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Artificial Intelligence–driven adaptive radiotherapy: Current developments, clinical applications and future perspectives

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Abstract

Radiotherapy remains a cornerstone in cancer treatment. Advanced techniques such as intensity-modulated radiotherapy (IMRT) and volumetric-modulated arc therapy (VMAT) enable highly conformal dose delivery while sparing organs at risk. However, anatomical variations and tumor motion during treatment limit the effectiveness of static treatment plans. Adaptive radiotherapy (ART) addresses these limitations by modifying treatment plans based on imaging feedback acquired during the treatment course.

The integration of artificial intelligence (AI) into radiotherapy has significantly improved ART workflows by automating segmentation, treatment planning, motion prediction, and toxicity assessment. This review summarizes recent advances in AI-driven adaptive radiotherapy, highlighting its clinical applications and future perspectives.

Keywords: Adaptive radiotherapy; Artificial intelligence; Auto-segmentation; Dose recalculation; Treatment optimization

1. Introduction

Radiotherapy (RT) is used in more than half of cancer patients. Modern techniques such as IMRT and VMAT improve dose conformity and reduce toxicity to organs at risk (OARs).

However, conventional RT planning relies on a single pre-treatment CT scan, which does not account for:

- Tumor shrinkage or progression
- Weight loss and anatomical deformation
- Respiratory and organ motion

Adaptive radiotherapy addresses these limitations by updating treatment plans during therapy based on anatomical changes. AI improves ART feasibility by automating key workflow steps such as contouring and planning (1;2)

2. Artificial Intelligence in Radiotherapy

AI in radiotherapy mainly includes machine learning (ML) and deep learning (DL) approaches applied to imaging, dosimetry, and clinical data. Convolutional neural networks (CNNs) and U-Net architectures are widely used.

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2.1. Auto-Segmentation and Contouring

Manual delineation of targets and OARs is time-consuming and subject to inter-observer variability. AI-based segmentation accelerates contouring while improving reproducibility, which is particularly important for repeated contour updates required in ART. (1;2)

2.2. Automated Treatment Planning

Knowledge-based and ML-driven systems can predict dose distributions and generate optimized plans rapidly. AI-assisted IMRT and VMAT planning has been shown to improve plan quality and efficiency compared with conventional manual planning. (3)

2.3. Motion Prediction

Respiratory and organ motion remain challenges in thoracic and abdominal radiotherapy. AI models using MRI or CBCT data enable real-time prediction of tumor and organ motion, allowing margin reduction and more accurate targeting. (4)

2.4. Outcome and Toxicity Prediction

AI models integrating clinical, dosimetric, imaging, and radiomic features can predict treatment response and toxicity risk, supporting personalized dose adaptation and proactive toxicity management. (5)

3. Adaptive Radiotherapy Enhanced by AI

Adaptive radiotherapy (ART) represents a transformative shift from static, one-time treatment planning to a dynamic, patient-specific approach. Rather than relying solely on a pre-treatment CT, ART incorporates repeated imaging sessions throughout the course of therapy to detect anatomical and biological changes and update treatment plans accordingly.

AI integration significantly enhances ART feasibility by addressing three critical workflow components:

- **Rapid Auto-Segmentation and Contour Propagation (1;2):** Deep learning algorithms, particularly CNN- and U-Net–based models, enable automated delineation of tumor targets and organs at risk on daily CBCT or MRI images. These models maintain geometric accuracy comparable to expert clinicians while reducing manual contouring time, which is a major bottleneck in repeated plan adaptation.
- **Fast Dose Recalculation and Plan Re-Optimization (3):** Knowledge-based planning systems and ML-driven dose prediction algorithms allow rapid recalculation and optimization of treatment plans. These tools can produce high-quality, patient-specific plans within minutes, making **online ART** at the treatment console feasible.
- **Predictive Modeling for Anatomical Evolution (6):** AI models trained on longitudinal imaging data can anticipate changes such as tumor regression, organ motion, or weight loss. By predicting these changes, clinicians can select the most appropriate plan or initiate proactive re-planning before deviations compromise dose coverage.
- **Synthetic CT Generation (7):** Deep learning models, including generative adversarial networks (GANs), can generate synthetic CT (sCT) images from CBCT or MRI. sCTs provide more accurate Hounsfield units, enabling reliable dose calculation and enhancing the technical precision of ART.
- **Outcome and Toxicity Prediction(8):** AI models can integrate imaging, dosimetry, radiomics, and clinical parameters to predict response and toxicity risk. This supports **personalized adaptation**, allowing clinicians to adjust plans proactively to reduce toxicity while maintaining therapeutic efficacy.

Table 1 AI-Assisted Adaptive Radiotherapy: Summary of Key Studies

Study	Tumor Site	AI/Technology	Imaging Modality	Adaptation Type	Patients / Study Design	Key Findings
Chen et al., 2020 (7)	Various	CNN-based sCT generation	CBCT	Offline	Retrospective	Accurate synthetic CT enabling reliable dose calculation
Maspero et al., 2018 (9)	Various	GAN-based synthetic CT generation	MRI	Offline	Prospective	High-quality sCT enables MRI-only radiotherapy workflows
Lambin et al., 2017 (10)	Multiple	Radiomics / ML outcome prediction	CT/MRI	Offline	Review	Radiomics enables prediction of outcome and toxicity
Krafft et al., 2017 (11)	Lung	Radiomics-based toxicity prediction	CT	Offline	retrospective	Prediction of radiation pneumonitis using imaging features
Bohoudi et al., 2017 (12)	Pancreas	ANN-based adaptive planning	MRI (MR-Linac)	Online	Clinical study	Fast online adaptive radiotherapy with improved workflow

This table highlights the growing body of evidence supporting AI-assisted ART across multiple tumor sites, imaging modalities, and adaptation strategies. Together, these studies demonstrate that AI can overcome traditional barriers to ART, including time constraints, manual workload, and variability in contouring and planning.

4. Clinical Applications

4.1. Head and Neck Cancer

Head and neck cancers present significant challenges for radiotherapy due to rapid anatomical changes during treatment. Tumor shrinkage, edema, and weight loss can alter the position of both the tumor and adjacent organs at risk (OARs), such as the spinal cord, parotid glands, and oral cavity. These changes may compromise target coverage and increase the risk of toxicity if not addressed.

AI-assisted adaptive radiotherapy (ART) addresses these challenges by:

- **Automating repeated contouring:** Deep learning algorithms can rapidly delineate targets and OARs on daily CBCT or MRI scans, reducing inter-observer variability and manual workload.
- **Optimizing dose distribution:** AI-driven plan adaptation ensures that tumor coverage remains adequate even as anatomy changes, while minimizing dose to critical structures.
- **Predicting anatomical evolution:** Predictive models anticipate tumor regression and soft tissue deformation, allowing proactive replanning before dose deviations occur.

Clinical studies have shown that AI-assisted ART in head and neck cancer reduces parotid gland dose, lowers xerostomia risk, and maintains robust tumor coverage throughout the treatment course (1;13) This approach is particularly beneficial in patients undergoing long treatment courses where anatomical changes are more pronounced.

4.2. Thoracic Tumors

Radiotherapy for thoracic tumors, particularly lung cancer, is complicated by respiratory motion, cardiac pulsation, and daily variations in lung volume. Conventional plans often include large margins to account for motion, which increases irradiation of healthy lung tissue and may elevate toxicity risk.

AI-assisted ART improves thoracic radiotherapy through:

- **Motion prediction and gating:** Machine learning models can forecast tumor motion based on prior imaging or real-time MR/CBCT data, allowing precise beam delivery during specific respiratory phases.
- **Margin reduction:** Accurate prediction and tracking reduce the need for large planning target volume (PTV) margins, sparing healthy lung tissue and other thoracic structures.
- **Online adaptation:** AI-driven dose recalculation and plan optimization enable immediate plan adjustment when tumor position deviates from baseline, supporting adaptive SBRT or conventionally fractionated therapy.

For example, studies using MR-guided ART with AI-based motion modeling demonstrated improved target coverage and reduced lung V20 and heart dose, highlighting the potential for safer and more precise thoracic radiotherapy (14; 15).

4.3. Stereotactic Treatments

Stereotactic body radiotherapy (SBRT) and stereotactic radiosurgery (SRS) deliver high doses in few fractions, requiring extreme precision. Even minor anatomical changes can result in substantial dose deviations, which may compromise tumor control or increase toxicity.

AI-enhanced ART benefits stereotactic treatments by:

- **Enhancing plan quality:** Deep learning–assisted optimization generates highly conformal plans that respect critical structures while delivering ablative doses.
- **Supporting ultra-hypofractionation:** AI allows for adaptive adjustment of dose per fraction based on daily imaging, which is crucial when delivering very high doses in 1–5 fractions.
- **Enabling real-time adaptation:** For moving targets such as lung metastases or small brain lesions, AI-assisted online ART ensures accurate dose delivery despite tumor shifts or deformation.

Clinical experience demonstrates that AI-driven ART in SBRT and SRS maintains target coverage, reduces dose to surrounding normal tissue, and supports more aggressive hypofractionated treatment schedules safely (16).

5. Challenges and Limitations

- **Data quality and bias:** AI models require diverse, high-quality datasets for generalizability.
- **Validation:** Most studies remain retrospective; prospective multicenter validation is needed.
- **Workflow integration:** Incorporating AI into clinical systems is technically demanding.
- **Ethical and regulatory considerations:** Transparency, accountability, and data protection must be ensured.

6. Future Perspectives

AI-enhanced ART has the potential to fully personalize radiotherapy, incorporating anatomical, functional, and biological parameters. Future directions include:

- Biological adaptation with radiomics and functional imaging;
- Digital twin models for individualized response and toxicity prediction;
- Prospective clinical trials integrating AI into ART workflows.

7. Conclusion

AI integration in radiotherapy enables automated segmentation, plan optimization, motion modeling, and outcome prediction. These developments make adaptive radiotherapy more practical and scalable. Multidisciplinary collaboration, rigorous validation, and careful clinical implementation are essential to fully realize the potential of AI-driven ART.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of ethical approval

This review report was conducted in accordance with ethical standards.

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