Dose distribution prediction for radiation therapy using Super-Convergence training routine

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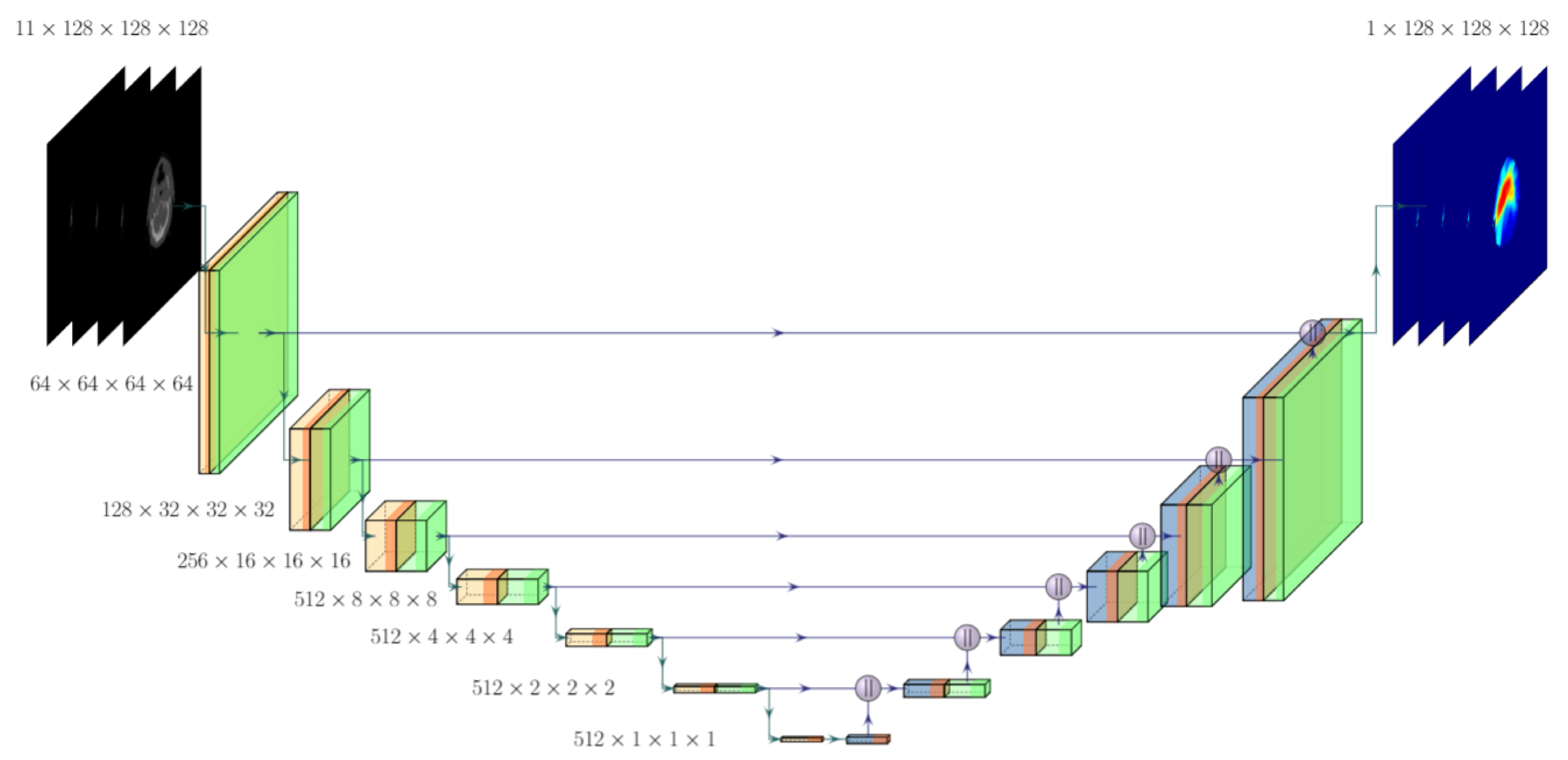

Figure 1: Depiction of the network design where green indicate ResNet blocks and orange/blue are convolution and transposed convolution layers, respectively.

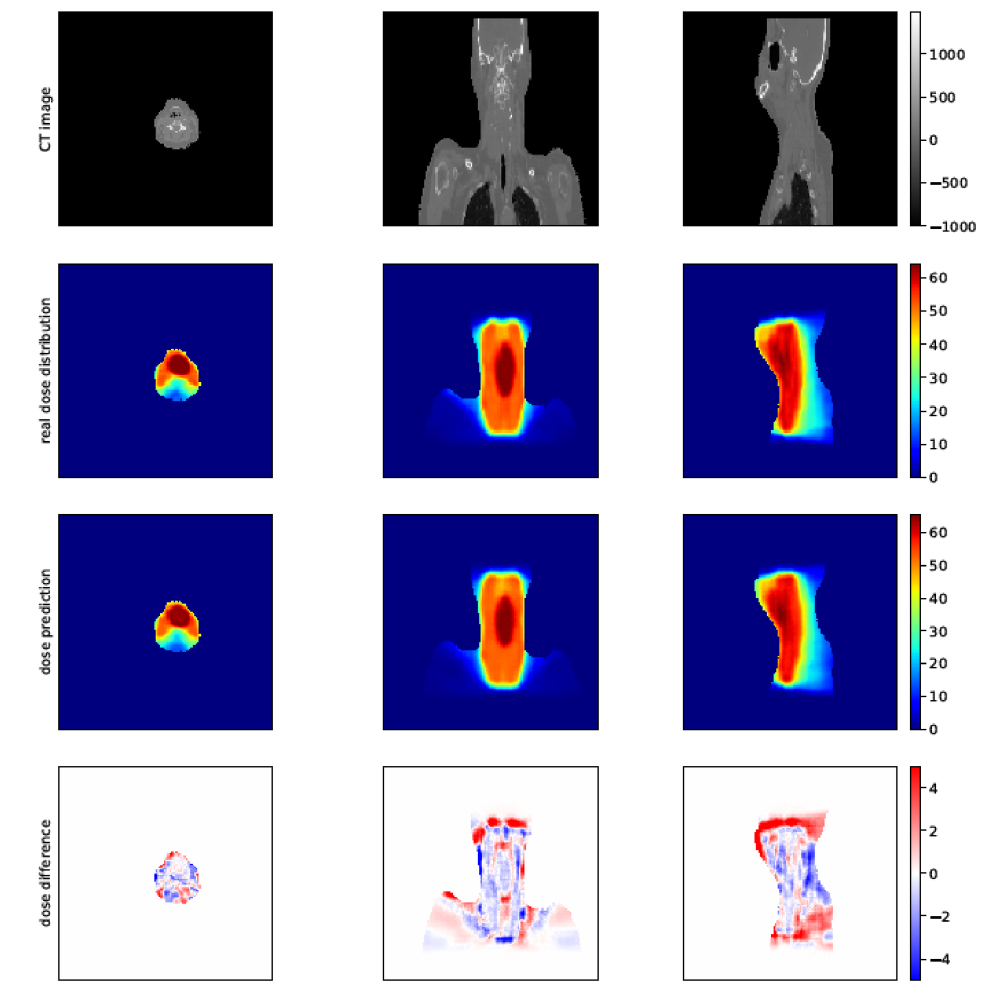

Figure 2: Example dose prediction and difference map.

Objective

With precision radiation therapy techniques, the dose distribution optimization according to clinical goals became very complex and time consuming. Multiple techniques were proposed to perform automatic dose prediction. However, due to inconsistent data sets a direct comparison is not possible.

Aim of study: to compete in the OpenKBP challenge of the American Association of Physicists in Medicine (AAMP) with a convolution neural network design with benchmarked data provided by the challenge organizers.

Methods

- 350 patients who were treated in the head & neck region
  - 200/50/100 split for training/validating/testing
- **Baseline model:** 3D U-Net trained with Adam and decoupled weight decay and OneCycle learning rate scheduling
- Hyperparameter tuning for:
  - Activation function/feature loss/loss masking
  - Pretrained 3D ResNet is used for feature extraction
- Dose and DVH score for metric comparison
- DVH parameter analysis for test set

Results

- *Table 1* reports the results of the hyperparameter search
  - Best model trained with ResNet blocks, Mish, feature loss together with outer contour masking (*Figure 1*)
- The median of all tested DVH parameters were distributed between -1.2 and 0.9% (inter-quartile range -4%-3%)(*Figure 3*)
- This network achieved 2nd place in the DVH score stream and 4th place in the dose score stream in the OpenKBP challenge of the AAMP

Discussion

- The dose distribution can be accurately predicted (*Figure 2*).
- Utilized pretrained model was trained on RGB data. Possible improvements can be obtained by pretraining the model on medical data.
- Including loss masking helped improving metrics. Including additional masks (*e.g.* organ masks) could further improve prediction accuracy.
- In future studies the predicted dose distributions must be optimized with respect to more realistic fluence modelling to be useable for clinical systems.

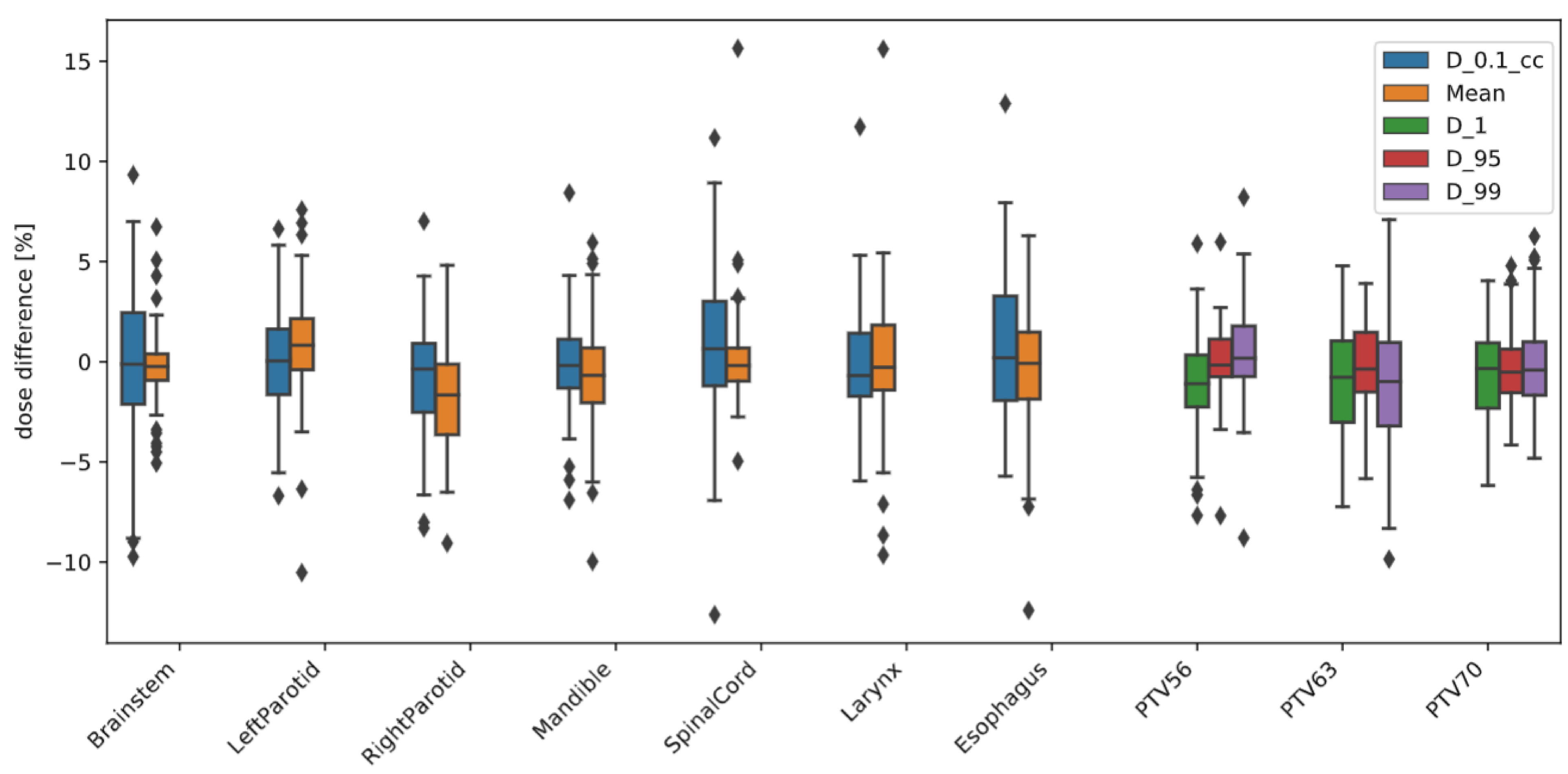

Figure 3: Dose volume parameters for the test data set of all organ and target structures.

	Dose score	Δ	DVH score	Δ
Baseline	2.651 ± 0.849	-	1.666 ± 0.853	-
+ ResNet blocks	2.548 ± 0.796	0.103	1.617 ± 0.759	0.049
+ Mish	2.534 ± 0.796	0.117	1.611 ± 0.777	0.055
+ Masking	2.530 ± 0.747	0.121	1.607 ± 0.789	0.059
+ Feature loss	2.503 ± 0.738	**0.148**	1.563 ± 0.790	**0.103**

Table 1: Hyperparameter tuning results.

Acknowledgement

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