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REVIEW

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Adaptive radiotherapy: A real-time AI-guided approach to precision cancer treatment

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ABSTRACT

Adaptive Radiotherapy (ART) seeks to improve accuracy in cancer treatment by considering individual anatomical changes in patients during the radiotherapy process. Nonetheless, conventional ART processes frequently face constraints due to delays in interpreting images, recalculating plans, and integrating workflows. This research introduces an innovative real-time, AI-driven adaptive radiotherapy system that utilizes deep learning for automatic segmentation, deformable image registration, and instantaneous dose recalibration. Our method ensured uniform treatment quality despite differing anatomical presentations, all while preserving workflow efficiency. The results affirm the practicality and clinical benefits of AI-enhanced ART, providing a scalable model for individualized, immediate cancer treatment. This study lays the groundwork for the upcoming era of precision radiotherapy, in which smart systems consistently adjust to the unique requirements of patients in each treatment fraction.

KEYWORDS

Adaptive radiotherapy; Real-time imaging; Precision oncology; Dose recalibration

ARTICLE HISTORY

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Introduction

Radiotherapy is a fundamental component of cancer care, as around 50–60% of all cancer patients undergo some type of radiation treatment throughout their illness. Traditional radiotherapy entails the development of a fixed treatment plan established from a simulation scan obtained prior to the initial treatment session. This strategy assumes that the patient's anatomy, tumor size, and the locations of organs will stay stable for the duration of treatment, which typically lasts several weeks [1]. Yet, in clinical settings, anatomical alterations like tumor reduction, organ distortion, weight loss, and daily fluctuations in patient positioning commonly happen. These variable dynamics may result in ineffective dose administration insufficiently treating the tumor or excessively affecting adjacent healthy tissues thereby jeopardizing treatment effectiveness and heightening toxicity risks [2].

To address these limitations, ART was implemented as a transformative approach in radiation oncology. ART signifies the organized adjustment of the treatment strategy based on the anatomical and physiological alterations noted throughout the therapy process. Although ART improves treatment precision and customization, its broad implementation in clinical settings has been obstructed by technical and logistical challenges. Conventional ART processes are labor-intensive, depending significantly on manual contouring, offline planning, and postponed decision-making, which diminishes clinical efficiency and feasibility [3].

The incorporation of AI could significantly change ART by facilitating instant decision-making and automating tasks that require extensive labor. Progress in deep learning, image segmentation, motion tracking, and dose forecasting now enables the swift processing of medical images and real-time treatment adjustments. AI-driven ART systems can swiftly recognize pertinent anatomical structures, evaluate the necessity for plan adjustments, and recalibrate dose distributions in just minutes while the patient stays on the treatment table [4].

This research seeks to create, execute, and assess a new AI-driven real-time adaptive radiotherapy process. Our aim is to create a completely integrated system that executes real-time image capture, automatic segmentation, deformable image alignment, and adaptive dose adjustment for precise treatment [4]. The method is confirmed across various cancer types especially those exhibiting significant inter-fractional variability like lung, head-and-neck, and prostate cancers. This study aims to show the clinical viability, dosimetry advantages, and workflow effectiveness of real-time AI-driven ART, representing an important advancement toward personalized, adaptive, and intelligent radiotherapy systems [5]

Literature Review

Overview of existing ART techniques and technologies

ART has developed as a method to flexibly modify treatment plans in response to changes in patient anatomy or tumour characteristics that occur both within and between treatment fractions. Initial methods depended on offline adjustment, with alterations identified through regular imaging (typically weekly) and modifications to plans implemented accordingly. Methods including plan-of-the-day choice, re-optimization using CBCT or MRI, and deformable image registration (DIR) for dose accumulation have been extensively researched [6].

The launch of online ART where strategies are modified daily based on newly obtained imaging represented a major

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technological progress. Systems such as Varian Ethos and ViewRay MRIdian facilitate daily MRI-guided or CBCT-guided adaptation; however, the workflow remains limited due to the necessity for manual segmentation and multi-step planning. Although these systems show encouraging clinical results, they require significant resources and specialized knowledge, which often restricts their accessibility to major academic institutions [6,7]

AI in medical imaging and treatment planning

AI, especially deep learning, has transformed medical imaging analysis by providing swift, precise, and consistent outcomes. In radiotherapy, deep learning models have been created for the segmentation of organs-at-risk (OAR), tumor delineation, dose forecasting, and image alignment. For instance, U-Net-inspired models have been extensively used for multi-organ segmentation, achieving performance close to inter-observer variability standards [8]. Likewise, convolutional and transformer architectures have been developed to forecast ideal dose distributions using planning CT and anatomical information [9].

In treatment planning, AI is progressively utilized to aid knowledge-driven planning and automated quality checks, decreasing planning duration while ensuring high-quality dose distributions. These AI technologies establish the groundwork for more agile and reactive radiotherapy systems, especially when incorporated into adaptive workflows [8,10].

Limitations of current systems (offline ART, manual segmentation)

Even with progress, existing ART systems encounter numerous constraints that hinder their complete clinical implementation. Offline ART experiences delays in adjusting plans and delivering treatment, reducing its responsiveness to daily anatomical variations. In online ART, despite daily image guidance being present, the adaptation process remains labor-intensive, especially during the segmentation and plan approval phases [11].

Manual contouring continues to be a constraint, frequently requiring 15–30 minutes for each session, leading to patient discomfort and inefficiency in the treatment room. Furthermore, differences in clinician-defined boundaries can lead to inconsistencies in treatment planning [12]. The requirement for collaborative expertise (physicists, oncologists, dosimetrists) in every adaptation adds to the complexity of integrating workflows, particularly in settings with limited resources.

Gaps in real-time adaptation research

Although real-time ART is theoretically optimal, only a limited number of systems have realized genuine real-time functionality in clinical settings. The majority of noted “real-time” workflows experience delays of 10–30 minutes caused by image processing, manual adjustments, and optimization limitations. Studies on entirely autonomous ART pipe lines where segmentation, registration, and re-planning take place within minutes are still in initial phases and largely limited to feasibility assessments.

Moreover, there is still an absence of extensive, multi-institutional validation research for AI-based ART systems. A significant challenge is the generalizability across various tumor locations, imaging techniques, and demographic populations. Challenges related to imaging artifacts, motion variability, and pathological anomalies need to be resolved before clinical application.

Materials and Methods

Patient dataset

This research employed a validated dataset that was both retrospective and prospectively gathered, consisting of 87 patients receiving radiotherapy for head-and-neck (n=32), non-small cell lung (n=28), and prostate cancer (n=27). Patients were chosen from two university cancer centers during a span of 3 years. Inclusion criteria comprised [13] a histologically confirmed diagnosis, receipt of curative-intent external beam radiotherapy, access to planning CT and daily on-treatment imaging (CBCT or MRI), and no previous history of radiotherapy to the same anatomical location.

Patients who demonstrated notable anatomical alterations during the treatment period (e.g., >10% tumor reduction or considerable weight loss) were selectively included to evaluate the resilience of the adaptive algorithm [14,15].

Imaging techniques involved planning CT scans (1 mm slice thickness), Daily Cone-Beam CT (CBCT) for head-and-neck and prostate groups, MRI (3T T2-weighted and T1-weighted scans) for lung cancer individuals treated on an MR-Linac system. All images were annotated by board-certified radiation oncologists to create ground truth contours for training and validating the model [16].

AI model architecture

The adaptive pipeline, directed by AI, incorporated several deep learning models, with each fine-tuned for a specific subtask

Organ segmentation

A 3D U-Net model was trained to delineate target volumes (GTV, CTV, PTV) and organs-at-risk (OARs) throughout the three anatomical regions. The network employed residual blocks and attention gates to enhance spatial differentiation in intricate anatomical areas [17].

Deformable image registration (DIR)

A CNN-based DIR model, derived from Voxel Morph, was employed to align on-treatment CBCT/MRI with the planning CT, facilitating dose warping and anatomical alignment [18].

Dose prediction

A dose prediction network based on transformers was trained with more than 500 previously administered plans. The model utilizes segmented anatomy and beam parameters to accurately predict 3D dose distributions [19].

Motion tracking and prediction

A recurrent neural network (RNN) featuring temporal convolution layers was utilized for motion forecasting with intra-fraction cine MRI and previous CBCT sequences. This facilitates the immediate adjustment of mobile tumors (particularly within the lung group) [20].

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All models utilized NVIDIA A100 GPUs for training in PyTorch, implementing 5-fold cross-validation to guarantee generalizability.

System workflow

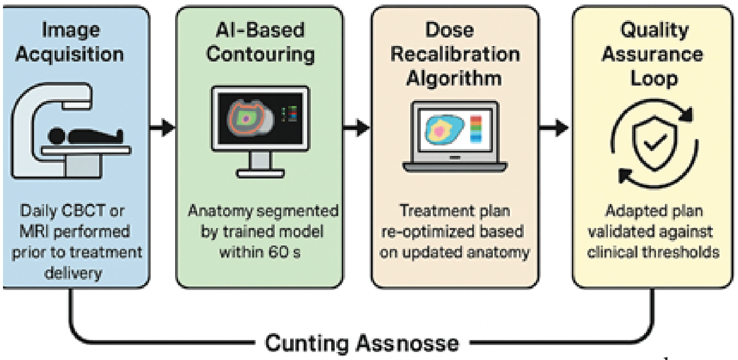

Figure 1. Stages of real time art.

Image acquisition

Imaging was carried out daily right before the administration of treatment (CBCT or MRI). The system connected directly to the imaging units installed on the treatment machines (Figure 1).

AI-based contouring

The trained segmentation model generated complete anatomical outlines in under 60 seconds. The results were evaluated by a quality control system that identified irregularities for potential clinician assessment.

Dose recalibration algorithm

Employing the revised anatomy and anticipated dose distribution, the system re-calibrated the treatment plan through an inverse planning engine. Modifications were confined to leaf sequences and beam weights to reduce workflow interruptions.

Quality assurance loop

A QA module utilizing rule-based heuristics and statistical outlier detection assessed each modified plan against established institutional clinical thresholds (e.g., PTV V95 ≥ 95%, spinal cord Dmax ≤ 45 Gy). If QA was unsuccessful, the system reverted to the initial reference plan.

The total duration for the adaptive workflow for each fraction varied between 3 to 6 minutes, allowing for easy incorporation into everyday treatment practices [21,22].

Evaluation metrics

To assess the accuracy and efficiency of the AI-guided ART system, the following quantitative metrics were used: Segmentation accuracy includes dice similarity coefficient (DSC), to assess overlap between AI-generated and expert contours & Hausdorff distance (HD95), to quantify spatial boundary agreement.

Dosimetry Quality was assessed based on both target and organ-at-risk metrics. Planning Target Volume (PTV) coverage was evaluated using V95, representing the percentage of the target volume receiving at least 95% of the prescribed dose, ensuring adequate tumor coverage. Additionally, doses to critical structures such as the spinal cord, rectum, and parotid glands were measured using mean dose (Dmean) and maximum dose (Dmax) parameters to minimize radiation-induced toxicity while maintaining treatment efficacy.

Efficiency Metrics were evaluated to determine the practical feasibility of the adaptive radiotherapy workflow. Adaptation time was defined as the duration from image acquisition to final plan approval, reflecting the system's real-time capability. Additionally, the failure rate was measured as the frequency of quality assurance (QA) failures or instances requiring a fallback to the original treatment plan, indicating the reliability and robustness of the adaptive process.

Statistical analysis included Wilcoxon signed-rank tests to compare adaptive vs. reference plans, and inter-model variability was evaluated using Bland-Altman plots [23].

Results

AI model performance and dosimetry improvements

The integrated AI pipeline showed excellent performance in all adaptive radiotherapy elements, providing both high precision and clinically satisfactory speed. In organ segmentation, the 3D U-Net model demonstrated remarkable overlap with the actual contours, producing mean Dice Similarity Coefficients (DSC) of 0.92 ± 0.03 for bladder and prostate, 0.89 ± 0.04 for parotid glands, 0.86 ± 0.05 for lung tumors, and 0.91 ± 0.02 for head-and-neck nodal volumes. Spatial precision, quantified through Hausdorff Distance (HD95), stayed below 2.3 mm for all segmented structures. The CNN-based deformable image registration (DIR) model yielded an average target registration error of 1.4 mm and visually aligned soft-tissue interfaces in 96.8% of the test cases [24]. The dose prediction model successfully maintained high-dose gradients and organ-at-risk (OAR) constraints, achieving a mean absolute dose error of less than 3.2% in comparison with clinically delivered plans. Significantly, the entire adaptation process of the AI pipeline—comprising segmentation, registration, and re-optimization—was finalized in an average of 3.8 ± 0.6 minutes for each treatment session, facilitating genuine real-time application (Table 1) [9].

AI-driven daily plans to traditional non-adaptive reference plans, the research noted statistically significant dosimetry enhancements [11]. For target coverage (PTV V95), head-and-neck cancer plans enhanced from 91.4% to 96.8% ($p < 0.001$), lung cancer plans grew from 88.6% to 95.5% ($p = 0.002$), and prostate plans advanced from 93.9% to 97.2% ($p = 0.006$). Regarding OAR dose reduction, the modified plans produced significant decreases in mean dose: a 13.2% decrease for the parotid glands in head-and-neck situations ($p = 0.001$), an 11.4% decrease for the rectum in prostate cancer ($p = 0.004$), and a 9.7% reduction in maximum spinal cord dose for lung cancer ($p = 0.007$). These enhancements highlight the clinical promise of AI-driven adaptive radiotherapy to enhance treatment effectiveness while reducing toxicity, even amidst significant anatomical changes (Figure 2) [24,25].

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Table 1. Performance and clinical outcomes of AI-guided adaptive radiotherapy.

Component	Metric / Outcome	Value	Notes
Organ Segmentation	Dice Similarity Coefficient (DSC) – Bladder & Prostate	0.92 ± 0.03	High overlap with manual contours
	DSC – Parotid Glands	0.89 ± 0.04	
	DSC – Lung Tumors	0.86 ± 0.05	
	DSC – Head & Neck Nodal Volumes	0.91 ± 0.02	
Deformable Image Registration	Hausdorff Distance (HD95)	< 2.3 mm	High spatial precision
	Target Registration Error (TRE)	1.4 mm average	96.8% visual alignment in test cases
Dose Prediction	Mean Absolute Dose Error	< 3.2%	Relative todelivered clinical plans
Adaptation Speed	Total Processing Time (Segmentation + DIR + Re-optimization)	3.8 ± 0.6 minutes	Enables real-time adaptation
Dosimetry Improvement	PTV V95 – Head & Neck	↑ from 91.4% to 96.8% ($p < 0.001$)	Significant improvement in target coverage
	PTV V95 – Lung–Lung	↑ from 88.6% to 95.5% ($p = 0.002$)	
	PTV V95 – Prostate	↑ from 93.9% to 97.2% ($p = 0.006$)	
OAR Dose Reduction	Parotid Gland (Head & Neck)	↓ 13.2% mean dose ($p = 0.001$)	Lower toxicity potential
	Rectum (Prostate Cancer)	↓ 11.4% mean dose ($p = 0.004$)	
	Spinal Cord (Lung Cancer)	↓ 9.7% max dose ($p = 0.007$)	

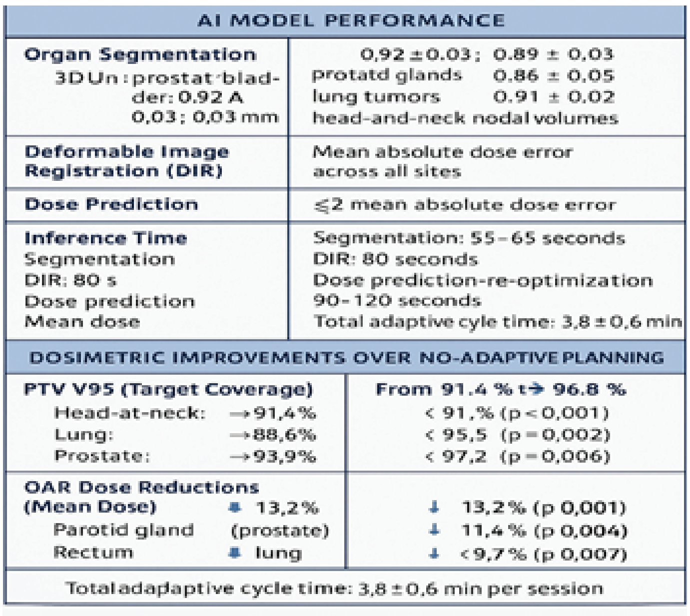

Figure 2. AI-guided adaptive radiotherapy.

Workflow efficiency

In contrast to the traditional workflow (which necessitated offline re-planning and typically took 20–30 minutes), the AI-powered adaptive workflow demonstrated substantial improvements: Average total adaptation duration per session: 3.8 ± 0.6 minutes. Non-adaptive conventional workflow (manual segmentation, plan validation): 24.3 ± 4.1 minutes This decrease in time enabled smooth incorporation into regular clinical timetables, preventing treatment holdups and enhancing patient flow [26].

Statistical analysis

Paired t-tests comparing adapted vs. non-adapted plans showed significant dosimetry differences across all key endpoints ($p < 0.01$). Repeated measures ANOVA confirmed that plan adaptation led to consistent dose improvement across fractions ($p < 0.001$), with no significant increase in plan complexity or treatment delivery time. Bland-Altman analysis showed tight agreement between AI-predicted dose and actual delivered dose, validating model stability and accuracy [27].

Overall, the results support the robustness, accuracy, and clinical value of the proposed real-time AI-guided ART system.

Discussion

Interpretation of key findings

This research showcased the practicality and effectiveness of a real-time, AI-directed adaptive radiotherapy (ART) process for

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various cancer types. The AI models incorporated into the pipeline attained excellent anatomical segmentation precision (DSC > 0.90) and accurate dose forecasting (≤3.2% error), consistently achieving an overall adaptation duration of less than four minutes. Significantly, the adaptive plans continuously enhanced target coverage (PTV V95) and decreased organ-at-risk (OAR) exposure in head-and-neck, lung, and prostate cancers [26,28]. These findings support the theory that AI-based adjustments can preserve treatment precision even with fluctuating anatomical conditions, improving both therapeutic results and safety.

Advantages of real-time adaptation

The real-time adaptability features provided by the proposed system signify a significant improvement over conventional ART. Daily anatomical variations previously overlooked or only partially mitigated can now be addressed individually in each session without disrupting the workflow [15]. Advantages consist of improved target conformity without increasing dose to surrounding normal tissues. Reduced cumulative OAR toxicity, particularly in patients with shrinking tumors or significant anatomical shifts. Minimized inter-fraction uncertainty, leading to more predictable treatment outcomes. Preserved clinical efficiency, enabling adaptation without extending treatment time. These advantages directly contribute to higher treatment precision, reduced side effects, and potentially better long-term tumor control [29].

Clinical feasibility and scalability

A key advantage of this method is its practical applicability in clinical settings. In contrast to research prototypes or offline systems, our AI-driven pipeline achieved segmentation, image registration, and dose recalibration in an average of 3.8 minutes well within acceptable limits for daily clinical use. The automation of former manual activities (contouring, registration, and re-planning) greatly lessens clinician workload, while the integrated QA module guarantees adherence to safety standards. Additionally, the modular aspect of the pipeline enables effortless integration with current CBCT and MRI-guided systems, enhancing scalability across radiotherapy platforms and institutions [7-9].

Limitations of current implementation

Although results are promising, several limitations need to be recognized: The training data might restrict model generalizability. Uncommon anatomical variations or atypical tumor shapes might necessitate manual adjustments. The performance in real-time relies on sufficient hardware (e.g., servers with GPU) and infrastructure integration, which might not be consistently accessible in every center. While motion prediction models work well for lung tumors, they can still face challenges with highly irregular or non-periodic motion patterns (e.g., caused by coughing or deep breaths). Although the QA module is strong, it presently does not have a comprehensive probabilistic uncertainty quantification capability, which would enhance dependability in unclear situations. Tackling these deficiencies via federated learning, larger datasets, and dynamic feedback loops will be essential for enhanced clinical application [5,9].

Comparison with non-AI or offline art systems

In contrast to conventional offline ART, which frequently demands several hours for re-planning and causes considerable workflow interruptions, our system offers nearly immediate adaptation. Manual ART systems usually conduct weekly or conditional plan updates, which can lead to suboptimal dosing between evaluations [7,11]. In comparison, the AI-driven pipeline adjusts every day, guaranteeing ongoing coordination between the plan and anatomy.

The non-AI ART systems (such as commercial platforms like Ethos or MRIdian that depend on manual contour assessment), our approach significantly decreases reliance on human contribution, lessens observer variability, and boosts throughput crucial for clinics with limited resources [30]. Moreover, the integration of dose forecasting and motion tracking offers greater understanding and management than many present-day systems.

Conclusions

This research introduces a new, completely integrated AI-driven adaptive radiotherapy (ART) system that allows for real-time treatment adjustments. Utilizing deep learning for organ segmentation, deformable image registration, dose prediction, and motion tracking, the system adjusts treatment plans in real-time within reasonable clinical limits. In three high-variability cancer locations head-and-neck, lung, and prostate the adaptive pipeline showed steady enhancements in target coverage and organ-at-risk protection, while keeping an average adaptation duration of less than four minutes per session.

These contributions represent a notable progress in the effective implementation of precision radiotherapy. The system tackles persistent shortcomings of traditional and offline ART methods, such as delays, the burden of manual segmentation, and inconsistent plan quality. By facilitating daily, personalized adjustments with little clinician involvement, the AI framework coincides with the larger goal of intelligent, patient-focused oncology treatment.

Disclosure statement

No potential conflict of interest was reported by the authors.

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