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Leveraging Advanced AI Technologies for Radiotherapy Dose Calculation: A Narrative Review

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Abstract

Context: Accurate radiotherapy dose calculation is critical for optimizing treatment efficacy and minimizing toxicity. Traditional algorithms, while clinically validated, often struggle with complex anatomical variations and heterogeneous tissue compositions. Recent advances in artificial intelligence (AI) offer promising alternatives for enhancing dose prediction accuracy and workflow efficiency.

Objectives: This review aims to critically appraise the current landscape of AI-based radiotherapy dose calculation methods, comparing their performance, interpretability, and clinical applicability across various algorithmic families.

Methods: A comprehensive literature search was conducted using PubMed, Scopus, and IEEE Xplore databases, focusing on studies published between 2015 and 2025. Included articles were categorized into six AI domains: Machine learning (ML), deep learning (DL), reinforcement learning (RL), Bayesian models, fuzzy logic systems, and evolutionary algorithms. Comparative analysis was performed based on dosimetric accuracy, computational efficiency, explainability, and integration with treatment planning systems (TPS).

Results: The DL models, particularly convolutional neural networks (CNNs) and transformer-based architectures, demonstrated superior performance in dose prediction for head and neck, prostate, and lung cancers. The RL approaches showed potential in adaptive planning scenarios, while Bayesian and fuzzy logic models offered enhanced interpretability. Evolutionary algorithms were effective in multi-objective optimization but required extensive computational resources. Despite promising results, most studies lacked external validation and standardized benchmarking.

Conclusions: The AI-driven dose calculation methods represent a transformative shift in radiotherapy planning. However, challenges remain in clinical translation, including algorithm transparency, regulatory approval, and integration with existing workflows. Future research should prioritize multi-institutional validation, hybrid model development, and human-AI collaboration frameworks to ensure safe and effective deployment.

Keywords: Radiotherapy, Dose Calculation, Artificial Intelligence, Deep Learning, Treatment Planning, Clinical Integration

1. Context

Accurate dose calculation is a cornerstone of modern radiotherapy, directly influencing tumor control and normal tissue sparing (1). Conventional algorithms such as Monte Carlo (MC), pencil beam convolution, and the analytical anisotropic algorithm (AAA) have long served as clinical standards. However, these methods often struggle with complex anatomical heterogeneities, dynamic organ motion, and computational inefficiencies in adaptive workflows (2-5).

Recent advances in artificial intelligence (AI) have introduced transformative possibilities for dose prediction, treatment planning, and quality assurance (6). The AI encompasses a broad spectrum of algorithmic families — including machine learning (ML), deep learning (DL), reinforcement learning (RL), Bayesian models, fuzzy logic systems, and evolutionary algorithms — each offering unique strengths in

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modeling nonlinear relationships, learning from large datasets, and generalizing across patient populations (7).

In radiotherapy, AI applications have expanded from image segmentation and contouring to dose estimation, plan optimization, and toxicity prediction. Particularly, convolutional neural networks (CNNs), transformer-based architectures, and hybrid ensemble models have demonstrated promising results in predicting three-dimensional (3D) dose distributions with high spatial fidelity. The RL has shown potential in adaptive planning scenarios, while Bayesian and fuzzy logic models offer enhanced interpretability and uncertainty quantification (8-12), (13-15).

Despite these advances, several challenges hinder clinical translation. Many AI models lack external validation, suffer from limited generalizability, and are often trained on institution-specific datasets (11). Moreover, explainability remains a critical barrier, especially in high-stakes clinical decisions where transparency and accountability are essential (16). Regulatory frameworks for AI in medicine are still evolving, and integration with existing treatment planning systems (TPS) requires robust interoperability and human-AI collaboration protocols (17).

2. Objectives

This review aims to critically evaluate the current landscape of AI-based dose calculation methods in radiotherapy. We categorize and compare six major algorithmic families — ML, DL, RL, Bayesian, fuzzy, and evolutionary — based on their dosimetric accuracy, computational efficiency, interpretability, and clinical applicability. By synthesizing findings from over 160 peer-reviewed studies, we highlight key trends, limitations, and future directions for AI integration in radiotherapy workflows.

Ultimately, this work seeks to bridge the gap between algorithmic innovation and clinical implementation, offering a structured roadmap for researchers, physicists, and oncologists navigating the evolving intersection of AI and radiation oncology.

3. Methods

This review was conducted through a structured and comprehensive evaluation of the literature on AI applications in radiotherapy dose calculation. A multi-step methodology was employed to ensure scientific rigor and relevance.

3.1. Literature Search

Databases including PubMed, Scopus, IEEE Xplore, and Google Scholar were queried for studies published up to August 3, 2025. Search terms included combinations of “radiotherapy dose calculation”, “AI in radiotherapy”, “machine learning”, “deep learning”, “Bayesian networks”, “fuzzy logic”, and “treatment planning optimization”. Boolean operators were used to refine results and capture a broad spectrum of traditional and AI-based approaches.

3.2. Criteria

3.2.1. Inclusion Criteria

Studies were selected if they (1) focused on radiotherapy dose calculation or treatment planning, (2) applied AI techniques such as ML, DL, RL, Bayesian, fuzzy, or evolutionary algorithms, (3) discussed clinical applications, challenges, or future directions, and (4) were published in peer-reviewed journals or reliable scientific repositories.

3.2.2. Exclusion Criteria

Articles were excluded if they (1) were not in English, (2) lacked methodological detail, (3) focused solely on non-radiotherapy AI applications, or (4) were opinion pieces without any underlying data.

3.3. Data Extraction and Analysis

After removing duplicates, titles and abstracts were screened for relevance. Full-text reviews were conducted to assess alignment with the review’s objectives. Extracted data included algorithm types, dosimetric performance, clinical integration, and reported limitations. Studies were categorized into six AI domains: The ML, DL, RL, Bayesian, fuzzy logic, and evolutionary algorithms.

3.4. Synthesis Strategy

Findings were synthesized into thematic sections: Traditional dose calculation methods, AI roles, algorithmic techniques, challenges, clinical applications, and future directions. Emphasis was placed on comparative performance, interpretability, and clinical feasibility. Citations were retained to ensure traceability and academic integrity.

3.5. Scope and Coverage

A total of 160 references were included, spanning experimental studies, technical reports, and systematic reviews. The selected literature reflects diverse cancer types, imaging modalities, and TPS, offering a panoramic view of AI's evolving role in radiotherapy.

4. Results

4.1. Comparative Analysis of Artificial Intelligence Models

The AI models for radiotherapy dose calculation span six major algorithmic families, each offering distinct advantages in terms of dosimetric accuracy, computational efficiency, and clinical feasibility. Below is a comparative synthesis of these approaches and Table 1 summarizes this section. In Table 1, performance metrics are synthesized from studies (18-23), (24-28) and reflect general trends across cancer types and imaging modalities. Table 2 also shows a summary of key studies on the applications of AI in radiotherapy dose calculation and treatment planning.

4.1.1. Machine Learning Models

The ML techniques such as Random Forest (RF), Support Vector Machines (SVM), Logistic Regression (LREG), and K-Nearest Neighbors (KNN) have been widely applied to dose prediction and plan classification tasks. The RF and SVM models demonstrated robust performance in identifying organ-at-risk (OAR) dose thresholds and predicting toxicity outcomes (35-37). However, their reliance on handcrafted features and limited scalability to 3D dose maps restrict broader clinical adoption (18, 19).

4.1.2. Deep Learning Architectures

The CNNs, U-Net variants, and transformer-based models have shown superior performance in voxel-level dose prediction. The CNNs trained on computed tomography (CT) and magnetic resonance imaging (MRI) datasets achieved high spatial fidelity in head and neck, prostate, and lung cancer cases. Transformer models further improved contextual learning and generalization across institutions. Despite their accuracy, DL models often lack interpretability and require large annotated datasets for training (20-23).

4.1.3. Reinforcement Learning Applications

The RL algorithms, particularly Deep Q-Networks (DQN), have been explored for adaptive planning and beam angle optimization. These models dynamically learn optimal dose delivery strategies based on reward functions tied to tumor coverage and OAR sparing. While promising, RL approaches remain computationally intensive and are rarely integrated into commercial TPS (24).

4.1.4. Bayesian and Fuzzy Logic Systems

Bayesian networks [e.g., Bayesian ensemble naive bayes (BENB), expert knowledge-naive Bayesian network (EK-NBN)] and fuzzy logic models offer enhanced transparency and uncertainty quantification. These systems are particularly useful in scenarios with incomplete data or ambiguous clinical inputs. Situational awareness Bayesian networks (SA-BN) have been applied to decision support in dose escalation protocols. Although interpretable, these models often underperform in high-dimensional imaging contexts (25, 26).

4.1.5. Evolutionary Algorithms

Genetic algorithms (GA), particle swarm optimization (PSO), and novel genetic algorithms (NGA) have been employed for multi-objective dose optimization. These methods excel in exploring large solution spaces and balancing trade-offs between tumor coverage and normal tissue sparing. However, they require extensive computational resources and are sensitive to parameter tuning (27, 28).

5. Discussion

5.1. Challenges and Strategic Considerations

While AI has demonstrated remarkable potential in radiotherapy dose calculation, its clinical integration remains constrained by several technical, ethical, and operational challenges. This section synthesizes key limitations and proposes strategic considerations for future implementation. A summary of key studies on AI applications in radiotherapy dose calculation and treatment planning is shown in Table 3.

5.1.1. Data Quality and Generalizability

The AI models require large, diverse, and high-quality datasets for training and validation. However, radiotherapy datasets often suffer from institutional bias, limited sample sizes, and inconsistent annotation standards (39-41). These limitations hinder model generalizability across patient populations, tumor types, and imaging modalities. Multi-institutional data sharing frameworks and federated learning approaches may help mitigate these issues while preserving patient privacy.

Table 1. Performance Comparison of Machine Learning, Deep Learning, and Other Artificial Intelligence Models in Clinical Dose Prediction

Algorithm Types	Accuracy	Interpretability	Clinical Integration	Computational Cost
ML (RF, SVM)	Moderate	Moderate	Moderate	Low
DL (CNN, transformer)	High	Low	Emerging	High
RL (DQN)	High	Low	Limited	Very high
Bayesian/fuzzy	Moderate	High	Moderate	Moderate
Evolutionary	High	Moderate	Experimental	High

Abbreviations: ML, machine learning; RF, Random Forest; SVM, Support Vector Machines; DL, deep learning; CNN, convolutional neural network; RL, reinforcement learning; DQN, Deep Q-Networks.

Table 2. Summary of Key Studies on Artificial Intelligence Applications in Radiotherapy Dose Calculation and Treatment Planning

Author(s), y	Countries	Sample	Disease	Algorithm	Evaluation Method	Result
Abdollahi, et al. (29), 2019	Iran	33 prostate cancer patients	Prostate cancer	LSVM, LREG, BENB, SGD, KNN, DT, RF, ADBO, GANB	Tenfold cross-validation	Post-T2 models predictive (AUC: 0.632); GS prediction higher with T2 (AUC: 0.739) vs. ADC (AUC: 0.70).
Bai, et al. (6), 2021	USA	199 prostate patients	Prostate cancer	Lightweight CNN	Time	Denoiser runs in 39 ms vs. 454 ms, 11.6x faster; completes MC dose in ~0.15 s.
Jalalimanesh, et al. (30), 2017	Iran	-	Vascular tumor	Distributed Q-learning	Simulation	Robust solutions for treatment plans under varying conditions.
Kalendralis, et al. (31), 2021	Netherlands	5238 patients	-	Bayesian network	AUC	AUC: 67.8% overall; 90.4% for table angle errors, 54.5% for PTV errors.
Leszczynski, et al. (32), 1999	Canada	328 breast images	Breast cancer	Fuzzy k-NN	Correlation	High agreement with expert (correlation 0.89).
Li, et al. (33), 2004	China	3 phantom cases	Prostate cancer	GA, CG	Time	Optimal angles found in < 5 min (cases A, B), 13 - 36 min (case C, spine, prostate).
Li and Lei (34), 2010	China	Simulated and chest tumor	Oropharyngeal tumor	GA	Iterations	DNA-GA optimized in 20 iterations vs. 45 for GA; improved OAR sparing.
Luo, et al. (25), 2021	USA	118 lung cancer patients	Lung cancer	SA-BN, EK-NBN	AU-FROC	SA-BN improved prediction (AU-FROC: 0.83) vs. EK-NBN (0.70).
Patnaikuni, et al. (35), 2022	India	-	Prostate cancer	Two-level fuzzy logic	Qualitative assessment	Acceptable rectal risk estimation without compromising tumor coverage.
Sher, et al. (17), 2021	USA	50 patients	Head and neck cancer	Decision tree	Dose reduction	Hybrid directive reduced OAR doses by 4.3-16 Gy vs. physician directive.
Torshabi (26), 2022	Iran	Real patient data	-	Fuzzy logic, NN	Setup error reduction	Setup error reduced from 1.47 mm to 0.4432 mm.
Valdes, et al. (36), 2017	USA	17 patients	Lung and head-neck	Statistical similarity	Efficiency	Enabled efficient identification of achievable prior plans.
Wu C, et al. (37), 2021	USA	290 patients	Multiple sites	DL	Gamma passing rate	Gamma passing rate (1 mm/1%) improved to 89.7 - 99.6% across sites.
Wu and Zhu (28), 2001	USA	3 cases	Brain and abdominal	GA	Dose conformity	NGA reduced max dose (102.6 - 104.6%) vs. manual (105.4 - 106.3%).
Xing, et al. (38), 2020	USA	120 lung cancer patients	Lung cancer	Hierarchically dense U-Net	Gamma passing rate	Boosted AAA dose improved gamma passing rate to 97.6% vs. 87.8%.

Abbreviations: LREG, Logistic Regression; KNN, K-Nearest Neighbors; RF, Random Forest; CNN, convolutional neural network; MC, Monte Carlo; GA, genetic algorithms; OAT, organ-at-risk; SA-BN, situational awareness Bayesian networks; DL, deep learning; NGA, novel genetic algorithms; AAA, analytical anisotropic algorithm; ADBO, AdaBoost; ADC, apparent diffusion coefficient; AU-FROC, area under free-response ROC curve; BENB, Bayesian ensemble naive bayes; CG, conjugate gradient; DT, decision tree; EK-NBN, expert knowledge-naive Bayesian network; GANB, gaussian naive bayes; GS, Gleason score; LSVM, linear support vector machine; NN, neural network; PTV, planning target volume; SGD, stochastic gradient descent.

5.1.2. Interpretability and Trust

The DL models, particularly convolutional and transformer-based architectures, are often criticized for their "black-box" nature (42-44). Clinicians may hesitate to adopt AI-driven dose recommendations without clear explanations of algorithmic reasoning. Incorporating explainable artificial intelligence (XAI) techniques — such as attention maps, feature attribution, and uncertainty quantification — can enhance transparency and foster clinical trust.

5.1.3. Regulatory and Ethical Barriers

Table 3. Key Challenges and Strategic Responses for Artificial Intelligence Integration in Radiotherapy Dose Calculation

Challenges	Strategic Response
Limited data diversity	Federated learning, multi-center data sharing
Lack of interpretability	Explainable AI, uncertainty modeling
Regulatory ambiguity	Joint guidelines from clinical and regulatory bodies
Poor clinical validation	Prospective trials, hybrid human-AI workflows
Algorithmic bias	Bias detection, fairness-aware training
Workflow disruption	Modular integration with existing TPS
Human-machine collaboration	Clinician training, collaborative interface design

Abbreviations: AI, artificial intelligence; TPS, treatment planning systems.

The regulatory landscape for AI in medicine is still evolving. Most jurisdictions lack standardized protocols for validating and approving AI-based dose calculation tools (45, 46). Ethical concerns also arise regarding data ownership, informed consent, and accountability for treatment outcomes. Collaborative efforts between developers, clinicians, and regulatory bodies are essential to establish robust guidelines and ethical safeguards.

5.1.4. Clinical Validation and Workflow Integration

Despite promising results in silico, few AI models have undergone rigorous clinical validation or prospective trials (7, 47). Integration into existing TPS requires seamless interoperability, user-friendly interfaces, and minimal disruption to clinical workflows. Hybrid models that combine AI predictions with human oversight may offer a pragmatic pathway toward adoption.

5.1.5. Algorithmic Bias and Robustness

The AI models trained on imbalanced datasets may inadvertently propagate biases related to age, gender, ethnicity, or tumor subtype (47-49). Such biases can lead to inequitable treatment recommendations and compromise patient safety. Strategies such as bias auditing, fairness metrics, and inclusive dataset curation are critical to ensure equitable AI deployment.

5.1.6. Human-Machine Collaboration

The AI should augment — not replace — clinical expertise. Effective human-machine interaction requires training clinicians to interpret algorithmic outputs, recognize limitations, and make informed decisions (7, 50, 51). Decision support systems must be designed to facilitate collaboration, not automation, preserving the clinician's role as the final arbiter of care.

By addressing these challenges through interdisciplinary collaboration, transparent development, and rigorous validation, AI technologies can be safely and effectively integrated into radiotherapy dose calculation. The path forward lies not only in algorithmic innovation but in thoughtful system design that respects clinical realities and ethical imperatives.

5.1.7. Conclusions

The AI has emerged as a transformative force in radiotherapy dose calculation, offering unprecedented capabilities in precision, adaptability, and computational efficiency. By leveraging diverse algorithmic families — including ML, DL, RL, Bayesian models, fuzzy logic, and evolutionary techniques — AI enables personalized treatment planning, real-time dose optimization, and enhanced clinical decision support.

This review synthesized findings from over 160 peer-reviewed studies, highlighting the comparative performance of AI models across cancer types and treatment modalities. The DL architectures demonstrated superior spatial accuracy, while Bayesian and fuzzy systems offered interpretability and uncertainty modeling. The RL and evolutionary algorithms showed promise in adaptive and multi-objective planning, albeit with significant computational demands.

Despite these advancements, several limitations persist. Most AI models are trained on institution-specific datasets, limiting their generalizability. The lack of external validation and standardized benchmarking impedes clinical trust and regulatory approval. Furthermore, the "black-box" nature of many algorithms raises concerns about transparency and accountability in high-stakes clinical environments. Ethical challenges — including data privacy, algorithmic bias, and human-machine interaction — must also be addressed to ensure equitable and safe deployment.

To bridge the gap between innovation and implementation, future research should prioritize:

- Multi-institutional data sharing and federated learning frameworks.

- Development of XAI tools for clinical interpretability.

- Prospective clinical trials and real-world validation studies.

- Integration of AI into existing TPS with modular design.

- Training programs for clinicians to foster effective human-AI collaboration.

In conclusion, AI-driven dose calculation represents a paradigm shift in radiation oncology. While the path to clinical integration is complex, the potential benefits — improved accuracy, efficiency, and personalization — are substantial. By addressing current limitations through interdisciplinary collaboration and ethical innovation, AI can redefine the future of radiotherapy and contribute meaningfully to precision cancer care.

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Footnotes

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References

1. Dudhe SS, Mishra G, Parihar P, Nimodia D, Kumari A. Radiation Dose Optimization in Radiology: A Comprehensive Review of Safeguarding Patients and Preserving Image Fidelity. *Cureus*. 2024;**16**(5). e60846. https://doi.org/10.7759/cureus.60846.
2. Naghiloo M, Khosroabadi M, Abaspour A, Sadeghi HR, Sadoughi H. Accuracy Evaluation of Isogray TPS Dose Calculations in Symmetric and Asymmetric Fields of the Elekta Compact Linear Accelerator. *J North Khorasan Univ Med Sci*. 2021;**13**(3):15-22. https://doi.org/10.52547/nkums.13.3.15.
3. Raghavi S, Sadoughi HR, Ravari ME, Tajik Mansoury MA, Behmadi M. Accuracy evaluation of dose calculation of ISOgray treatment planning system in wedged treatment fields. *Int J Radiat Res*. 2024;**22**(2):303-8. https://doi.org/10.61186/ijrr.22.2.303.
4. Sadoughi H, Nasseri S, Momennezhad M, Sadeghi H, Bahreyni-Toosi M. A Comparison between GATE and MCNPX monte carlo codes in simulation of medical linear accelerator. *J Med Signals Sens*. 2014;**4**(1). https://doi.org/10.4103/2228-7477.128433.
5. Peng H, Wu C, Nguyen D, Schuemann J, Mairani A, Pu Y, et al. Recent Advancements of Artificial Intelligence in Particle Therapy. *IEEE Trans Radiat Plasma Med Sci*. 2023;**7**(3):213-24. https://doi.org/10.1109/trpms.2023.3241102.
6. Bai T, Wang B, Nguyen D, Jiang S. Deep dose plugin: Towards real-time Monte Carlo dose calculation through a deep learning-based denoising algorithm. *Mach Learn: Sci Technol*. 2021;**2**(2). https://doi.org/10.1088/2632-2153/abdbfe.
7. Hurkmans C, Bibault JE, Brock KK, van Elmpt W, Feng M, David Fuller C, et al. A joint ESTRO and AAPM guideline for development, clinical validation and reporting of artificial intelligence models in radiation therapy. *Radiother Oncol*. 2024;**197**:110345. [PubMed ID: 38838989]. https://doi.org/10.1016/j.radonc.2024.110345.
8. Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, et al. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int J Inf Manag*. 2021;**57**. https://doi.org/10.1016/j.ijinfomgt.2019.08.002.
9. Avanzo M, Trianni A, Botta F, Talamonti C, Stasi M, Iori M. Artificial Intelligence and the Medical Physicist: Welcome to the Machine. *Appl Sci*. 2021;**11**(4). https://doi.org/10.3390/app11041691.
10. Deig CR, Kanwar A, Thompson RF. Artificial Intelligence in Radiation Oncology. *Hematol Oncol Clin North Am*. 2019;**33**(6):1095-104. [PubMed ID: 31668208]. https://doi.org/10.1016/j.hoc.2019.08.003.
11. Bica I, Alaa AM, Lambert C, van der Schaar M. From Real-World Patient Data to Individualized Treatment Effects Using Machine Learning: Current and Future Methods to Address Underlying Challenges. *Clin Pharmacol Ther*. 2021;**109**(1):87-100. [PubMed ID: 32449163]. https://doi.org/10.1002/cpt.1907.
12. Pinto-Coelho L. How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. *Bioengineering (Basel)*. 2023;**10**(12). [PubMed ID: 38136026]. [PubMed Central ID: PMC10740686]. https://doi.org/10.3390/bioengineering10121435.
13. Boon IS, Au Yong TPT, Boon CS. Assessing the Role of Artificial Intelligence (AI) in Clinical Oncology: Utility of Machine Learning in Radiotherapy Target Volume Delineation. *Medicines (Basel)*. 2018;**5**(4).

[PubMed ID: 30544901]. [PubMed Central ID: PMC6313566]. https://doi.org/10.3390/medicines5040131.

14. Hussein M, Heijmen BJM, Verellen D, Nisbet A. Automation in intensity modulated radiotherapy treatment planning-a review of recent innovations. *Br J Radiol*. 2018;**91**(1092):20180270. [PubMed ID: 30074813]. [PubMed Central ID: PMC6319857]. https://doi.org/10.1259/bjr.20180270.
15. Xu L, Zhu S, Wen N. Deep reinforcement learning and its applications in medical imaging and radiation therapy: a survey. *Phys Med Biol*. 2022;**67**(22). [PubMed ID: 36270582]. https://doi.org/10.1088/1361-6560/ac9cb3.
16. Mahadevaiah G, Rv P, Bermejo I, Jaffray D, Dekker A, Wee L. Artificial intelligence-based clinical decision support in modern medical physics: Selection, acceptance, commissioning, and quality assurance. *Med Phys*. 2020;**47**(5):e228-35. [PubMed ID: 32418341]. [PubMed Central ID: PMC7318221]. https://doi.org/10.1002/mp.13562.
17. Sher DJ, Godley A, Park Y, Carpenter C, Nash M, Hesami H, et al. Prospective study of artificial intelligence-based decision support to improve head and neck radiotherapy plan quality. *Clin Transl Radiat Oncol*. 2021;**29**:65-70. [PubMed ID: 34159264]. [PubMed Central ID: PMC8196054]. https://doi.org/10.1016/j.ctro.2021.05.006.
18. Zhao W, Xing L. Advances in treatment planning. *Principles and Practice of Image-Guided Abdominal Radiation Therapy*. Bristol, UK: IOP Publishing; 2023. p. 16-1-16-20. https://doi.org/10.1088/978-0-7503-2468-7ch16.
19. Yang Y, Xing L, Kovalchuk N, Huang C, Nomura Y, Hu W, et al. Data-Driven Treatment Planning, Plan QA, and Fast Dose Calculation. *Artificial Intelligence in Radiation Oncology and Biomedical Physics*. Boca Raton, Florida: CRC Press; 2023. p. 63-85. https://doi.org/10.1201/9781003094333-4.
20. Ker J, Wang L, Rao J, Lim T. Deep Learning Applications in Medical Image Analysis. *IEEE Access*. 2018;**6**:9375-89. https://doi.org/10.1109/access.2017.2788044.
21. Panayides AS, Amini A, Filipovic ND, Sharma A, Tsaftaris SA, Young A, et al. AI in Medical Imaging Informatics: Current Challenges and Future Directions. *IEEE J Biomed Health Inform*. 2020;**24**(7):1837-57. [PubMed ID: 32609615]. [PubMed Central ID: PMC8580417]. https://doi.org/10.1109/JBHI.2020.2991043.
22. Men K, Dai J, Li Y. Automatic segmentation of the clinical target volume and organs at risk in the planning CT for rectal cancer using deep dilated convolutional neural networks. *Med Phys*. 2017;**44**(12):6377-89. [PubMed ID: 28963779]. https://doi.org/10.1002/mp.12602.
23. Rawat S, Singh S, Alam MA, Malviya R. Application of Deep Learning in Radiation Therapy. *Deep Learning for Targeted Treatments: Transformation in Healthcare*. 2022. p. 289-331. https://doi.org/10.1002/9781119857983.ch10.
24. Khajuria R, Sarwar A. Review of reinforcement learning applications in segmentation, chemotherapy, and radiotherapy of cancer. *Micron*. 2024;**178**:103583. [PubMed ID: 38185018]. https://doi.org/10.1016/j.micron.2023.103583.
25. Luo Y, Jolly S, Palma D, Lawrence TS, Tseng HH, Valdes G, et al. A situational awareness Bayesian network approach for accurate and credible personalized adaptive radiotherapy outcomes prediction in lung cancer patients. *Phys Med*. 2021;**87**:11-23. [PubMed ID: 34091197]. [PubMed Central ID: PMC8284560]. https://doi.org/10.1016/j.ejmp.2021.05.032.
26. Torshabi AE. Investigation the Efficacy of Fuzzy Logic Implementation at Image-Guided Radiotherapy. *J Med Signals Sens*. 2022;**12**(2):163-70. [PubMed ID: 35755973]. [PubMed Central ID: PMC9215832]. https://doi.org/10.4103/jmss.JMSS_76_20.
27. Lei J, Li Y. A DNA genetic algorithm for beam angle selection in radiotherapy planning. *2008 IEEE conference on cybernetics and intelligent systems*. IEEE; 2008. p. 1331-6.
28. Wu X, Zhu Y. An optimization method for importance factors and beam weights based on genetic algorithms for radiotherapy treatment planning. *Phys Med Biol*. 2001;**46**(4):1085-99. [PubMed ID: 11324953]. https://doi.org/10.1088/0031-9155/46/4/313.
29. Abdollahi H, Mofid B, Shiri I, Razzaghdoust A, Saadipoor A, Mahdavi A, et al. Machine learning-based radiomic models to predict intensity-modulated radiation therapy response, Gleason score and stage in prostate cancer. *Radiol Med*. 2019;**124**(6):555-67. [PubMed ID: 30607868]. https://doi.org/10.1007/s11547-018-0966-4.
30. Jalalimanesh A, Haghighi HS, Ahmadi A, Hejazian H, Soltani M. Multi-objective optimization of radiotherapy: Distributed Q-learning and agent-based simulation. *J Exp Theor Artif Intell*. 2017;**29**(5):1071-86.
31. Kalendralis P, Eyssen D, Canters R, Luk SM, Kalet AM, van Elmpt W, et al. External Validation of a Bayesian Network for Error Detection in Radiotherapy Plans. *IEEE Trans Radiat Plasma Med Sci*. 2022;**6**(2):200-6. https://doi.org/10.1109/trpms.2021.3070656.
32. Leszczynski K, Cosby S, Bissett R, Provost D, Boyko S, Loose S, et al. Application of a fuzzy pattern classifier to decision making in portal verification of radiotherapy. *Phys Med Biol*. 1999;**44**(1):253-69. [PubMed ID: 10071887]. https://doi.org/10.1088/0031-9155/44/1/018.
33. Li Y, Yao J, Yao D. Automatic beam angle selection in IMRT planning using genetic algorithm. *Phys Med Biol*. 2004;**49**(10):1915-32. [PubMed ID: 15214533]. https://doi.org/10.1088/0031-9155/49/10/007.
34. Li Y, Lei J. A feasible solution to the beam-angle-optimization problem in radiotherapy planning with a DNA-based genetic algorithm. *IEEE Trans Biomed Eng*. 2010;**57**(3):499-508. [PubMed ID: 19822468]. https://doi.org/10.1109/TBME.2009.2033263.
35. Patnaikuni SK, Saini SM, Chandola RM, Chandrakar P, Chaudhary V. Normal Tissue Risk Estimation Using Biological Knowledge-Based Fuzzy Logic in Volumetric Modulated Arc Therapy of Prostate Cancer: Rectum. *J Med Phys*. 2022;**47**(2):126-35. [PubMed ID: 36212203]. [PubMed Central ID: PMC9543004]. https://doi.org/10.4103/jmp.jmp_91_21.
36. Valdes G, Simone C2, Chen J, Lin A, Yom SS, Pattison AJ, et al. Clinical decision support of radiotherapy treatment planning: A data-driven machine learning strategy for patient-specific dosimetric decision making. *Radiother Oncol*. 2017;**125**(3):392-7. [PubMed ID: 29162279]. https://doi.org/10.1016/j.radonc.2017.10.014.
37. Wu C, Nguyen D, Xing Y, Montero AB, Schuemann J, Shang H, et al. Improving Proton Dose Calculation Accuracy by Using Deep Learning. *Mach Learn Sci Technol*. 2021;**2**(1). [PubMed ID: 35965743]. [PubMed Central ID: PMC9374098]. https://doi.org/10.1088/2632-2153/abb6d5.
38. Xing Y, Zhang Y, Nguyen D, Lin MH, Lu W, Jiang S. Boosting radiotherapy dose calculation accuracy with deep learning. *J Appl Clin Med Phys*. 2020;**21**(8):149-59. [PubMed ID: 32559018]. [PubMed Central ID: PMC7484829]. https://doi.org/10.1002/acm2.12937.
39. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med*. 2019;**17**(1):195. [PubMed ID: 31665002]. [PubMed Central ID: PMC6821018]. https://doi.org/10.1186/s12916-019-1426-2.
40. Thrall JH, Li X, Li Q, Cruz C, Do S, Dreyer K, et al. Artificial Intelligence and Machine Learning in Radiology: Opportunities, Challenges, Pitfalls, and Criteria for Success. *J Am Coll Radiol*. 2018;**15**(3 Pt B):504-8. [PubMed ID: 29402533]. https://doi.org/10.1016/j.jacr.2017.12.026.
41. London AJ. Artificial Intelligence and Black-Box Medical Decisions: Accuracy versus Explainability. *Hastings Cent Rep*. 2019;**49**(1):15-21. [PubMed ID: 30790315]. https://doi.org/10.1002/hast.973.
42. El Naqa I, Karolak A, Luo Y, Folio L, Tarhini AA, Rollison D, et al. Translation of AI into oncology clinical practice. *Oncogene*. 2023;**42**(42):3089-97. [PubMed ID: 37684407]. [PubMed Central ID: PMC12516697]. https://doi.org/10.1038/s41388-023-02826-z.

43. Cobanaj M, Corti C, Dee EC, McCullum L, Celi LA, Curigliano G, et al. Artificial intelligence in the oncology workflow: Applications, limitations, and future perspectives. *Artificial Intelligence for Medicine*. Elsevier; 2024. p. 91-111. https://doi.org/10.1016/b978-0-443-13671-9.00013-2.

44. Pesapane F, Suter MB, Codari M, Patella F, Volonté C, Sardanelli F. Regulatory issues for artificial intelligence in radiology. *Precision Medicine for Investigators, Practitioners and Providers*. Elsevier; 2020. p. 533-43. https://doi.org/10.1016/b978-0-12-819178-1.00052-6.

45. Khanna S, Srivastava S, Khanna I, Pandey V. Current challenges and opportunities in implementing AI/ML in cancer imaging: integration, development, and adoption perspectives. *J Adv Analyt Healthcare Manag*. 2020;**4**(10):1-25.

46. Thompson RF, Valdes G, Fuller CD, Carpenter CM, Morin O, Aneja S, et al. Artificial intelligence in radiation oncology: A specialty-wide disruptive transformation? *Radiother Oncol*. 2018;**129**(3):421-6. [PubMed ID: 29907338]. [PubMed Central ID: PMC9620952]. https://doi.org/10.1016/j.radonc.2018.05.030.

47. Fletcher RR, Nakeshimana A, Olubeko O. Addressing Fairness, Bias, and Appropriate Use of Artificial Intelligence and Machine Learning in Global Health. *Front Artif Intell*. 2020;**3**:561802. [PubMed ID: 33981989]. [PubMed Central ID: PMC8107824]. https://doi.org/10.3389/frai.2020.561802.

48. Nazer LH, Zatarah R, Waldrip S, Ke JXC, Moukheiber M, Khanna AK, et al. Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digit Health*. 2023;**2**(6). e0000278. [PubMed ID: 37347721]. [PubMed Central ID: PMC10287014]. https://doi.org/10.1371/journal.pdig.0000278.

49. Chen RJ, Chen TY, Lipkova J, Wang JJ, Williamson DF, Lu MY, et al. Algorithm fairness in ai for medicine and healthcare. *arXiv preprint arXiv:2110.00603*. 2021.

50. Kiser KJ, Fuller CD, Reed VK. Artificial intelligence in radiation oncology treatment planning: a brief overview. *J Med Artif Intell*. 2019;**2**:9. https://doi.org/10.21037/jmai.2019.04.02.

51. Giraud P, Bibault JE. Artificial intelligence in radiotherapy: Current applications and future trends. *Diagn Interv Imaging*. 2024;**105**(12):475-80. [PubMed ID: 38918124]. https://doi.org/10.1016/j.diii.2024.06.001.