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Medical Image Synthesis for Expediting the Diagnosis to Treatment Pathway In Radiation Oncology

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ABSTRACT

Purpose: To expedite the diagnosis-to-treatment workflow in radiation oncology, this work evaluates the use of machine learning for generating synthetic simulation CT images directly from diagnostic CT images.

Methods: Paired diagnostic and RT simulation CT images for 80 prostate cancer patients were used (split: 70% training, 10% validation, 20% testing). We employed image-to-image translation methods based on Generative Adversarial Networks (GANs) to generate synthetic RT simulation CTs from diagnostic CTs. To evaluate both image fidelity and clinical utility, the synthetic CTs were assessed using the Structural Similarity Index Measure (SSIM) and Mean Absolute Error (MAE), as well as task-based validation through automated organ segmentation and dose prediction.

Results: The CycleGAN model achieved an average SSIM of 0.65 ± 0.03, while the conditional GAN (cGAN) with SPADE improved performance with an average SSIM of 0.77 ± 0.03, indicating closer similarity to the ground truth RT planning CT images. Automated segmentation demonstrated that the cGAN with SPADE architecture outperforms CycleGAN in structural similarity to the real simulation CT. SPADE improved the dice similarity coefficient (DSC) in 100% of cases for the urinary bladder and 84% for the prostate, translating to better target and organ-at-risk dose volume histogram (DVH) alignment with the real simulation baseline, while maintaining comparable performance for the small bowel and colon.

Conclusion: ML can generate synthetic RT simulation images from diagnostic images, offering an approach that has the potential of improving clinical efficiency and patient outcomes.

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INTRODUCTION

Current radiation therapy (RT) workflows require the patient to undergo an imaging session to replicate their treatment position, which is used for treatment planning.

Diagnostic scans are often already available but lack the geometric and positioning requirements needed for direct RT planning.

We hypothesize machine learning (ML) could bridge this gap, eliminating the need for redundant imaging sessions and reducing treatment delays.

Objective: Build and evaluate the performance of ML models that generate synthetic RT simulation CTs from diagnostic CTs.

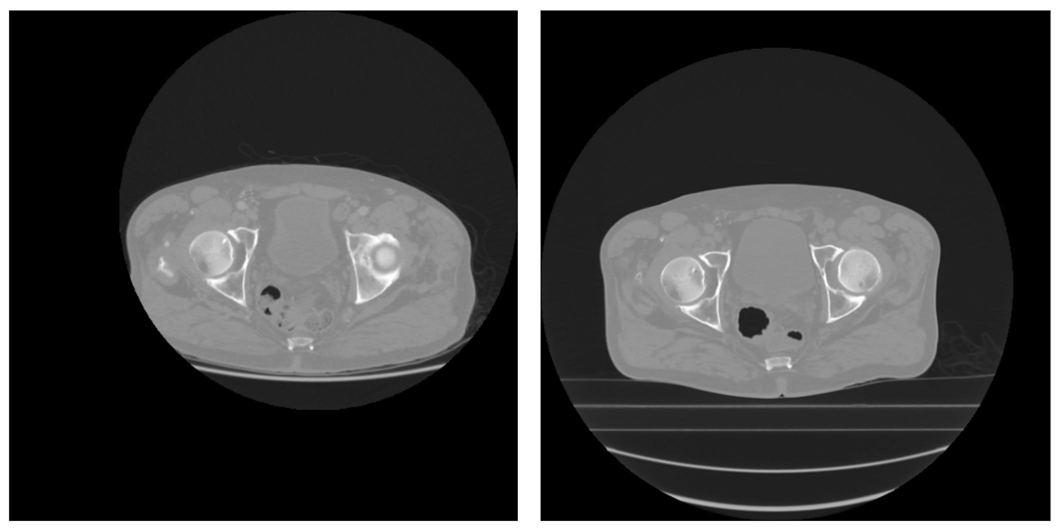
Diagnostic Images → ML Model → Synthetic Images → RT Planning and Delivery

Benefits:
- Reduced wait times
- Optimized clinical resource use
- Fewer hospital visits
- Improved treatment outcomes

METHODS

Data:
- Paired 3D diagnostic and RT planning images acquired for 80 prostate cancer patients
- Preprocessed: rigid registration, intensity normalization

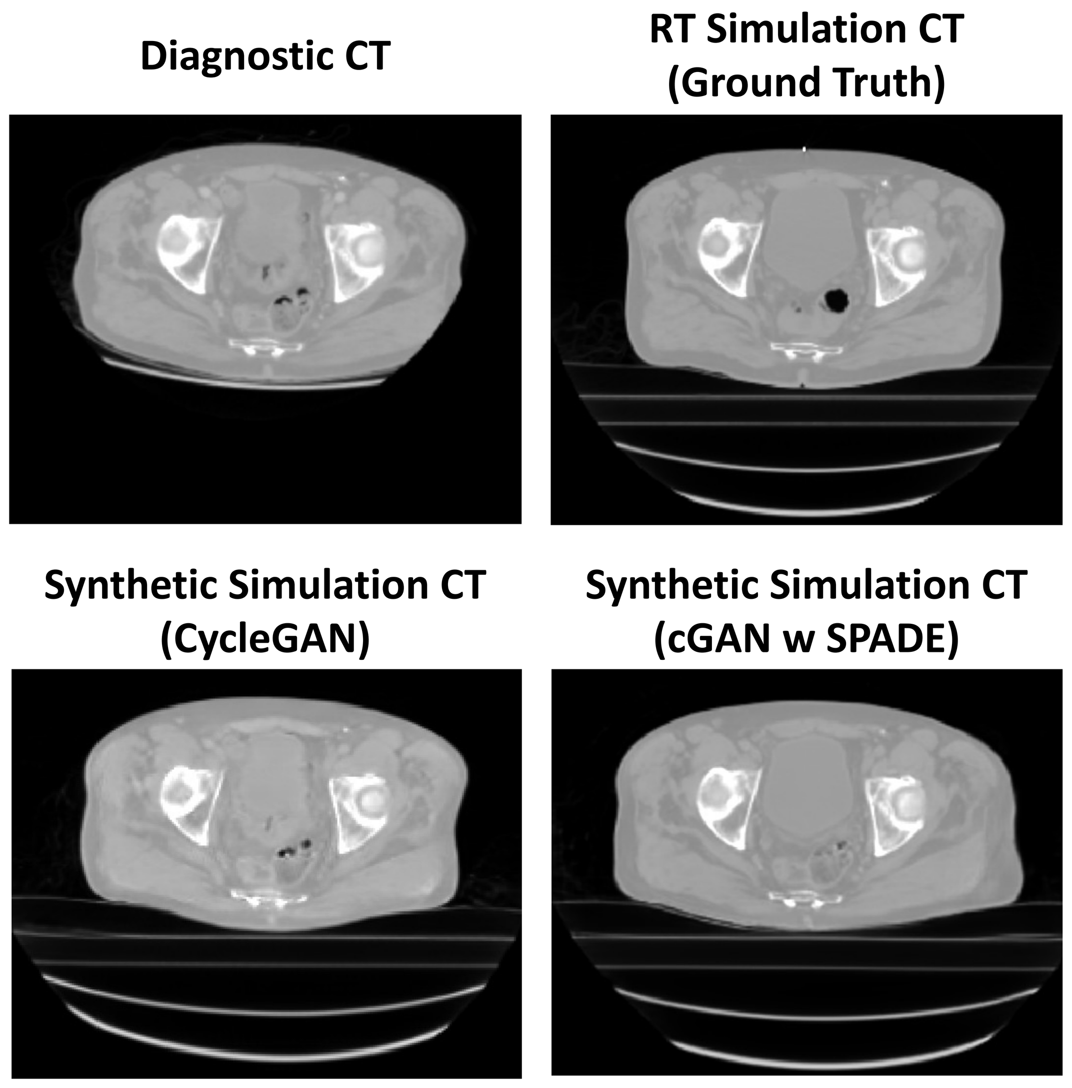
Diagnostic CT | RT Simulation CT



Model:
- Random split of 70%/10%/20% for training/validation/testing
- Compared two generative adversarial network (GAN) architectures: CycleGAN [1] and a conditional GAN (cGAN) incorporating spatially adaptive normalization (SPADE) [2]

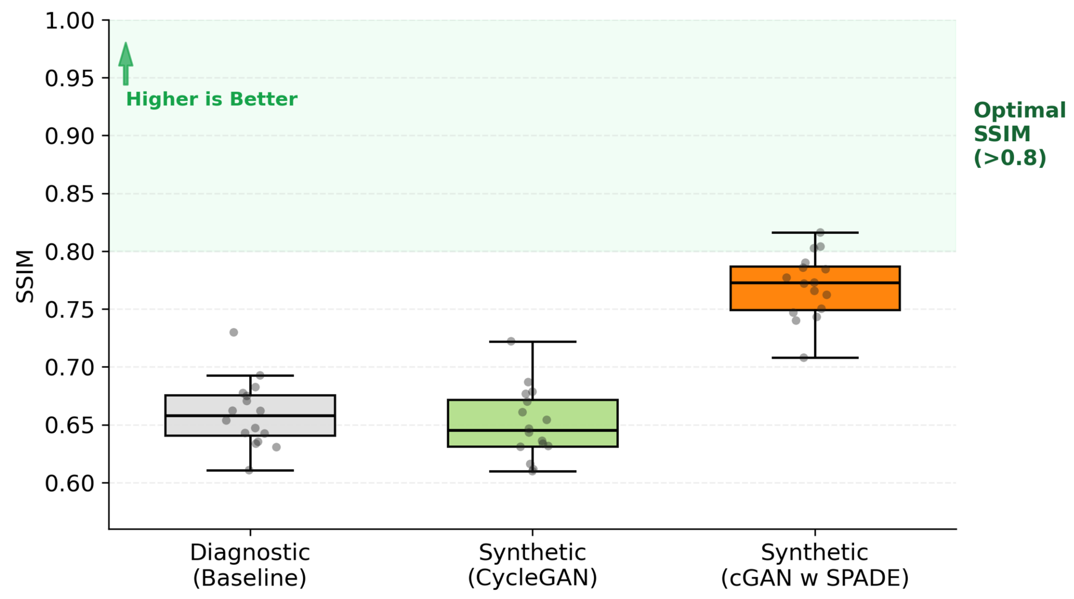
Architecture	Pros	Cons	Role
CycleGAN	Unpaired inputs	Fine details lost	Baseline
cGAN with SPADE	High fidelity	Needs conditioning	Current
Diffusion	Image quality	GPU intensive	Future

RESULTS



Structural Similarity (SSIM)

Relative to Real RT Simulation Image: Measures similarity in structure, edges, and textures



Mean Absolute Error (MAE)

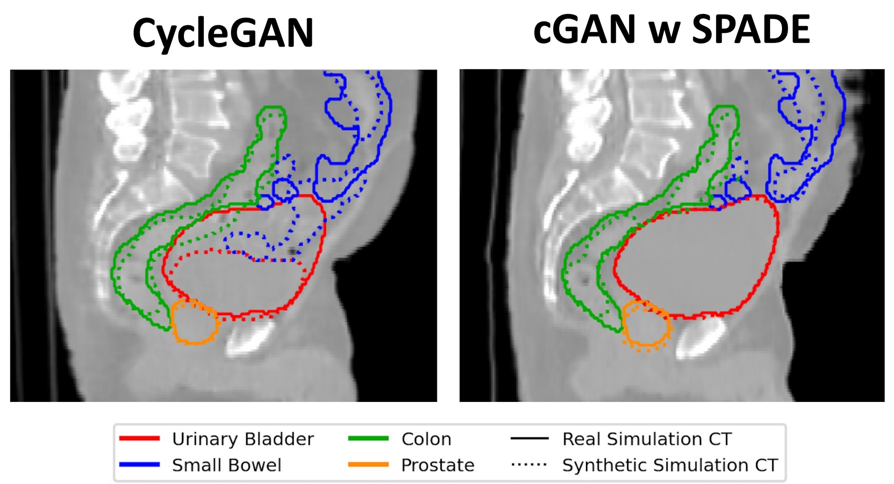
Relative to Real RT Simulation Image: Measures average Hounsfield Units (HU) difference

Image	MAE (HU)	Improvement vs Diagnostic
Diagnostic	135.04	–
CycleGAN	126.41	8.63 HU (6.4%)
cGAN w SPADE	114.18	20.86 HU (15.4%)

Improvements statistically significant (pairedS t-test, p < 0.001)

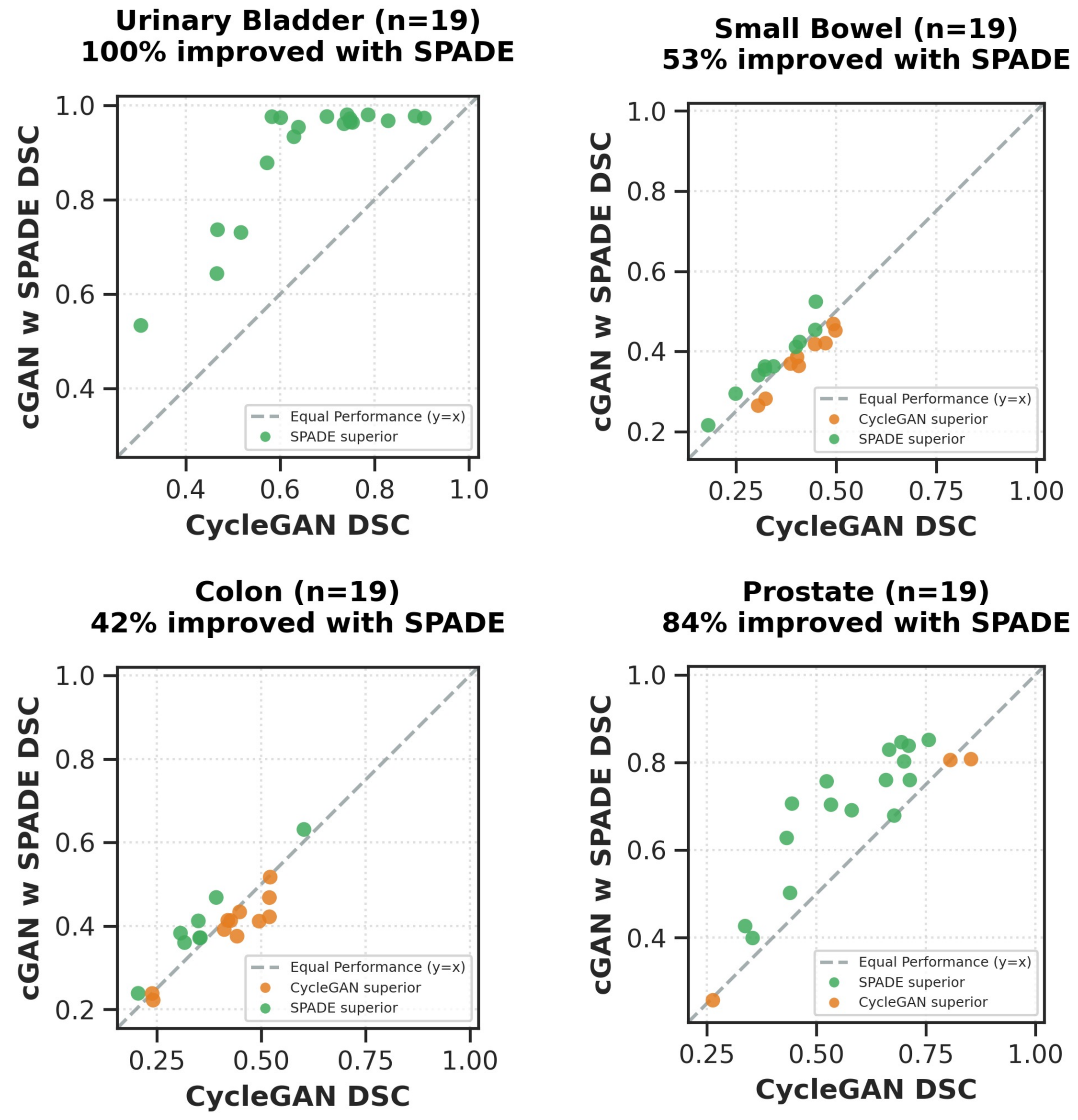
Automated Segmentation

Performed with TotalSegmentator [3, 4]



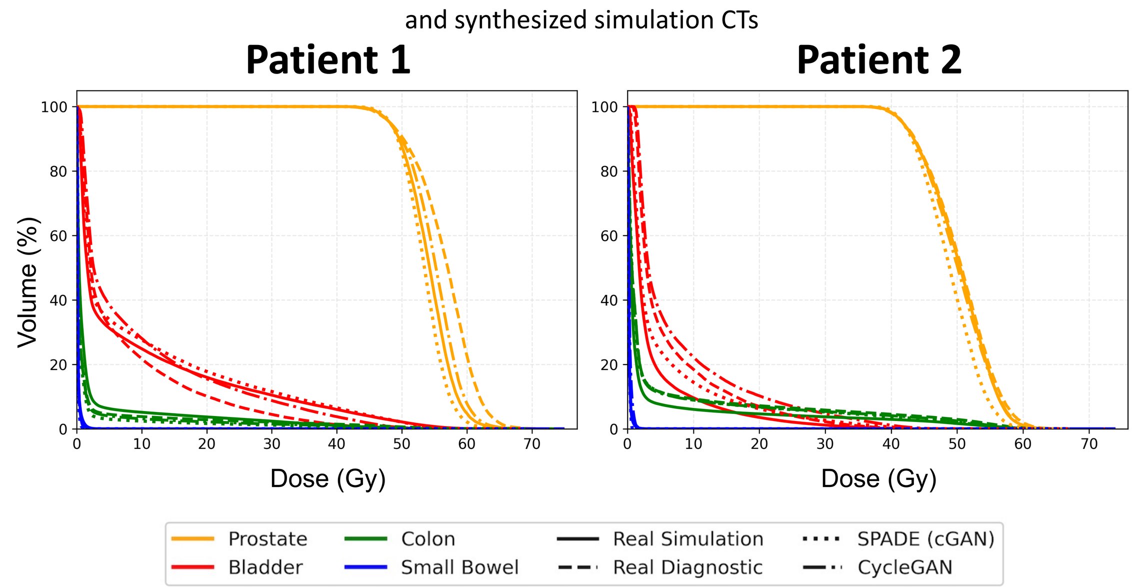
Dice Similarity Coefficient (DSC)

Relative to Real RT Image: Measures the overlap between a predicted segmentation and a ground truth



Dose Volume Histogram (DVH)

Comparison of automated dose prediction on real, diagnostic, and synthesized simulation CTs



DISCUSSION

cGAN with SPADE improves overall visual similarity over CycleGAN with the real simulation CT.

cGAN with SPADE minimizes HU (pixel intensity) deviations with the real RT simulation image, providing the most accurate tissue density representation for synthetic RT planning.

Clinical task-based validation supported our technical findings, demonstrating that the cGAN with SPADE architecture consistently outperforms CycleGAN. SPADE improved segmentation accuracy (DSC) in 100% of bladder cases and 84% of prostate cases, consistently aligning target and organ-at-risk DVH trajectories with the real simulation baseline.

Next Steps:
- ~200 head and neck cancer patients to test pipelines on

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REFERENCES

1. Zhu, J.-Y., Park, T., Isola, P., & Efros, A. A. (2020). *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*. http://arxiv.org/abs/1703.10593
2. Park, T., Liu, M.-Y., Wang, T.-C., & Zhu, J.-Y. (2019). *Semantic Image Synthesis with Spatially-Adaptive Normalization*. http://arxiv.org/abs/1903.07291
3. Wasserthal, J., Breit, H.-C., Meyer, M. T., Pradella, M., Hinck, D., Sauter, A. W., Heye, T., Boll, D. T., Cyriac, J., Yang, S., Bach, M., & Segeroth, M. (2023). TotalSegmentator: Robust Segmentation of 104 Anatomic Structures in CT Images. *Radiology: Artificial Intelligence*, *5*(5). https://doi.org/10.1148/ryai.230024
4. Isensee, F., Jaeger, P. F., Kohl, S. A. A., Petersen, J., & Maier-Hein, K. H. (2021). nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation. *Nature Methods*, *18*(2), 203–211. https://doi.org/10.1038/s41592-020-01008-z