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Hard Constraints Approximation for Deep Learning in Radiation Therapy

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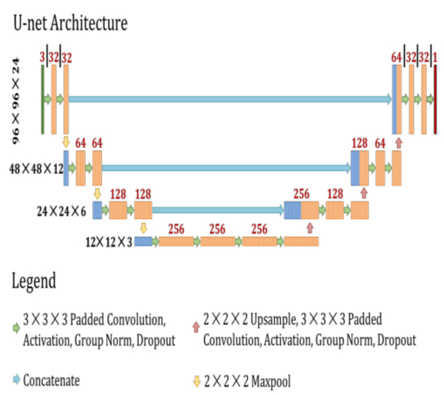
INTRODUCTION

Purpose: Many publications have shown that deep learning can be used to generate clinically acceptable plans for radiation therapy treatment. Our previous work showed that for prostate and head and neck patients, plans could be generated within 5 percent of clinically delivered plans. Furthermore, we developed a DVH based loss function that could be used to directly map both the desired dose distribution and the DVH curves to the predicted plan. However, there is no methodology available to enforce hard constraints on a trained deep learning model. Enforcing constraints such as the maximum allowable hot-spot or maximum dose allowed to a specific organ at risk were not possible. We have developed a novel training method that can incorporate multiple hard constraints with user specified priority. We believe this methodology will be a valuable tool for deep learning based treatment plan creation.

METHOD

Our robust in house model based on a Hierarchically Densely Connected U-net was used as the foundational for this work. A custom loss function was written to approximate a hard dose constraint in the training process. This loss function allows the user to select the desired structure and assign a priority to the hard constraint. The model was then trained, validated and tested on a patient dataset of 300 VMAT head and neck patient plans.

DEEP LEARNING ARCHITECTURE



DATA AND TRAINING

- The model was trained on 300 patients treated in our clinic
- 210 train, 60 val, 30 test
- 30 different H&N treatment sites
- 1 to 5 PTV levels
- Prescription doses (42.5 Gy to 72 Gy)
- 22 total OARs

U-net

Input:
 clinical OAR contours
 PTV prescription scheme

Output:
 3D dose distribution

Loss function:
 Custom loss function

RESULTS

Innovation/Impact:

Implementation of a deep learning based dose prediction model into clinical workflow is a difficult task due to the "black box" nature of neural networks. Physicians desire more control over the treatment planning process to implement patient specific treatment protocols. Although our in house dose predictor is capable of creating clinically realistic plans that represent the average accepted and treated plan, to this point we were unable to fine tune features in the predicted doses, such as hotspots or hard organ at risk dose constraints. This work is a proof of concept that shows we can now control the output of the dose prediction on a structure level while still maintaining the robust baseline dose prediction network that was trained on a large dataset of clinically accepted plans. We selected two hard constraints to test the method. The first was to remove hotspots in the PTV greater than 103% of the prescription dose. The second was to limit the dose above 25 Gy to the oral cavity. Although these constraints may result in unrealistic plans, further tuning of this method will allow us to control the dose prediction model. This methodology will also allow us to create patient specific dose predictions that meet physician goals while still mimicking the clinically delivered plans.

Key Results: Across all patient in the testing dataset the hard constraint dose predictor was able to push the dose distribution towards the enforced goal. Figure 1 shows an axial slice for a patient which was treated with an oral sparing treatment plan. This clearly shows the dose to the oral cavity was reduced from our baseline dose prediction model and more closely matches the delivered clinical dose distribution. Figure 2 and 3 show boxplots of the percent of voxels that are compliant with the hard constraint for both the PTV and the oral cavity.

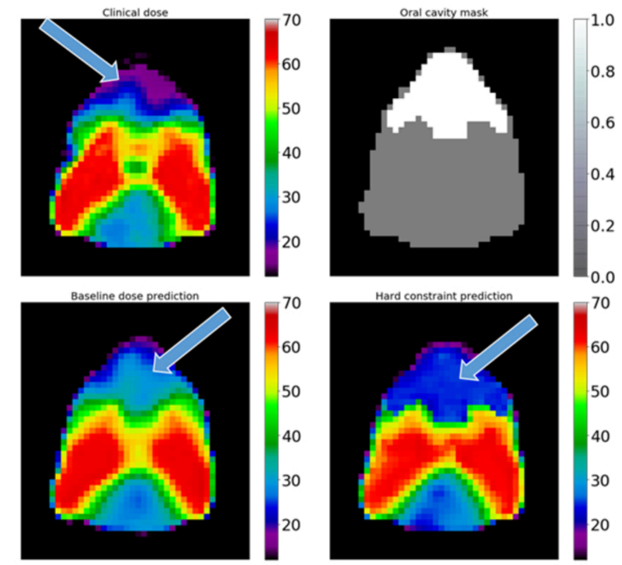


Figure 1: Axial slice of a patient in this study. The top left shows the clinically delivered dose, the top right shows the structure outline of the oral cavity, the bottoms left shows our current baseline prediction model and the bottom right shows our dose prediction after implementing the hard constraint custom loss function.

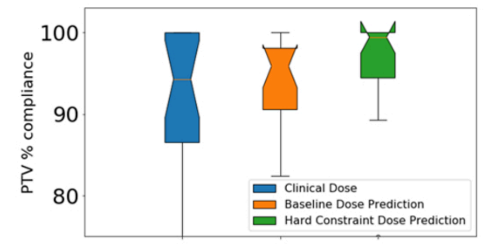


Figure 2: Boxplot showing the percentage of voxels in the patient PTV plan that meet the hotspot constraint. Our hard constraint dose prediction model increased the conformity to the dose index and reduced the variability in PTV plans across all the patients.

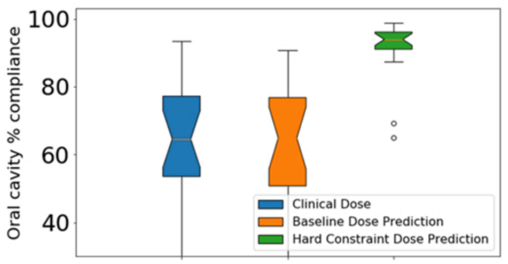


Figure 3: Boxplot showing the percentage of voxels in the patient oral cavity that are less than the 25 Gy dose constraint. Our hard constraint dose prediction model pushed the oral cavity dose to meet the constraint while not modifying the dose distribution to other structures.

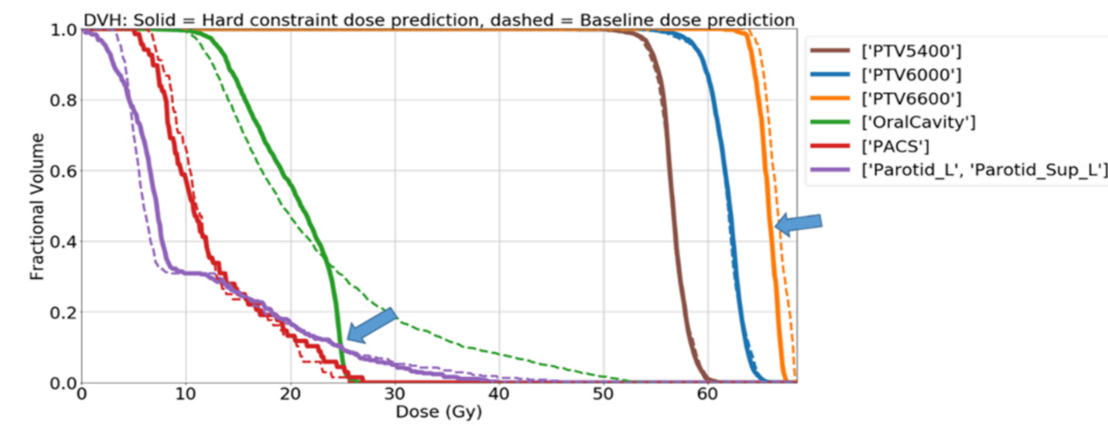


Figure 4: DVH for a patient in the testing data set. The compliance of the hard constraint for both the PTV (dose > 103%) and oral cavity (dose < 25 Gy) was increased when adding the custom loss function to the prediction model.

CONCLUSIONS

This methodology will allows for our in-house deep learning models to be modified to meet specific physician and patient specific treatment goals, while still harnessing the power, speed and accuracy of a deep learning based dose distribution prediction.

REFERENCES

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