. Third, there exist problems of data scarcity and heterogeneity, which restrict the possibility of the generalizability of models to new patient groups and clinical settings (Vuong, 2021). Lastly, the concept of multi-modal data (imaging, genomics, clinical records) integration into unified predictive models is a significant technical and operational challenge (Khansari, 2024).

The objective of the review is to synthesise these advances and issues, critically reviewing the adoption of ML in the main fields of radiation oncology treatment planning, predictive modelling, and therapy personalisation. This work will attempt to bring a clear roadmap on how responsible and effective adoption of ML in clinical practice can be done by consolidating the current state of the art and by clearly solving the identified gaps.