

Commissioning of a Deep Learning-Based Radiotherapy Dose Calculation Engine

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INTRODUCTION

Previous study has shown the feasibility of boosting the accuracy of a simple and fast dose calculation method such as ray-tracing (RT) to that of an accurate one such as collapsed cone convolution/superposition dose through deep learning (DL). [1] In this work, we propose and evaluate three different ways to commission this DL-based dose calculation engine for different linacs.

Although the generalizability issue of the deep learning model in the medical field is widely known, how to better accommodate the trained model to different beam energy, machines and sites is still not well explored yet. This work will help the clinical implementation of the deep learning model.

AIM

In this work, we propose and evaluate a model commissioning method using transfer learning.

METHODS

The proposed model commissioning method is summarized in Figure 1. Here we use Acuros dose from the Eclipse treatment planning system as the ground truth dose calculation method and use a general ray-tracing (RT) model [2] together with CT images as the input of the DL model.

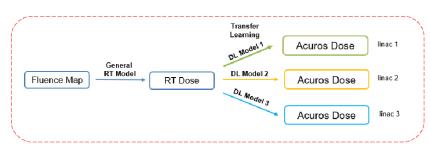


Figure 1. Workflow of the proposed Method

The HD U-net model structure in previous work is modified to accommodate for the dose calculation ground truth modification. Once one source model is trained, transfer learning is used for commissioning the DL model on the target machine.

DATASETS

 112 lung patients treated on Elekta Versa, which consisted beam energy of 6MV, 6FFF, 10MV and 10FFF

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- 29 head and neck patients treated on Varian TrueBeam, which consisted of beam energy of 6MV and 6FFF
- We trained the DL model using 104 lung patients and validated on 8 lung patients (source model).
- The model was then deployed on head and neck cases directly and transferred to head and neck patients (target model). 25 cases were used in the transfer learning training and 4 cases were used in validation.

RESULTS

- The 3mm/3% gamma index passing rate of the source model on lung plans is 96.0 % ± 3.2%
- The 3mm/3% gamma index passing rate of the source model on head and neck plans is 49.4 % ± 15.3%
- The 3mm/3% gamma index passing rate of the target model on head and neck plans is 77.2 $\% \pm 5.1\%$
- Transfer learning improved model performance on head and neck patients, but it cannot fully ensure the generalizability.

RESULTS

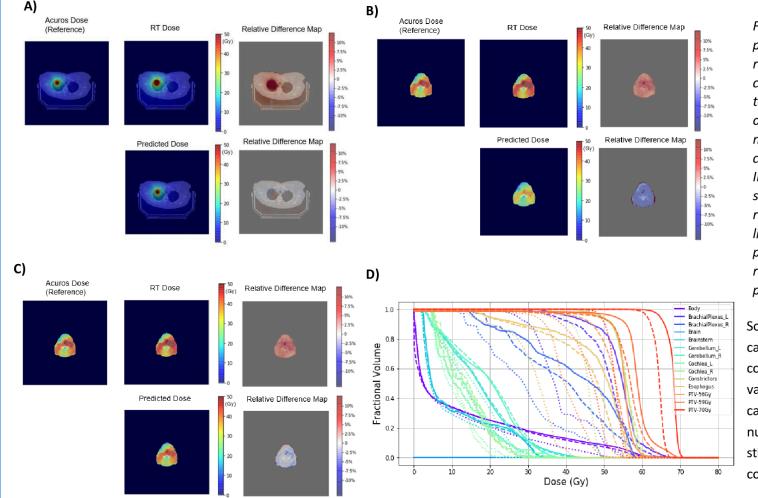


Figure 2. A): Source model performance on a representative lung validation case. Source model B) and target model C) performance on one validation head and neck case and the DVH comparison of the same case. In the DVH comparison D), solid line represents the reference Acuros dose, dotted line represents source model prediction and dashed line represents the target model prediction

Source model validated on lung cases have better performance compared to target model validated on head and neck cases, showing that limited case number on the target domain is still a limitation in model commissioning process.

CONCLUSIONS

- We proposed to use transfer learning to commission a DL-based dose calculation engine and evaluated the performance on lung cases from Varian machines and head and neck cases from Elekta machines.
- The proposed method improved the model performance but did not fully resolve model generalizability problem.
- Increasing cases on target machines might help with the commissioning process.

REFERENCES

[1] Xing, Yixun, Dan Nguyen, Weiguo Lu, Ming Yang, and Steve Jiang. "A feasibility study on deep learning-based radiotherapy dose calculation." *Medical physics* 47, no. 2 (2020): 753-758.

[2] Lu, Weiguo, and Mingli Chen. "Fluence-convolution broadbeam (FCBB) dose calculation." *Physics in Medicine & Biology* 55, no. 23 (2010): 7211.

