An Ultra-Fast Dose Calculation Algorithm with Transformer Neural Networks: Model Fine-Tuning and Validation

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SUMMARY

This work fine-tunes the existing improved dose transformer algorithm (iDoTA) [1] via additional training using institutional clinical breast and chest wall treatment plans with various photon energies. Although the original iDoTA model demonstrated poorer performance in lung geometries compared to pelvic sites [1], fine-tuning the model on breast and chest wall cases improved site-specific dose prediction and demonstrated that the model can generalize to photon energies outside its original training.

INTRODUCTION

- Accurate and ultra-fast dose calculation is crucial in the adaptive radiation therapy (RT) workflow [1], where the goal is to account for inter- and intra-fractional anatomical changes using image-guided RT systems.
- Monte-Carlo (MC) is the gold standard for dose calculation, but its long computation time makes it impractical for adaptive RT applications [2], with traditional computation times of up to several hours [3] and accelerated computation times of ~40 s for full VMAT/IMRT plans[4].
- Standard treatment planning systems (TPS) use algorithms such as pencil-beam or collapsed-cone to improve calculation speeds by making approximations that may lead to less accurate results, especially in complex treatment setups [5].
- These existing methods are not fast enough for real-time adaptive radiotherapy [3], necessitating the development of an accurate and ultra-fast dose calculation algorithm.

METHODS

- Deep learning methods have been investigated for developing ultra-fast dose engines by mapping patient images and physics information (e.g., high-noise MC, fluence or TERMA maps) to a 3D dose distribution.
- iDoTA combines a 3D U-net architecture with a transformer backbone to predict a 3D dose distribution from input computed tomography (CT) and ray-tracing volumes [1].

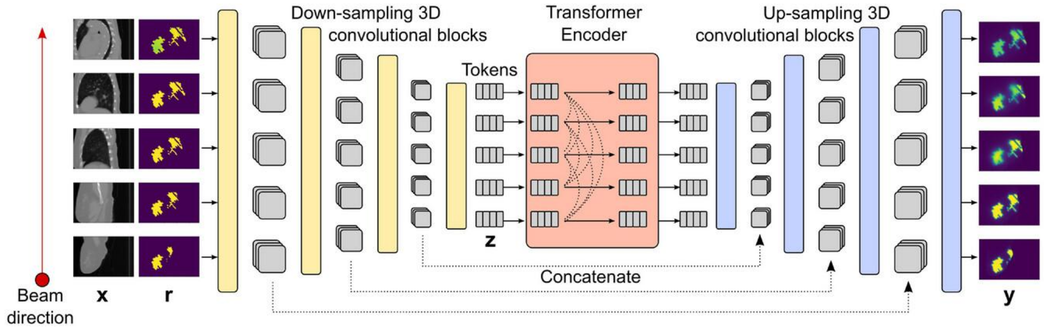

Figure 1: iDoTA model architecture which combines a convolutional neural network with a transformer backbone [1].

- The published iDoTA weights were trained on 17 clinical patient CTs across a variety of anatomical sites and randomly generated 6 MV photon beams incident on the patient anatomy [1].
- **In this work,** the existing model was fine-tuned with additional training on institutional breast and chest wall field-in-field plans of a variety of photon energies – called **"pyDoTA".**
  - A dataset of 79 breast and chest wall patients was compiled, comprising of 596 individual fields, and a 60-20-20 split was used for model training, validation, and testing (see **Table 1**).
- The corresponding ground-truth dose distributions were calculated with the AcurosXB v15.6.06 algorithm from the Varian Eclipse TPS.

Dataset	No. of Patients	No. of Fields			
		TOTAL	6 MV	10 MV	15 MV
Training	59	389	200	131	58
Validation	10	102	60	25	17
Testing	10	105	62	19	24
SUM	79	596	322	175	99

Table 1: Breakdown of patients and fields for model training and evaluation (validation and testing).

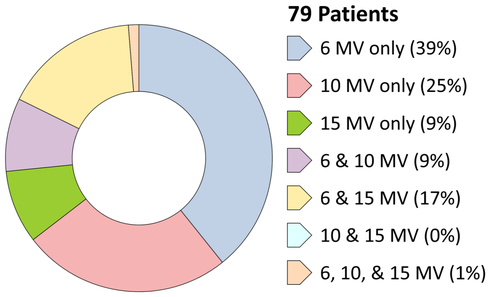

Figure 2: Distribution of patient plan energies

- The model output predictions are compared with the dose grid calculated with the AcurosXB algorithm using average relative error (ARE, normalized to the maximum TPS dose) and gamma analysis metrics for eligible voxels within 10-100% of the maximum TPS dose distribution.

RESULTS

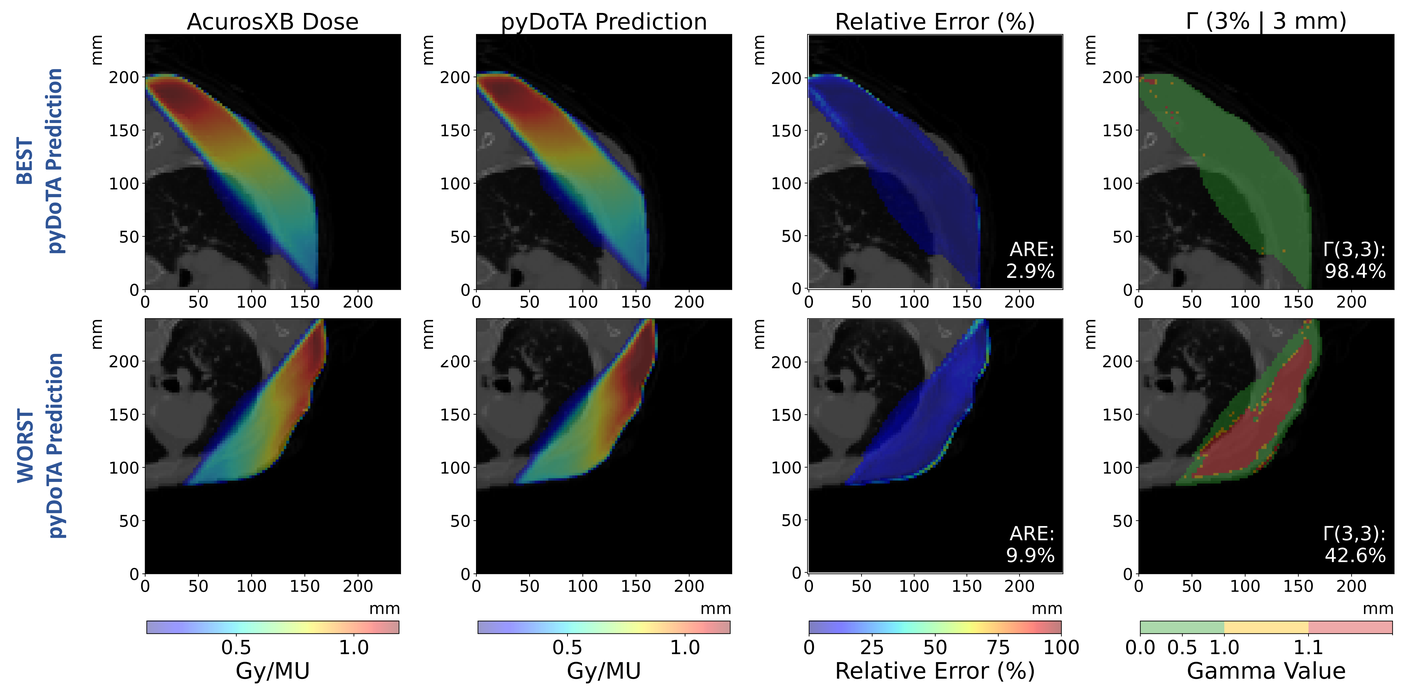

Figure 3: Best (top) and worst (bottom) pyDoTA predicted dose distributions for individual fields from the unseen testing dataset, as determined by the Γ (3%|3mm) gamma passing rates. The corresponding ground truth dose distribution from AcurosXB is shown in the leftmost column.

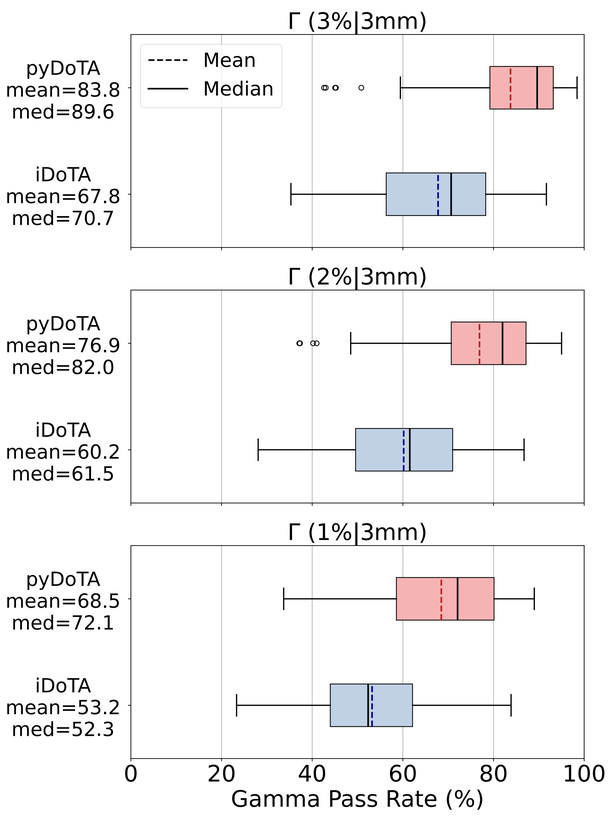

Figure 4: Gamma pass rates for (1%|3mm), (2%|3mm), and (3%|3mm) gamma criteria for the 105 individual fields from 10 unseen test patients predicted by the published iDoTA model and the fine-tuned pyDoTA model as compared to the ground truth AcurosXB dose distribution.

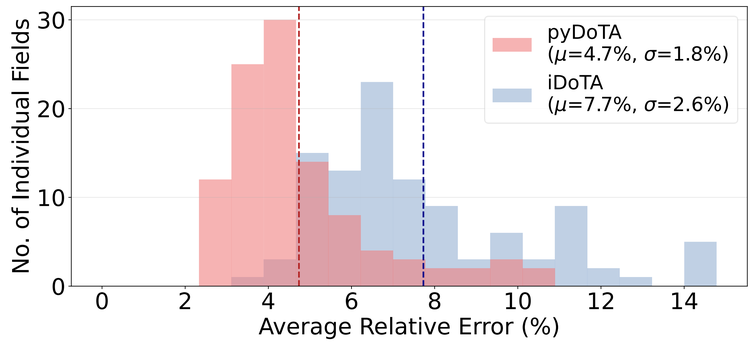

Figure 5: Distribution of the average relative error for each the 105 individual fields across 10 unseen patient treatment plans in the testing dataset.

Beam Energy (MV)	No. of Fields in Testing Dataset	ARE (%) μ ± σ		Γ (3%|3mm) (%) μ ± σ	
		pyDoTA	iDoTA	pyDoTA	iDoTA
6	62	5.1 ± 2.1	7.9 ± 3.0	81.8 ± 14.1	70.1 ± 14.3
10	19	3.6 ± 0.7	6.6 ± 0.7	93.8 ± 3.8	73.5 ± 8.2
15	24	4.8 ± 1.2	8.2 ± 2.1	80.9 ± 11.1	57.2 ± 12.4

Table 2: Breakdown of patients and fields for model training and evaluation.

Our pyDoTA model was developed by fine-tuning the iDoTA model with the same training parameters as in the original paper [1], starting from the published, pretrained weights. The model was trained using a mean squared error loss function, batch size of four, the LAMB optimizer, and a custom cyclic learning rate scheduler while training over 1200 epochs. To avoid overfitting, we employed early-stopping methods and identified the best performing model using a five-epoch moving window to average the model loss and identify the epoch with the lowest validation loss. The best performing model was identified at epoch 1100.

DISCUSSION & CONCLUSION

Fine-tuning the existing transformer-based photon dose prediction model "iDoTA" using institutional clinical treatment plans improved the ARE and gamma pass rates across all photon energies without modifying the underlying architecture. These results support the feasibility of extending fine-tuning to a variety of treatment sites and photon energies. Future work will also include comparison to gold-standard MC simulations.

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