Machine Learning Approaches for Adaptive Radiotherapy in Head and Neck Squamous Cell Carcinoma (HNSCC)

Somiya Rauf, Abdul-Malik Mohammed, Joshua Piña

July 1, 2025

Significance:

According to the World Health Organization (WHO), cancer remains a leading cause of death worldwide. Advances in experimental healthcare and the rapid rise of machine learning (ML) have enabled new data-driven approaches in oncology, supporting risk assessment, diagnosis, prognosis, and prediction of therapy responses [1, 2, 3]. Radiotherapy (RT) has increasingly leveraged ML-based clinical decision support systems to match new patients with treatment plans that are adaptable based on individual responses.

Tumor Control Probability (TCP): TCP estimates the probability of eliminating all clonogenic tumor cells with a given radiation dose d, typically using formulations of cell survival based on the linear-quadratic model.

Normal Tissue Complication Probability (NTCP): Patients receiving radiation may develop pneumonitis (RP2), a harmful inflammation. Clinicians aim to reduce the normal tissue toxicity with NTCP models to predict the probability of radiation-induced complications in healthy tissues, often using dose-response curves to quantify risk as a function of dose distribution.

Mission Statement

Our aim is *Knowledge-Based Response-Adapted Radiotherapy (KBR-ART)* to optimize personalized RT treatment by maximizing $P = TCP \cdot (1 - NTCP)$.

We propose developing an innovative machine learning (ML) framework that employs convolutional neural networks (CNNs), specifically U-Net architectures, for real-time adaptive radiotherapy (RT) in Head and Neck Squamous Cell Carcinoma (HNSCC). By integrating patient-specific clinical and imaging data, this framework will personalize and adapt RT dose fractionation, predicting optimal dosing schedules for each fraction based on early treatment responses. Our model aims to recommend dose adjustments after the first fraction to maximize tumor control, minimize normal tissue toxicity, and evaluate applicability across diverse patient profiles

Data sets

We will utilize a dataset of 493 HNSCC patients, sourced from publicly accessible repositories (TCIA-HNSCC and HN1). This dataset is comprised of de-identified clinical data, CT imaging, and RT plans. CT imaging is available for 336 patients, the remaining 157 without imaging may be considered for exploratory data analysis not requiring radiomic implementation. This version of the dataset employed in this innovation was by a third-party research group led by Zakari Aliti and Hamza Idmoudi. This group did not conduct the original clinical investigations but their data wrangling is noted. The anonymized dataset is publicly available on Kaggle: https://www.kaggle.com/datasets/hamzaidmoudi/hnscc-zip."

Model Steps

1. **Data Types for KBR-ART:** We will use clinical data (e.g., gender, age, smoking status, tumor laterality, T & N categories) and imaging data (CT scans). These features will define N patient samples at baseline and during treatment.
2. **Tumor segmentation and detection:** Apply traditional image processing followed by U-Net CNNs to auto-segment tumor vs normal tissue regions in CT scans.
3. **Dose prediction model:** Train regression models using radiomic features and clinical variables to predict optimal initial doses to maximize $P = \text{TCP} \times (1 - \text{NTCP})$.
4. **Adaptive dose scheduling:** Implement rule-based triggers with a linear feedback control [4] to dynamically adjust doses by through simulated patient responses (e.g., tumor shrinkage, estimated toxicity) after each fraction, allowing response-adapted radiation therapy.

Timeline

Week 1: Foundation, Framework Design, & Data Structuring

- Complete proposal, data exploration, and construct KBR-ART architecture with project repository.
- Load HNSCC dataset and deploy Digital Image Processing pipeline for initial segmentation.

Week 2: Tumor Segmentation & Feature Extraction

- Train CNN to classify tumor vs normal segments using ground truth labels and data augmentation.
- Extract radiomic features and align with clinical data through feature normalization pipeline

Week 3: Dose Prediction & Model Training

- Train regression models for dose prediction with baseline comparisons and cross-validation.
- Implement TCP/NTCP calculations with literature parameters and optimize objective function.

Week 4: Adaptive Dose Scheduling & Results Synthesis

- Implement rule-based triggers and linear feedback control for dynamic dose adjustments.
- Evaluate model performance across patient profiles and document results with visualizations.

Collaborations

This interdisciplinary student research team includes: **Somiya Rauf** - Graduate Student (srauf2@student.gsu.edu), **Abdul-Malik Mohammed** (amohammed23@student.gsu.edu), and **Joshua Piña** (jpina4@student.gsu.edu)

References

[1] Yawei Li, Xin Wu, Deyu Fang, and Yuan Luo. Informing immunotherapy with multi-omics driven machine learning. *npj Digital Medicine*, 7(1):67, 2024.

[2] Renato Cuocolo, Martina Caruso, Teresa Perillo, Lorenzo Ugga, and Mario Petretta. Machine learning in oncology: a clinical appraisal. *Cancer letters*, 481:55–62, 2020.

[3] Yuting Fang, Xiaozhong Chen, and Caineng Cao. Cancer immunotherapy efficacy and machine learning. *Expert Review of Anticancer Therapy*, 24(1-2):21–28, 2024.

[4] Huan-Hsin Tseng, Yi Luo, Randall K Ten Haken, and Issam El Naqa. The role of machine learning in knowledge-based response-adapted radiotherapy. *Frontiers in oncology*, 8:266, 2018.