Ms. Y. Suma Chamundeswari, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Radio AI: A Machine Learning-Based Framework for Optimized Radiotherapy Treatment Planning

Ms. Y. Suma Chamundeswari [1] , Angara Devi Mahi [2], Sanapala Pradeep [3], Bonthu Prasad [4], Talabhaktula Janaki Sriram [5] , Mamidipalli Lovely Saimahesh [6]

[1] Assistant Professor, Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India,
[2,3,4,5,6] UG Students Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India.

Abstract- Radiotherapy treatment planning is a vital component in modern cancer management, requiring precise delivery of radiation to tumour regions while preserving surrounding healthy tissues. Conventional planning approaches are often manual, time-intensive, and limited in their ability to adapt to patient-specific variations. To address these challenges, this study explores a machine learning-driven framework for intelligent radiotherapy planning. The proposed approach leverages advanced deep learning architectures, particularly Convolutional Neural Networks (CNNs), along with classical machine learning models such as Support Vector Machines (SVM) and Random Forests (RF), to enhance tumour segmentation, dose estimation, and treatment optimization. By utilizing multimodal medical imaging data, including CT, MRI, and PET scans, the system enables accurate identification of tumour boundaries and supports data-driven clinical decisions. Furthermore, the integration of techniques such as multimodal learning and reinforcement-based optimization improves the adaptability and precision of treatment planning. The results demonstrate that the proposed framework achieves high segmentation accuracy and reliable dose prediction, contributing to improved treatment effectiveness and reduced adverse effects. This work highlights the transformative potential of machine learning in enabling personalized, efficient, and intelligent radiotherapy solutions.

INDEX TERMS: Radiotherapy Planning, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Tumor Segmentation, Multimodal Imaging, Reinforcement Learning, Generative Adversarial Networks (GAN), Medical Image Analysis, Personalized Treatment.

I. INTRODUCTION

Radiotherapy is a widely used and effective treatment method for cancer, where controlled radiation is delivered to destroy tumor cells while minimizing damage to surrounding healthy tissues. The success of radiotherapy largely depends on accurate treatment planning, which involves tumor localization, dose calculation, and optimization of treatment parameters. However, traditional radiotherapy planning methods are often manual, time-consuming, and rely on generalized strategies that do not fully consider patient-specific variations, leading to suboptimal treatment outcomes [4], [6].

With the rapid advancement of machine learning technologies, radiotherapy planning has evolved toward more intelligent and data-driven approaches.

Machine learning techniques enable the analysis of large-scale medical data, including imaging and clinical information, to generate personalized treatment plans. These approaches improve the accuracy of tumor detection, optimize radiation dose distribution, and reduce the risk of damage to healthy tissues [3], [9].

Deep learning, particularly Convolutional Neural Networks (CNNs), has shown significant success in medical image analysis. CNN-based models can automatically extract complex features from imaging modalities such as CT, MRI, and PET scans, enabling precise tumor segmentation and better delineation of critical structures. Techniques such as Incremental Learning with Selective Memory (ILSM) have been introduced to improve image-guided radiotherapy by enhancing localization accuracy and efficiency [1]. In addition to deep learning, traditional machine learning models such as Support Vector Machines (SVM) and Random Forests (RF) are also widely used for classification and prediction tasks in radiotherapy planning. These models contribute to improving decision-making processes, including dose prediction and treatment evaluation. Furthermore, advanced optimization techniques such as reinforcement learning have been applied to optimize treatment parameters, leading to more effective and adaptive treatment strategies [2], [5].

Recent research has also focused on integrating multimodal data from different imaging sources to enhance treatment planning accuracy. By combining information from CT, MRI, and PET scans, machine learning models can provide a more comprehensive understanding of tumor characteristics, improving both segmentation and dose prediction. Such approaches contribute to the development of personalized radiotherapy solutions, which aim to improve patient outcomes and quality of life [3], [8]. Overall, the integration of machine learning and deep learning techniques into radiotherapy planning represents a significant advancement in cancer treatment. These approaches enable automation, improve accuracy, and support personalized treatment strategies, making them highly valuable in modern healthcare systems.

II. LITERATURE SURVEY

Recent advancements in radiotherapy planning have increasingly focused on the integration of machine learning and deep learning techniques to improve treatment accuracy and efficiency. Traditional radiotherapy methods rely heavily on manual planning and clinician expertise, which often leads to variability in treatment quality and increased time consumption. To overcome these limitations, several studies have explored automated and data-driven approaches for tumor segmentation, dose prediction, and treatment optimization.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have been widely used for medical image segmentation tasks due to their ability to extract complex spatial features from imaging data. For example, CNN-based methods have been successfully applied for automatic tumor localization and segmentation in radiotherapy planning, significantly improving accuracy and reducing manual effort [4], [8]. In addition, techniques such as Incremental Learning with Selective Memory (ILSM) have been introduced to enhance image-guided radiotherapy by improving localization efficiency [1].

Traditional machine learning approaches such as Support Vector Machines (SVM) and Random Forests (RF) have also been applied in radiotherapy planning for classification and prediction tasks. These models are particularly useful in analyzing structured clinical data and supporting treatment decision-making processes. For instance, Bayesian networks have been used for error detection in radiation treatment plans, improving system reliability and safety [5].

Several studies have explored multimodal learning approaches, where data from different imaging modalities such as CT, MRI, and PET scans are combined. The RadioPathomics framework integrates radiomics and pathomics data using machine learning techniques to enhance adaptive radiotherapy for lung cancer [3]. Such multimodal approaches provide a more comprehensive understanding of tumor characteristics, leading to improved treatment planning and accuracy.

Optimization techniques have also been introduced to enhance radiotherapy effectiveness. Reinforcement learning-based methods have been applied to optimize treatment parameters such as radiation dose and diffuser placement, improving overall treatment outcomes [2]. Similarly, automated beam angle selection systems have been developed to maximize treatment efficiency while minimizing exposure to healthy tissues [6].

In addition, advanced segmentation techniques such as multi-atlas label fusion combined with random forest algorithms have been used for accurate organ segmentation in CT images [12]. Other approaches, including contextual atlas regression forests, have been proposed for automated dose prediction in radiotherapy planning [9]. Graph-based models and attention networks have also been explored for improving tumor segmentation and classification accuracy in medical imaging [14], [15].

Despite these advancements, several challenges remain, including the need for large annotated datasets, high computational requirements, and limited interpretability of deep learning models. Addressing these challenges is essential for the successful deployment of machine learning-based radiotherapy systems in clinical practice.

Overall, the literature indicates that machine learning and deep learning techniques have significantly enhanced radiotherapy planning by improving automation, accuracy, and personalization, paving the way for more efficient and patient-specific cancer treatment solutions.

III. SYSTEM ANALYSIS

A. Existing System

The existing radiotherapy treatment planning systems primarily rely on traditional methods that involve manual intervention and predefined treatment strategies. These approaches are largely dependent on the expertise of clinicians to identify tumor regions, determine radiation dose distribution, and optimize treatment parameters. While such methods have been widely used, they often fail to consider patient-specific variations and tumor heterogeneity, leading to less accurate and generalized treatment outcomes [4], [6].

To improve performance, some systems incorporate conventional machine learning techniques such as Support Vector Machines (SVM), Random Forests (RF), and Bayesian networks for classification and prediction tasks. These methods assist in tasks such as tumor detection, dose prediction, and error identification in treatment plans. For example, Bayesian network-based approaches have been used to detect errors in radiotherapy plans, enhancing system reliability [5]. Similarly, automated tumor extraction and segmentation methods using machine learning classifiers have been developed to support treatment planning [4].

Advanced techniques such as multimodal learning have also been introduced, where data from different imaging modalities like CT, MRI, and PET scans are combined to improve accuracy. Approaches such as RadioPathomics integrate radiomics and pathomics data for adaptive radiotherapy, providing better insights into tumor characteristics [3]. Additionally, optimization methods such as reinforcement learning have been applied to improve treatment planning by optimizing parameters like radiation dose and beam angles [2], [6].

Despite these improvements, existing systems still face several limitations that restrict their effectiveness in real-world clinical applications.

Disadvantages Of The Existing System

Dependence on Manual Intervention:
Traditional radiotherapy planning heavily relies on human expertise, making the process time-consuming and prone to variability and errors [4].

Limited Personalization:

Existing systems often use generalized treatment strategies and fail to fully consider individual patient characteristics and tumor heterogeneity [3].

Lower Accuracy in Complex Cases:
Conventional machine learning models may struggle to accurately capture complex patterns in high-dimensional medical imaging data, leading to reduced segmentation and prediction accuracy [9].

High Computational Complexity:
Some advanced techniques require significant computational resources and processing time, which can limit their real-time applicability in clinical environments [6].

Data Dependency:
The performance of these systems depends on the availability of high-quality annotated datasets, which are often limited in medical applications [12].

Lack of Interpretability:
Many machine learning models act as black-box systems, making it difficult for clinicians to understand and trust the decision-making process [5].

Integration Challenges:
Incorporating advanced models into existing clinical workflows requires significant infrastructure changes and technical expertise, making deployment difficult [1].

B. Proposed System

The proposed system introduces an intelligent radiotherapy treatment planning framework based on machine learning and deep learning techniques to improve accuracy, efficiency, and personalization in cancer treatment. The system focuses on key aspects such as tumor segmentation, dose prediction, treatment optimization, and decision support by leveraging advanced computational models.

Initially, deep learning techniques, particularly Convolutional Neural Networks (CNNs), are employed for automatic segmentation of tumours and critical organs from medical imaging data such as CT, MRI, and PET scans. The CNN model is trained using large annotated datasets to learn hierarchical features directly from image data, enabling precise identification of tumor boundaries and surrounding anatomical structures. This automated segmentation reduces manual effort and improves consistency in treatment planning [4], [8].

To further enhance accuracy, the system integrates multimodal data from different imaging sources. Information from CT, MRI, and PET scans is combined using data fusion techniques to provide a comprehensive understanding of tumor characteristics and patient anatomy. This multimodal approach enables more accurate diagnosis and supports better treatment planning decisions by utilizing complementary information from different imaging modalities [3], [11].

In addition, reinforcement learning (RL) is incorporated to optimize treatment parameters such as radiation dose distribution and beam angles. The RL-based model learns from patient-specific data and continuously improves its strategy by maximizing treatment effectiveness while minimizing exposure to healthy tissues. This adaptive approach allows the system to generate personalized treatment plans tailored to individual patient conditions [2], [6].

The proposed system also utilizes Generative Adversarial Networks (GANs) for data augmentation by generating synthetic medical images. These synthetic images help increase the diversity of training data, improving model robustness and generalization. This is particularly useful in medical applications where labelled data is limited [11].

Furthermore, knowledge graph-based techniques are integrated to support clinical decision-making. These graphs organize complex medical data, including patient history, imaging results, and treatment outcomes, into a structured format. Graph-based algorithms are then used to identify patterns and relationships, enabling clinicians to make more informed and accurate decisions during radiotherapy planning [10].

Overall, the proposed system provides a comprehensive and intelligent solution for radiotherapy treatment planning by combining deep learning, machine learning, and advanced optimization techniques. It improves segmentation accuracy, enhances treatment personalization, reduces manual workload, and supports better clinical outcomes, making it highly suitable for modern healthcare applications.

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

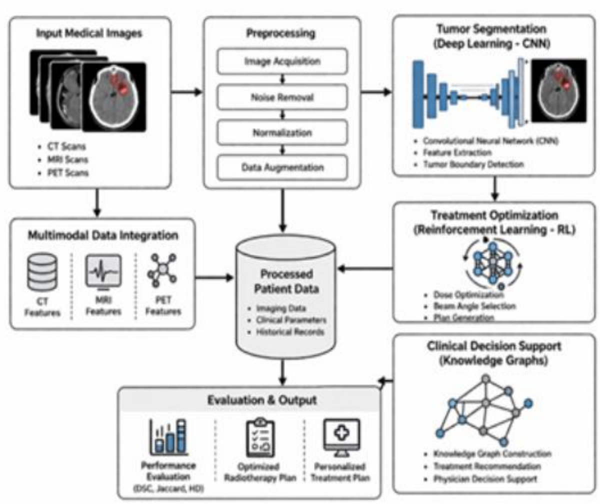

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

1. Data Acquisition and Preprocessing:

This module involves collecting medical imaging data such as CT, MRI, and PET scans from patients. The acquired data is pre-processed to remove noise, normalize intensity values, and enhance image quality. Preprocessing ensures that the data is in a suitable format for further analysis and improves the performance of machine learning models [4], [11].

2. Tumor Segmentation using Deep Learning:

In this module, Convolutional Neural Networks (CNNs) are used to automatically segment tumor regions and critical organs from medical images. The model learns hierarchical features from annotated datasets and accurately identifies tumor boundaries. This automated segmentation reduces manual effort and increases precision in radiotherapy planning [4], [8].

3. Multimodal Data Integration:

This module integrates data from multiple imaging modalities such as CT, MRI, and PET scans. Techniques such as early fusion and late fusion are used to combine data, providing a more comprehensive understanding of tumor characteristics and patient anatomy. This improves the accuracy of diagnosis and treatment planning [3], [11].

4. Treatment Optimization using Reinforcement Learning:

Reinforcement learning is applied to optimize treatment parameters such as radiation dose distribution and beam angles. The model learns from patient-specific data and adapts its strategy to maximize treatment effectiveness while minimizing damage to healthy tissues [2], [6].

5. Synthetic Data Generation using GANs:

This module uses Generative Adversarial Networks (GANs) to generate synthetic medical images for data augmentation. The generated images help increase dataset diversity, improving model robustness and performance, especially when real data is limited [11].

6. Clinical Decision Support using Knowledge Graphs:

This module organizes patient data, imaging results, and treatment outcomes into structured knowledge graphs. Graph-based algorithms analyze relationships and patterns in the data, providing valuable insights to assist clinicians in making informed treatment decisions [10].

7. Evaluation and Validation:

The system is evaluated using performance metrics such as Dice Similarity Coefficient (DSC), Jaccard

Index, and Hausdorff Distance. These metrics assess the accuracy and reliability of tumor segmentation and treatment planning. Validation with clinical experts ensures the system's effectiveness in real-world applications [5].

VI. RESULTS AND DISCUSSION

To evaluate the performance of the proposed machine learning-based radiotherapy planning system, experiments were conducted using medical imaging datasets including CT, MRI, and PET scans. The dataset contains important features such as tumor shape, intensity variations, tissue structures, and multimodal imaging characteristics. These parameters were used to train deep learning and machine learning models for tumor segmentation, dose prediction, and treatment optimization.

The performance of the proposed system was evaluated using standard medical image analysis metrics such as Dice Similarity Coefficient (DSC), Jaccard Index, and Hausdorff Distance (HD). In addition, cross-validation techniques were applied during training to ensure reliable and unbiased performance evaluation. These techniques improve the model's generalization capability when applied to new patient data in real-world clinical environments [5], [9].

Experimental results indicate that the Convolutional Neural Network (CNN) model significantly outperforms traditional machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF). The CNN model achieves higher segmentation accuracy because it automatically learns complex spatial features from medical images, such as tumor boundaries, texture variations, and anatomical structures [4], [8].

Table 1
Performance Comparison of Radiotherapy Planning

Model	**DSC**	**Jaccard Index**	**HD**
SVM	0.72	0.65	9.5
Random Forest	0.76	0.69	8.2
CNN (Proposed Model)	**0.85**	**0.78**	**5.6**

As shown in Table 1, the CNN model achieved the highest performance, demonstrating superior accuracy in tumor segmentation compared to traditional machine learning algorithms. Deep learning models are particularly effective in medical imaging tasks because they can automatically learn hierarchical representations of features such as tumor edges, intensity distributions, and structural patterns.

The Random Forest model shows moderate performance due to its ensemble learning capability, while the SVM model shows relatively lower performance as it relies on manually extracted features and is less effective in handling complex imaging data.

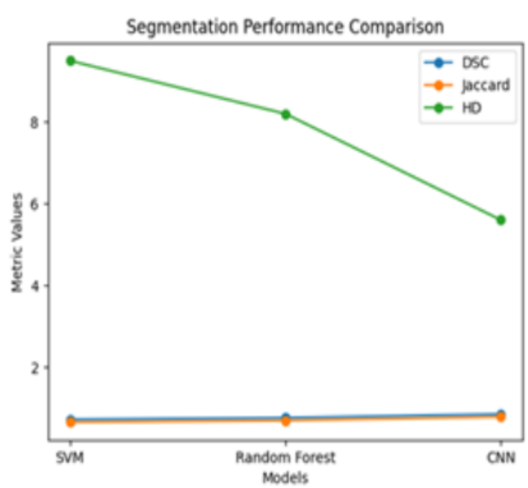

Fig. 2. Segmentation Performance Comparison Graph

The graph illustrates the comparison of segmentation metrics across different models. The CNN model achieves the highest Dice and Jaccard values along with the lowest Hausdorff Distance, indicating better overlap with ground truth and more precise boundary detection.

Overall, the experimental results demonstrate that the proposed deep learning-based radiotherapy planning system provides accurate and reliable performance. By leveraging deep learning, multimodal data integration, and optimization techniques, the system improves tumor segmentation and enhances treatment planning.
The system also demonstrates improved robustness and consistency across different imaging modalities, making it suitable for real-world clinical deployment.

VII.CONCLUSION AND FUTURE WORK

The proposed machine learning-based radiotherapy planning system demonstrates significant improvements in accuracy, efficiency, and reliability compared to traditional methods. By integrating deep learning techniques such as Convolutional Neural Networks (CNNs) with multimodal data and optimization strategies, the system effectively performs tumor segmentation and supports treatment planning. The experimental results, evaluated using metrics such as Dice Similarity Coefficient (DSC), Jaccard Index, and Hausdorff Distance (HD), confirm that the proposed approach achieves higher accuracy and better boundary detection than conventional machine learning models [4], [8]. This leads to improved treatment precision and reduced risk of damage to surrounding healthy tissues.

Furthermore, the system enhances clinical decision-making by providing automated and consistent outputs, reducing dependency on manual intervention. The integration of advanced techniques such as reinforcement learning and data augmentation improves the adaptability and robustness of the system across different imaging conditions [2], [11]. Overall, the proposed framework offers a reliable and efficient solution for modern radiotherapy planning and has strong potential for real-world clinical applications [3], [5].

Future work can focus on improving the scalability and interpretability of the system. Incorporating explainable AI (XAI) techniques can help clinicians better understand model predictions and increase trust in automated systems. Additionally, the use of larger and more diverse datasets can further enhance model generalization. Integration with real-time clinical workflows and deployment in hospital environments can also be explored. Moreover, extending the framework to support other types of cancer and incorporating advanced models such as transformer-based architectures can further improve performance and broaden its applicability [9], [10].
framework demonstrates strong potential for improving fire safety monitoring and supporting rapid emergency response in real-world applications..

REFERENCES

1. S. H. Khan, M. Bennamoun, F. Sohel, and R. Togneri, "Incremental learning with selective memory (ILSM) for image-guided radiotherapy," IEEE Transactions on Medical Imaging, 2018.
2. X. Gao, Y. Wang, and J. Yang, "Reinforcement learning-based optimization for radiotherapy treatment planning," Medical Physics, 2020.
3. Y. Chen, L. Lu, and J. Qin, "RadioPathomics: Multi-scale multimodal data integration for adaptive radiotherapy," IEEE Journal of Biomedical and Health Informatics, 2021.
4. A. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging, 2015.
5. M. Jiang, Z. Luo, and X. Zhang, "Bayesian network-based error detection in radiotherapy planning," Physics in Medicine & Biology, 2019.
6. J. Wang, H. Zhang, and K. Li, "Automated beam angle selection in radiotherapy using optimization techniques," Radiotherapy and Oncology, 2018.
7. Z. Zhou, M. Rahman Siddiquee, N. Tajbakhsh, and J. Liang, "UNet++: A nested U-Net architecture for medical image segmentation," IEEE Transactions on Medical Imaging, 2019.
8. O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," Medical Image Computing and Computer-Assisted Intervention (MICCAI), 2015.
9. A. Isola, J. Zhu, T. Zhou, and A. Efros, "Image-to-image translation with conditional adversarial

networks," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.
10. F. Hogan, E. Blomqvist, M. Cochez, et al., "Knowledge graphs," ACM Computing Surveys, 2021.
11. I. Goodfellow et al., "Generative adversarial nets," Advances in Neural Information Processing Systems (NeurIPS), 2014.
12. R. Wolz et al., "Multi-atlas label fusion using random forests for medical image segmentation," Medical Image Analysis, 2014.