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### **Purpose/Objective:**

Radiotherapy (RT) planning is a long iterative process that requires time and effort from highly trained doctors, dosimetrists and physicists. With the advancement of treatment technology, the modularity of radiotherapy machines has increased dramatically. Techniques such as Volumetric Modulated Arc Therapy (VMAT) are incredibly powerful, but require even more time and skills to achieve good results.

In order to reduce this time and bring more automation to the planning process, we present in this work a dose volume prediction neural network. It takes the form of a Convolutional Neural Networks (CNN) that uses the patient CT image with associated planning target volume (PTV) and organ-at-risk (OAR) contours to predict a dose map. This dose map can then serve as a reference to construct a RT plan e.g. reproduce it with a dose mimicking algorithm or via Dose Volume Histogram (DVH) constraints extraction.

### **Material/Methods:**

The network is trained on a set of 92 prostate cancer patients and tested on 31 cases from a prestigious European cancer treatment center. All plans have a prescription of 80Gy to prostate (PTV2) and 56Gy to the seminal vesicle (PTV1). The OARs are rectum, bladder and femoral heads.

The planning CT, OARs, and PTVs are resampled to the dose map resolution (2.5mm), and the PTVs contours are filled with their prescription to better condition the network. These volumes are then concatenated and cropped randomly to patched.

The CNN neural network architecture used is a 3D Unet with skip connections. The network is trained with a combination of a reconstruction loss and an adversarial loss. The reconstruction loss is a weighted Mean Absolute Error (MAE). PTVs and OARs voxels are given a greater weight to promote better PTV coverage and OAR sparing. An adversarial loss is added by training a discriminator CNN to differentiate between real and predicted dose maps. It results in more conformal dose maps with steeper gradients.

**Results:**

Table 1 shows the mean relative difference between clinical and predicted doses on the test set (in Gy). Results for PTVs and important OARs (rectum and bladder) are below 1Gy. Larger deviations were observed for maximal doses to the femoral heads (up to 6Gy). In Figure 1, a comparison between a clinical and a predicted dose of a test case is shown. The predicted DVHs match closely the clinicals, especially in the high dose regions. Moreover, hard dose constraints, such as maximum dose to the rectum ( $D_{max} \leq 76\text{Gy}$ ), are successfully respected.

Structures	D95 (Gy)	D50 (Gy)	D02 (Gy)
PTV1 (prostate + seminal vesicles)	0.48	1.76	0.94
PTV2 (prostate)	-0.32	-0.04	-0.71
Rectum	0.53	-1.85	0.86
Bladder	0.87	3.31	0.23
Left femoral head	-0.01	3.23	3.33
Right femoral head	-0.29	4.24	5.94

Table 1. Mean relative difference between clinical and predicted doses.

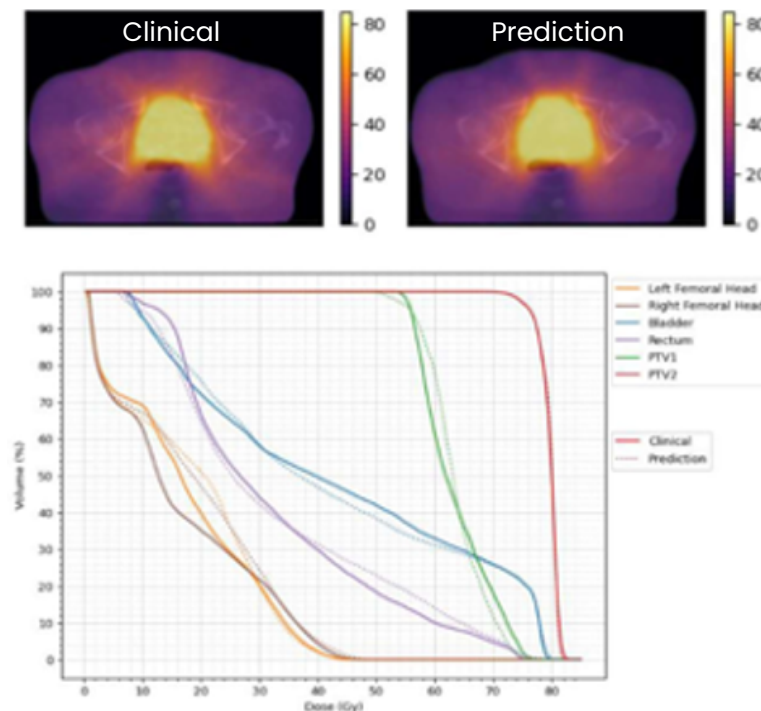


Figure 1. Comparison between clinical and predicted dose: axial slice visualization (top) and dose volume histogram (bottom)

**Conclusion:**

The proposed CNN model trained to predict RT doses was successfully tested for treatments of prostate cancers. The DVHs obtained on the predicted doses were on par with the clinical ones. These results can further be used as input of a knowledge transfer system such as dose mimicking of DVH constraints extraction.