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Region specific dose prediction using deep neural networks: a feasibility study on the planning target volume of prostate IMRT patients

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INTRODUCTION

For dose prediction, the initial expectation is that the prediction of a full volumetric dose would have the best performance, due to the fact that the deep learning model has to utilize all the information in the patient body. However, deep learning-based volumetric dose prediction models may be hindered by an inherent smoothness and continuity constraint on the dose distribution. Prediction errors from one region may be propagated to another region by such a constraint. We investigate whether a volumetric dose prediction model, using deep learning, on the whole body or only on the planning target volume (PTV) has any effect on the model's performance on the PTV.

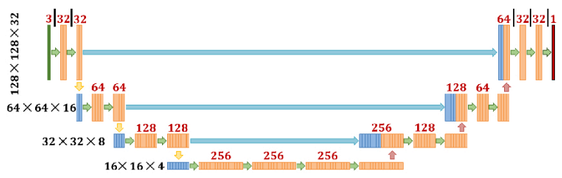
METHODS

For Comparison, we investigated 2 models:

- PTV Model
  - Model is trained to only predict the PTV dose distribtion and ignores predicting and dose outside the PTV
  - $Loss\ function = \frac{1}{n_{PTV}} \sum_i M_{i,PTV}(T_i - P_i)^2$
    - $n_{PTV} = number\ of\ voxels\ in\ PTV$
    - $M_{i,PTV} = value\ of\ PTV\ mask\ at\ i^{th}\ voxel$
    - $T_i = ground\ truth\ at\ i^{th} voxel$
    - $P_i = prediction\ at\ i^{th} voxel$
- Body Model
  - Model is trained to predict all the dose defined within the body
  - $Loss\ function = \frac{1}{n_{Body}} \sum_i M_{i,Body}(T_i - P_i)^2$
    - $n_{Body} = number\ of\ voxels\ in\ Body$
    - $M_{i,Body} = value\ of\ Body\ mask\ at\ i^{th}\ voxel$
- To maintain fairness, both models used the:
  - Entire data volume as input and predicted the entire output volume.
  - Same voxel resolution (5 mm^3).
  - Identical model architectures.
  - Same training hyperparameters
  - Training done on same machine
- See DATA AND TRAINING for specific details

DEEP LEARNING ARCHITECTURE

U-net Architecture



DATA AND TRAINING

- 72 clinical prostate patients
  - 57 training, 5 validation, 10 test patients
  - 128 x 128 x 32 array
  - 5 mm x 5 mm x 5 mm voxel size
- Training the network
  - U-net style architecture
  - Mean squared error (MSE)
  - Adam optimization algorithm
    - Learning rate = 1×10^{-3}
  - Dropout set to 0.1 throughout the network
  - Group Normalization
  - Rectified Linear Unit (ReLU) activation
- Machine Specifications
  - Intel Core i7-7800X CPU
  - NVIDIA 1080 Ti GPU (11 GB Memory)
  - 32 GB RAM

RESULTS

Prediction Error Statistics

On the 10 test patients we evaluated the error of the predicted doses of the PTV and body model using the following clinical metrics: PTV mean dose, max dose, dose coverage (D95, D98, D99), and homogeneity $\frac{D2-D98}{D50}$. The results are shown in Table 1.

Prediction Errors	PTV Model	Body Model	p-val
Dmean	0.86±0.29%	2.30±1.51%	<0.05
Dmax	0.99±0.93%	1.79±1.60%	0.0787
D95	1.22±0.40%	3.68±1.10%	<0.05
D98	1.25±0.54%	4.20±1.20%	<0.05
D99	1.7±0.61%	4.76±2.47%	<0.05
Homogeneity	0.011±0.008	0.026±0.014	<0.05

Table 1: Prediction errors of the predicted doses versus the ground truth dose. Both the PTV model and Body model were evaluated.

The PTV Model outperformed across every metric compared to the Body Model. Except for Dmax(p-value=0.0787), all other differences were statistically significant(p-value<0.05). Figures 1-3 show several metrics and washes of the ground truth clinical dose, PTV model's dose, and Body model's dose for test patient. In all cases, the PTV model's dose more closely resembles the ground truth clinical dose.

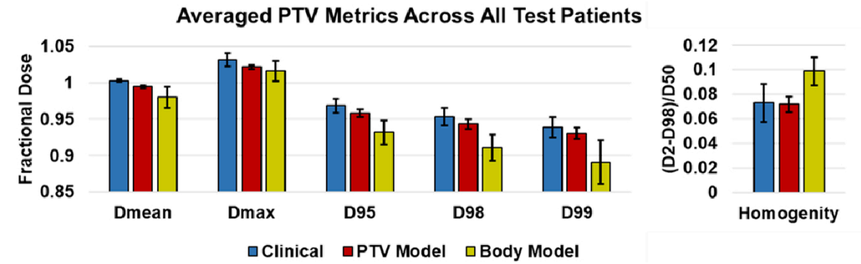


Figure 1: Clinical metrics averaged across all 10 test patients. Error bars = 1 standard deviation.

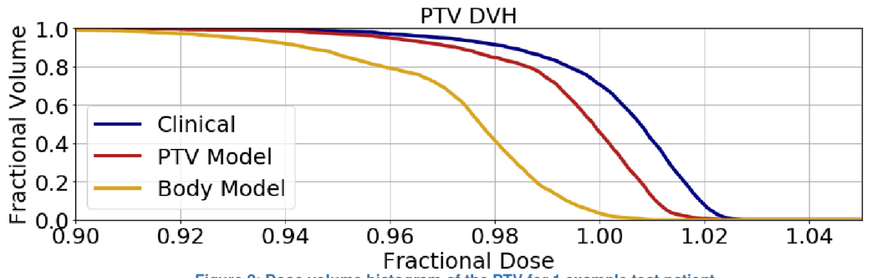


Figure 2: Dose volume histogram of the PTV for 1 example test patient.

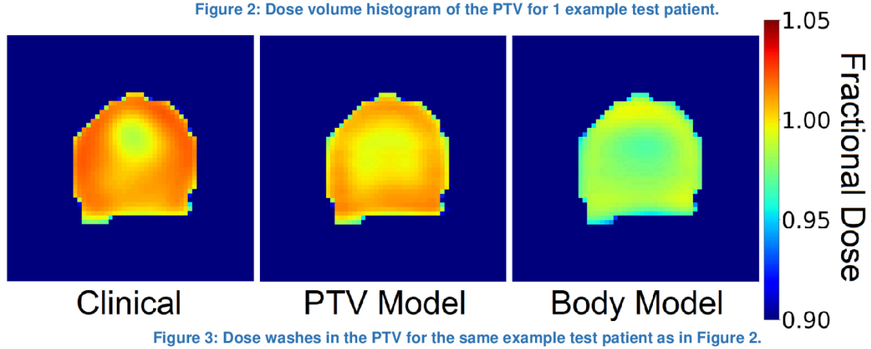


Figure 3: Dose washes in the PTV for the same example test patient as in Figure 2.

CONCLUSIONS

Focusing a dose prediction model to learn a particular ROI may significantly improve the performance of the model. By only allowing a loss value inside the PTV, the model no longer has concerns for PTV boundary smoothness and continuity constraints as before, and potential error outside the PTV is no longer propagated. We found that the PTV Model easily outperformed the Body Model in every metric of interest, with only the maximum dose to the PTV as not statistically significant. We intend to expand this study to all organs-at-risk to develop a complete framework.

REFERENCES

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[2]Nguyen, D., Jia, X., Sher, D., Lin, M. H., Iqbal, Z., Liu, H., & Jiang, S. (2019). 3D radiotherapy dose prediction on head and neck cancer patients with a hierarchically densely connected U-net deep learning architecture. Physics in medicine & Biology, 64(6), 065020.