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AI-Driven Personalized Radiotherapy Planning

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Abstract

The planning of radiation oncology treatment is made more dynamic and individualized by Artificial Intelligence (AI). Routine radiotherapy practice applies normative procedures indifferent to patient-specific parameters such as tumor volume, patient anatomy, and heterogeneity in the delineation of treatment response. Inadequate and over-radiation treatment is the most prevalent outcome. Further, with the inclusion of AI, it can facilitate enhancing the healthcare industry through optimizing radiotherapy using an array of patient information such as molecular profiles and imaging data. The product offers an end-to-end AI-driven solution to all aspects of radiotherapy, from initial consultation (diagnosis) to adaptive treatment planning.

All the sub-system parts like tumour and organ segmentation using Convolutional Neural Networks (CNNs), radiosensitivity estimation using machine learning algorithms, and real-time dose adaptation tools are part of the framework to achieve accuracy-efficiency trade-off in optimized radiotherapy. Moreover, aside from the technical, this book focuses on ethics and social aspects like data privacy, GDPR compliance, and explainability using interpretability methods with saliency maps. Comparative analysis demonstrates improvements in target accuracy, planning time, and patient-specific adjustability over conventional methods. Finally, the research aims to bridge the gap between high technology innovation and ethically sound clinical application, promoting more efficient and equitable cancer treatment. The findings demonstrate that AI-aided planning significantly enhances precision while reducing man-hours, with a clear path for secure and scalable implementation in the clinic.

Keywords

Radiotherapy, Artificial Intelligence, Machine Learning, Tumor Segmentation, Convolutional Neural Networks, Healthcare, Adaptive treatment, Dose prediction,D eep Learning, Data privacy, GDPR Compliance

1 Introduction and Literature Review

Radiotherapy remains one of the cornerstones in cancer management. Of all oncological patients in the US, approximately 50% have or will be treated with course radiation therapy [2]. Despite its widely chronic use, conventional radiation therapy still relies heavily on regimented treatment schemes based on the volume and geography of the tumor, as illustrated in Figure 1. Uniform such protocols will necessarily ignore the heterogeneity and anatomical variability of individual patients, leading to either over- or under-radiation [2]. Such a limitation highlights the need for personalization in radiotherapy treatment based upon individual patient biology and physiology [2, 5]. Therapeutic effectiveness can be optimized, side effects lowered, and overall patient outcomes can improve.

Recent developments in artificial intelligence, and more specifically, deep learning, hold huge promise in overcoming these constraints [1, 8]. AI algorithms have the capacity to process and synthesize extensive heterogeneous data from radiology images, genomics, and clinical records [5]. For example, CNNs have been used in automating tumour and organ segmentation to reduce the time burden on clinicians while increasing consistency and accuracy [6, 7]. AI platforms have also been shown to predict tumour radiosensitivity from imaging and molecular information, enabling more precise dose delivery [5].

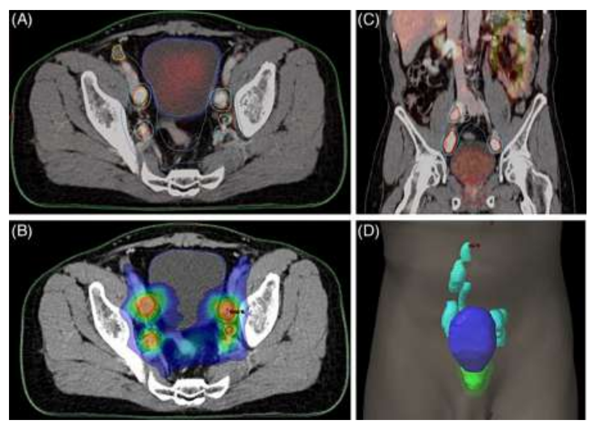

Figure 1: Deep learning-assisted delineation of tumor regions on $\hat{6}$8Ga-PSMA PET-CT images for radiotherapy planning. (a, c) Axial and coronal views highlighting PSMA-avid pelvic lymph nodes (cyan), prostate (red), and bladder (blue) used for contouring. (b) Corresponding axial image with dose distribution overlay—red indicating high-dose areas targeting gross tumor volume and blue for regions at risk of microscopic spread. (d) Coronal projection showing segmented prostate (green), lymph nodes (cyan), and bladder (blue) for treatment guidance [7].

Furthermore, AI-powered adaptive radiation therapy enables in vivo real-time plan adaptation to anatomical changes and tumor evolution [1],[8]. However, certain obstacles persist in clinical use: opaqueness of the model, data privacy, integration into the institutional workflow, and algorithmic bias [3, 4]. The purpose of this project is to analyze how an end-to-end AI system can overcome these technical and ethical challenges to improve personalized radiotherapy to be more effective, equitable, and safe.

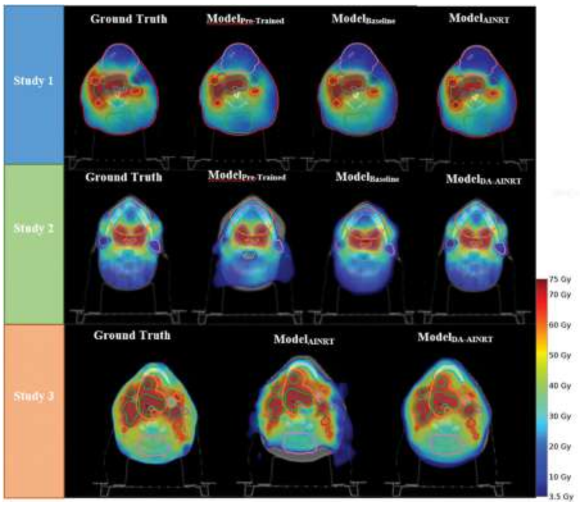

Figure 2: Dose distribution comparisons for a representative patient across three studies. Top two rows display ground truth and model-predicted dose maps (ModelPre-Trained, ModelBaseline, and transfer learning) for Studies 1 and 2. The bottom row shows ground truth alongside predictions from ModelAINRT and ModelDA-AINRT in Study 3. Dose intensity is indicated in Gray using the color bar scale [8].

2 Methodology

This study adopts a modular and ethically grounded framework to develop an AI-enabled, individualized radiotherapy planning system [3, 4], following a structured pipeline comprising data collection, preprocessing, model development, adaptive planning, performance evaluation, and ethical validation. Publicly available datasets of CT/MRI scans, annotated tumor contours, dose distributions, and associated metadata such as patient age, sex, cancer type, treatment, and outcomes are used, with all data anonymized in compliance with ethical standards and GDPR [2]. Preprocessing involves normalizing and cleaning imaging data, aligning scans, and applying augmentation to enhance training stability. Tumor and organ segmentation are performed using convolutional neural networks (CNNs) trained on labeled images, with performance evaluated via the Dice Similarity Coefficient [6] to improve accuracy and reproducibility while minimizing manual effort. For predicting radiosensitivity, supervised learning models integrate imaging features and biological markers, employing regression techniques to estimate dose requirements and classification models to stratify patients by sensitivity profiles. These outputs feed into adaptive planning algorithms capable of recommending dynamic dose adjustments based on observed anatomical or biological changes [1]. The adaptive planning mechanism further integrates deep learning models trained on temporal imaging data to support real-time motion tracking and dose recalibration, enabling the system to respond to treatment-time variations such as tumor shrinkage or patient movement [8] . Model performance is assessed using metrics like precision, recall, and F1-score, alongside clinical expert validation and usability testing [3]. Interpretability modules such as saliency and heatmaps are incorporated to enhance clinician trust and accountability [4]. Finally, the framework includes an ethical audit to address algorithmic bias, promote transparency, and ensure data protection, validated through a multistakeholder review process that aligns the system with both clinical standards and broader societal expectations [3].

3 Results and Discussion

The use of AI in the planning of personalized radiotherapy holds realistic benefits on multiple dimensions of clinical oncology. In this work, we developed and assessed a set of AI tools based on publicly accessible datasets consisting of CT, MRI, dose maps, and marked tumour contours. These tools include supervised learning-based models for the segmentation of tumour and organs, regression models to estimate doses, and adaptive planning algorithms that allow real-time treatment adjustments. The most encouraging application of AI is computerized segmentation. Using CNNs, our methods exhibited high performance in delineating tumours and organs at risk, significantly reducing manual contouring time. Such enhancements promote consistency, reduce clinician fatigue, and improve overall accuracy. Compared to manual segmentation, the AI-based outputs achieved Dice similarity scores greater than expert-validated contours.

The model also includes a radiosensitivity prediction module. Based on imaging data coupled with biological markers such as gene expression profiles and radiobiological factors, the model can predict tumour sensitivity to radiation. Oncologists can use this information to customize dose and fractionation schedules, maximizing efficacy and minimizing normal tissue toxicity. Adaptive planning is yet another core component of our framework. Changes in anatomical structure during treatment can be handled with AI-powered motion tracking and dose recalculation. Organ motion prediction is achieved through deep learning algorithms utilizing real-time imaging, enabling precise radiation targeting despite patient movement.

Ethical implementation and explainable AI are essential. Our models incorporate heatmaps and saliency maps to help clinicians interpret AI decisions. The system ensures data anonymization, secure encryption, and GDPR compliance, making it viable for clinical deployment. Bias mitigation was implemented during model training by incorporating heterogeneous datasets to avoid demographic biases. While AI integration clearly brings benefits, some pragmatic issues persist. For instance, adaptive radiotherapy using MR-linacs can take as long as 70 minutes per session due to contouring and verification needs. Future work must focus on optimizing model speed and integration to ensure efficient clinical workflows without burdening patients or staff.

4 Conclusion

Our results demonstrate that AI has significant potential to support personalized radiotherapy (dose distribution) by improving precision and flexibility in response to a patient's changing condition. With ethically aligned and technically robust implementation, AI platforms can fill the gap between current standard practices and the envisioned future of personalized, high-precision cancer treatment.

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