

# A deep image-to-image network organ segmentation algorithm for radiation treatment planning: principles and clinical evaluation

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## Background

Auto contouring algorithms in radiotherapy aim at reducing the time needed for organ segmentation and to reduce inter-observer variations. In this work, we introduce and evaluate a deep network algorithm which automatically contours organs at risk in the thorax (lungs, heart) and pelvis (bladder, rectum) on computed tomography (CT) for radiation treatment planning.

## Methods

First, the region of interest (ROI) is automatically identified by detecting anatomical landmarks around the specific organs using a deep reinforcement learning technique. The segmentation is then restricted to this ROI and performed by a deep image-to-image network (DI2IN) based on a convolutional encoder-decoder architecture combined with multi-level feature concatenation.

For evaluation, thoracic CT images of 237 patients and pelvic CT images of 102 patients were manually contoured by an expert following the RTOG guidelines for organs at risk, and on the same CT images the DI2IN algorithm generated the contours automatically. The manual and automatic contours were quantitatively compared using geometric metrics for volume, overlap (Figure 1) and distance (Figure 2), e.g. Dice Similarity Coefficient (DSC) and Hausdorff Distance (HD<sub>95</sub>). The contours were also compared visually slice by slice.

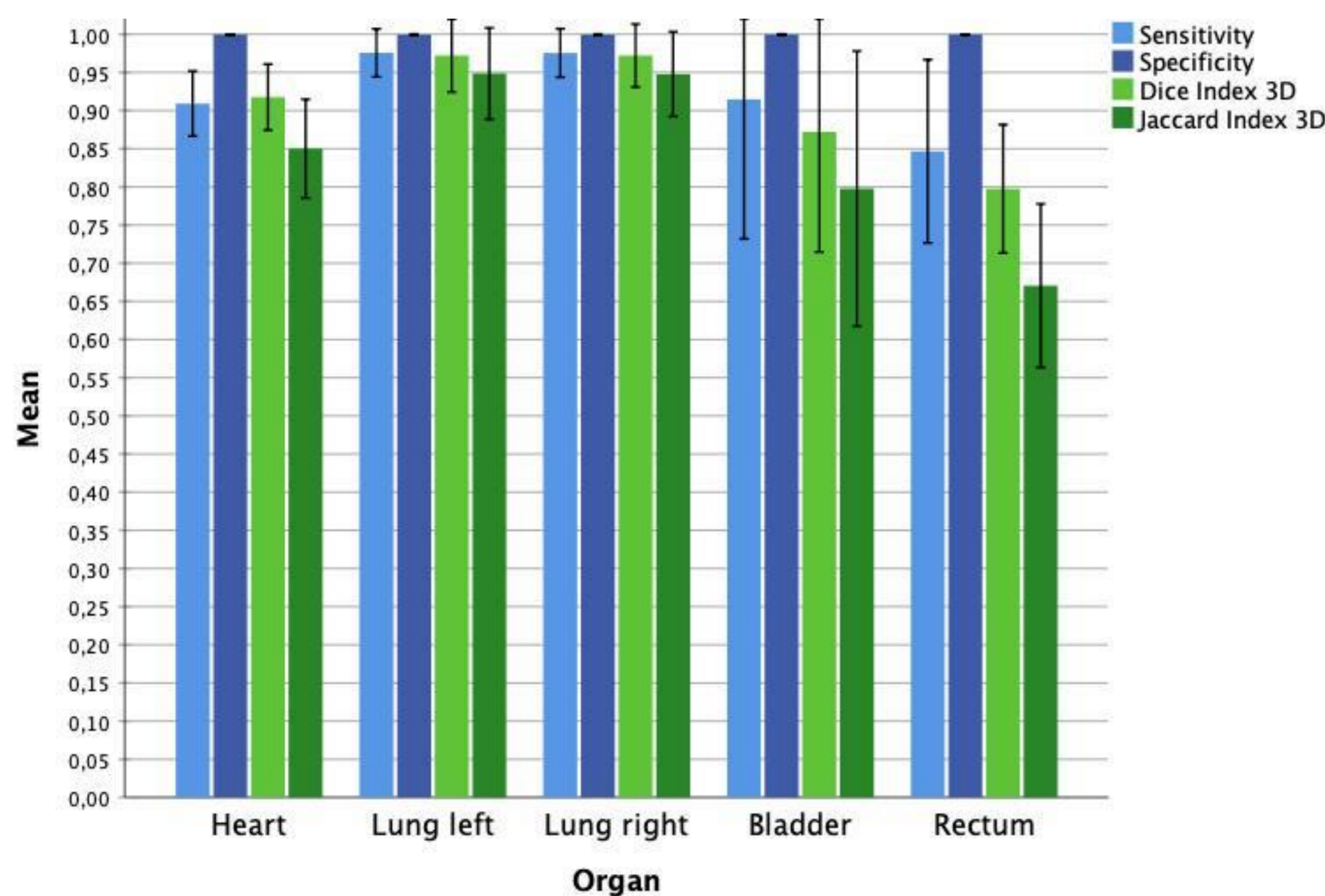


Figure 1: Overlap measurements of manual and automated contours. Mean values and standard deviation

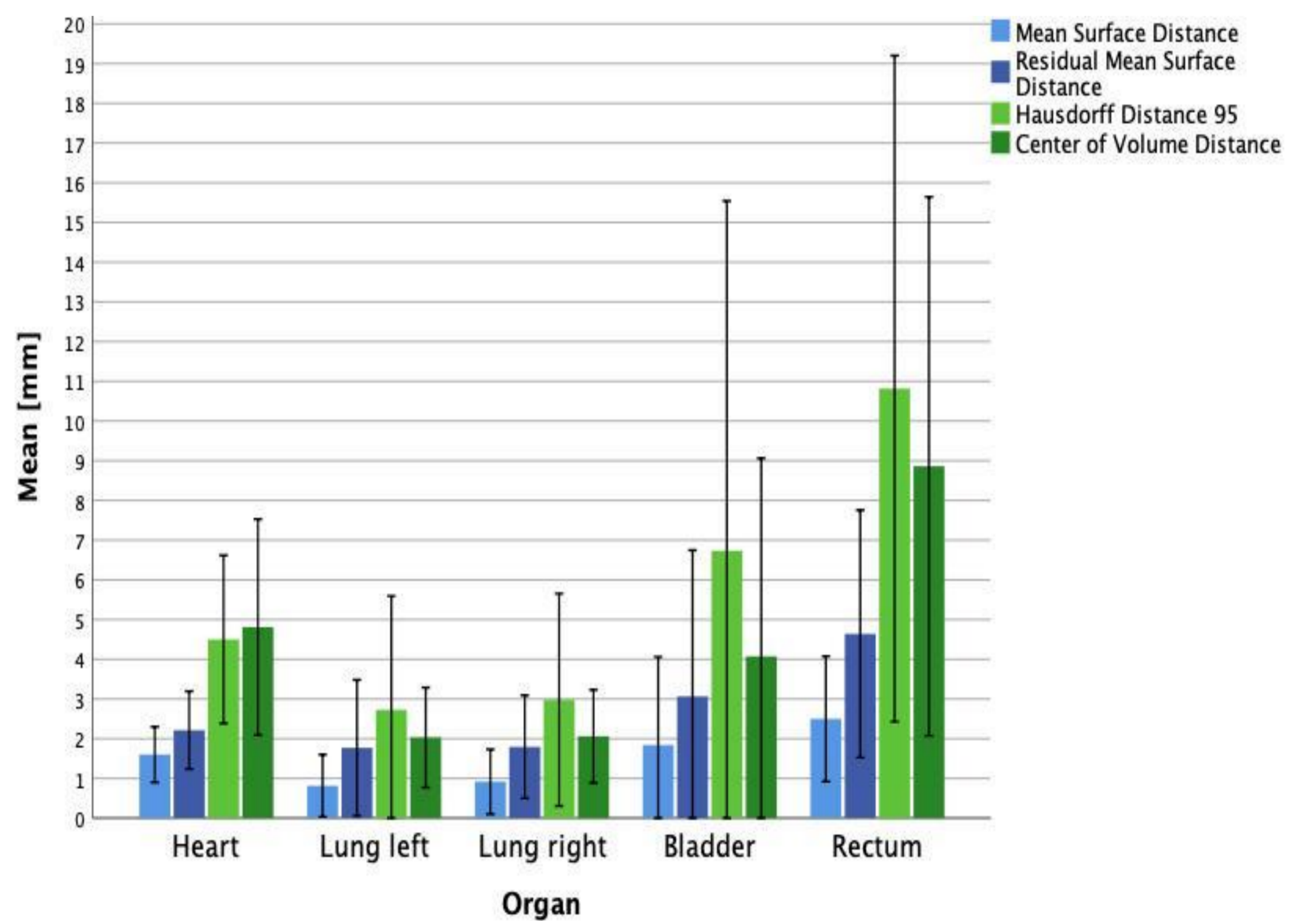


Figure 2: Distance measurements between manual and automated contours. Mean values and standard deviation.

## Results

We observed high correlations between automatic and manual contours. The best results were obtained for the lungs with a mean DSC of 0.97 and mean HD95 of 2.7mm (left lung) and 2.9mm (right lung). For the the heart the DSC was 0.92 and HD95 4.4mm, followed by the bladder (DSC 0.88 and HD95 6.7mm) and the rectum (DSC 0.79 and HD95 10.8mm). Comparison of boundary values and visual inspection showed excellent agreements of automatic and manual contours, with some notable exceptions for the heart at the caudal boundary and for the rectum at the cranial and caudal boundaries. The deviations for the rectum can be explained by the fact that the automatic algorithm was trained to also include the sigmoideum.

## Conclusion

The DI2IN algorithm automatically generated contours for organs at risk in the thorax and pelvis region close to those by a human expert, making the contouring step in radiation treatment planning simpler and faster. In few cases manual corrections were still necessary, mainly for the caudal boundary of the heart and cranial and caudal boundaries of the rectum.