Re-imagining Knowledge-Based Planning: Development and Validation of a Recurrent Neural Network-Based Direct Aperture Optimization Initialization Predictor for VMAT Radiotherapy Treatment Planning

2026 JULY 19–22 VANCOUVER, BC
JOINT AAPM | COMP MEETING

Sadiki Daniel[1], Ara Alexandrian,PhD[2], Nathan Dobranski[1], Sotiri Stathakis,PhD[2]
1) Physics Department, Louisiana State University, Baton Rouge, LA
2) Mary Bird Perkins Cancer Center, Baton Rouge, LA

LSU

MARY BIRD PERKINS CANCER CENTER™

Abstract

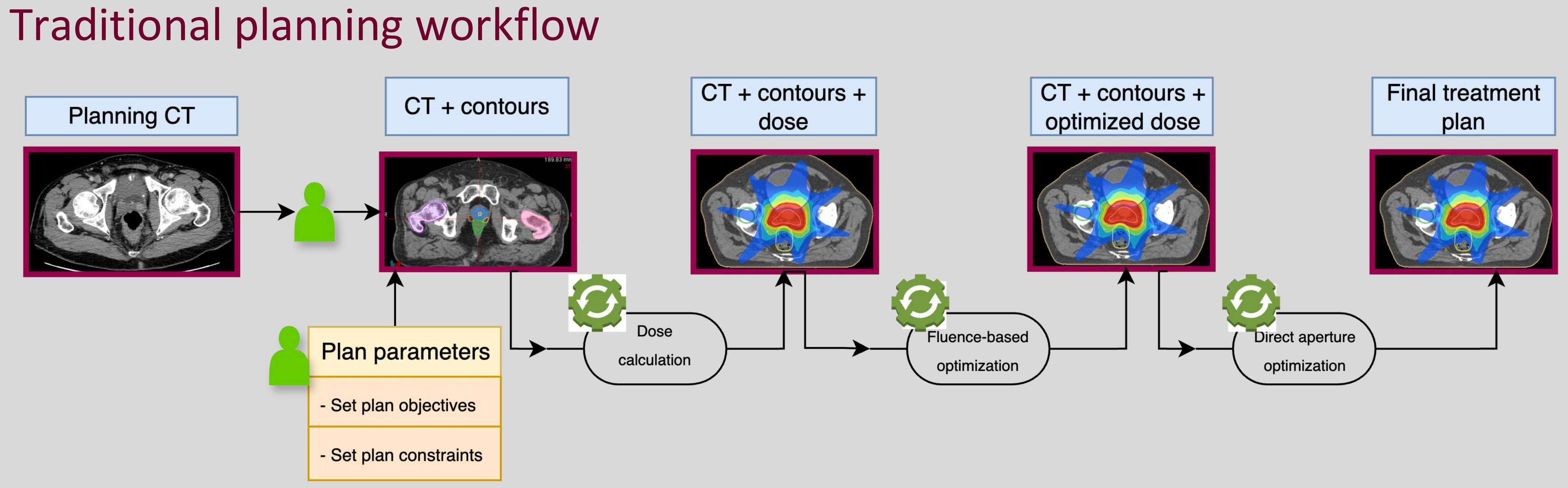
Direct Aperture Optimization (DAO) is the standard approach for VMAT treatment planning, directly optimizing the shapes and intensities of radiation beams. However, conventional DAO faces efficiency limitations that bottleneck clinical workflows.

The primary challenge is the initialization strategy. Most systems start from random or heuristic positions, ignoring knowledge from previously optimized plans. Consequently, optimizers require hundreds to thousands of iterations to reach clinically acceptable solutions. This can take approximately 30 minutes to an hour to plan per patient and in the cases of re-planning, this time multiplies.

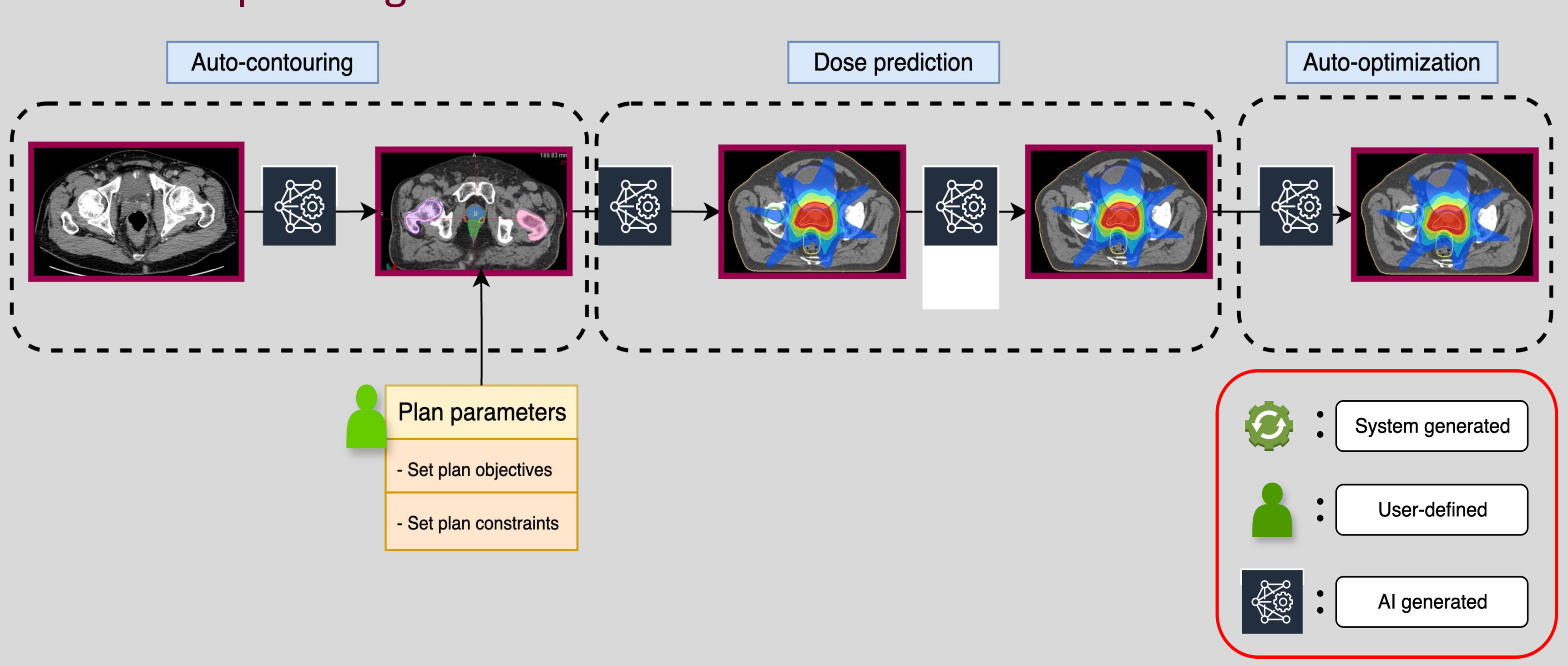
This inefficiency compounds as each patient starts from scratch. Despite treating many similar patients, systems fail to leverage patterns from previous optimizations, repeatedly "relearning" similar trajectories. This research proposes a solution by learning from a dataset of prostate patients' treatment optimization data of MLC positions and weights of segments for each iteration to predict control points that are closer to the optimal plan, i.e. traditionally last iteration, for a smarter initialization technique.

Methodology

Traditional planning workflow



Automated planning workflow



Results

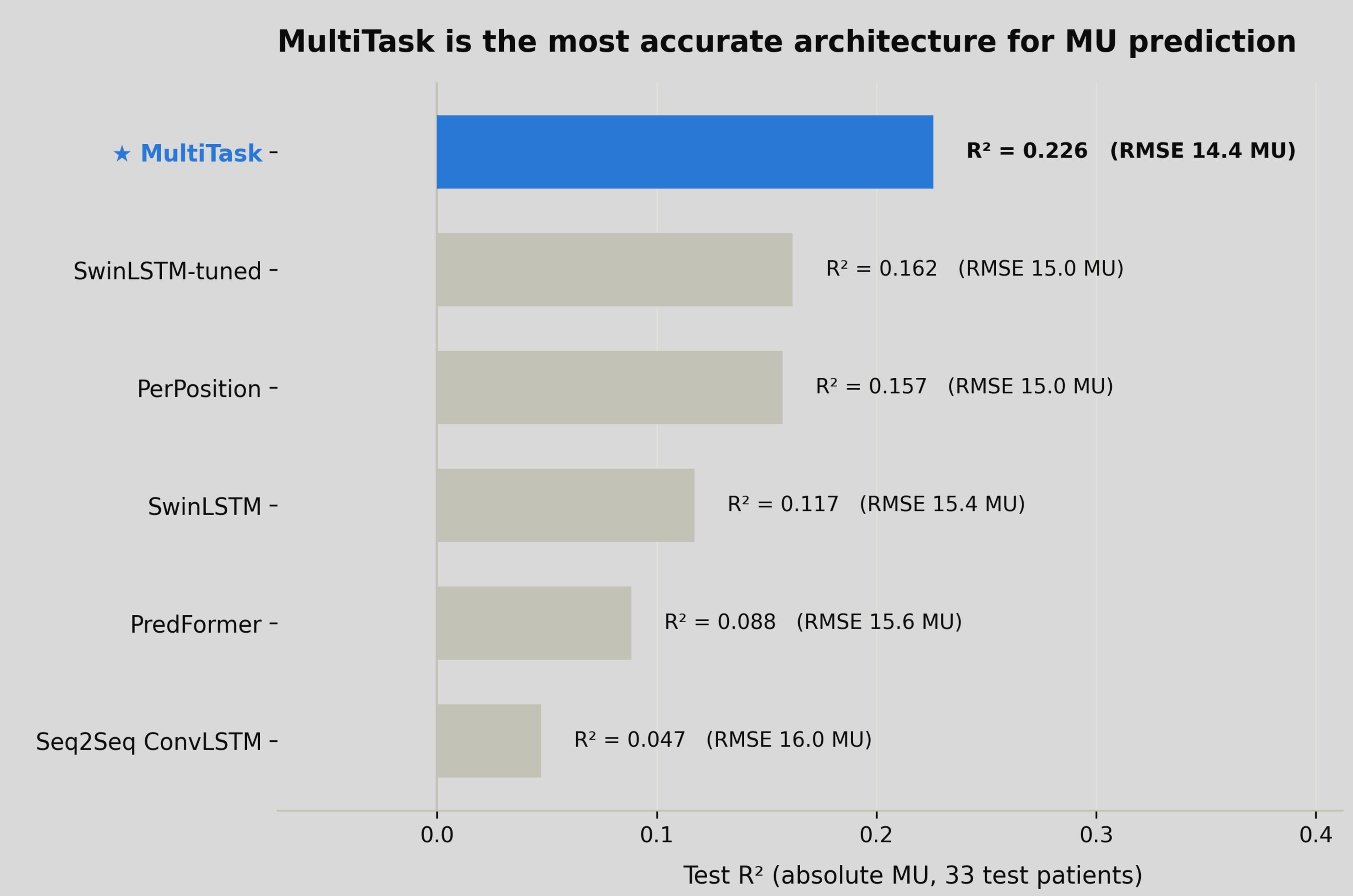


Figure 1: Architecture comparison. Six sequence architectures predicting final beam monitor units (MU) from the first 50 of a DAO optimization's iterations, evaluated on 33 held-out patients.

The model demonstrated strong performance in predicting:

- MLC leaf positions, achieving an R^2 of 0.8603 with an RMSE of 3.248 mm and an MAE of 1.755 mm for the left leaf positions, and an R^2 of 0.8219 with an RMSE of 3.648 mm and an MAE of 1.511 mm for the right leaf positions for all test patients.
- For beam weight prediction, the model achieved an R^2 of 0.5950, with an RMSE of 1.375 mm and an MAE of 0.383 mm, indicating moderate correlation with relatively low absolute prediction error.
- When the aperture shapes and weights were used to initialize the DAO, a mean reduction in iterations of 13.7% and a mean reduction in optimization time of 5.5% were observed.

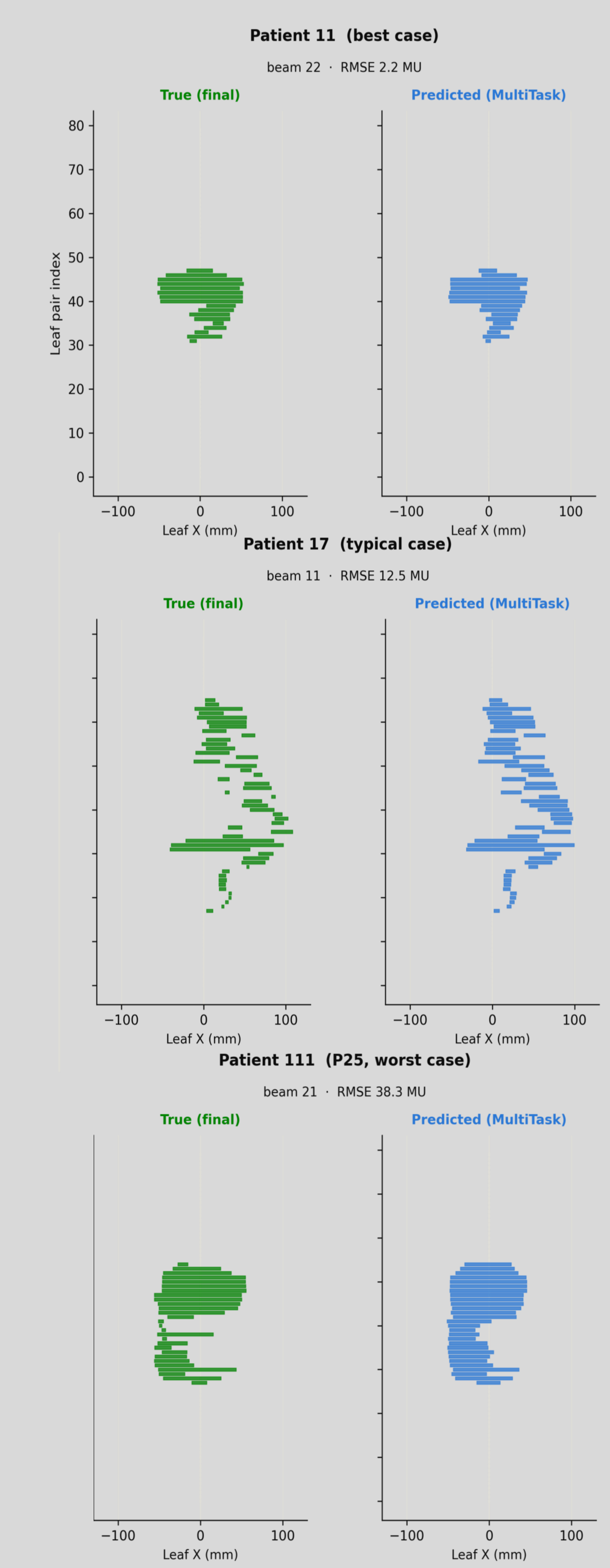


Figure 2: Aperture shape fidelity. Predicted vs. true MLC leaf-pair openings for the highest-weight beam in a best-, typical-, and worst-case patient.

Discussion

Novel Application of Sequential Learning

- First application of RNNs to learn DAO optimization trajectories rather than directly predicting final dose distributions
- Captures the temporal dynamics of how optimizers navigate the solution space, not just the endpoint

Limitations of Current Dataset

- 162 patients provides proof-of-concept but limited anatomical diversity for robust generalization
- Single treatment site (prostate) - model transferability to other sites unknown
- Single institution data may not capture full range of clinical practice variations

Model Predictions vs. Clinical Requirements

- Predicted machine parameters must be physically deliverable (leaf position constraints, speed limits)
- Trade-off between prediction speed and plan quality needs quantification
- May require fine-tuning iterations after AI initialization to meet all clinical constraints

Conclusion

This study demonstrates that recurrent neural networks can learn optimization patterns from historical treatment planning data, potentially accelerating VMAT planning by predicting near-optimal solutions and bypassing traditional iterative processes.
Future work involves clinical deployment to quantify real-world time savings by integrating the model into treatment planning workflows.

References

Otto K. Volumetric modulated arc therapy: IMRT in a single gantry arc. *Med Phys*. 2008;35(1):310-317.
Bortfeld T. IMRT: a review and preview. *Phys Med Biol*. 2006;51(13):R363-R379.
Wieser HP, et al. Development of the open-source dose calculation and optimization toolkit MatRad. *Med Phys*. 2017;44(6):2556-2568.
Nguyen D, et al. A feasibility study on the use of deep learning for knowledge-based planning in radiotherapy. *Med Phys*. 2019;46(2):478-486.
Sheng Y, et al. Deep learning for accelerated dose calculation in radiation therapy treatment planning. *Phys Med Biol*. 2020;65(7):075006.
McIntosh C, Purdie TG. Voxel-based dose prediction with multi-patient atlas selection for automated radiotherapy treatment planning. *Phys Med Biol*. 2017;62(2):415-431.
Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Computation*. 1997;9(8):1735-1780.