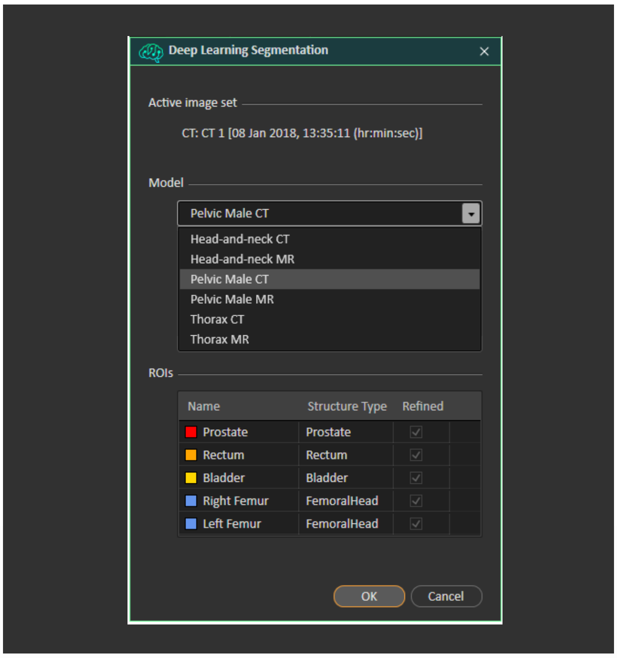
DEEP-LEARNING SEGMENTATION

High quality contours of anatomical structures are a vital aspect of radiation therapy, but the process of manually delineating regions of interest is time-consuming and suffers from inter- and intra-practitioner variability. With the automatic tools in RayStation®, this process can be greatly simplified. The latest technique is deep-learning segmentation*, which is able to learn from unlimited number of patients and still automatically generate contours of all relevant region of interests in under a minute. This makes it a very powerful tool for patient modeling in RayStation.

DEEP-LEARNING SEGMENTATION IN RAYSTATION

With deep-learning segmentation, the user can rapidly delineate anatomical structures in CT, CBCT and MR image sets. The machine learning technique can be utilized to train many different segmentation models. Deep-learning segmentation is designed to identify common organs and structures, but not intended to identify lesions.

The deep-learning approach moves the computation time off-line, so that once the model is trained, producing new segmentations is very fast. RaySearch offers pre-trained models for specific sites and region of interests (ROIs), but clinics also have the option of tailoring models to their own needs (such as any ROI not covered by the pre-trained models) by training on their own data. The trained model contains no personal data, which makes it possible to share and distribute models between clinics.



Deep Learning Segmentation

Active image set

CT: CT 1 [08 Jan 2018, 13:35:11 (hr:min:sec)]

Model

Pelvic Male CT

ROIs

Name	Structure Type	Refined
🟥 Prostate	Prostate	✓
🟧 Rectum	Rectum	✓
🟨 Bladder	Bladder	✓
🟦 Right Femur	FemoralHead	✓
🟦 Left Femur	FemoralHead	✓

Figure 1. *Drop-down selection for available models. The window also shows the ROIs that will be created by the selected model.*

GENERATING SEGMENTATIONS

Deep-learning models are stored in the machine learning database and managed in the machine learning management application. This application is used to import, configure and approve the machine learning models for RayStation. This is also the place where you can see the originator of the model, edit the name of the model and change the model settings such as the names and the colors of the ROIs.

There are typically many deep-learning segmentation models in RayStation, corresponding to various body sites, image modalities and delineation protocols. Figure 1 shows an example of the drop-down menu where the available segmentation models can be selected.

Generating the anatomical structures is fast, usually under a minute, but the exact running time depends on hardware and the number of structures to be generated. Figure 2 shows an example of organs at risk generated by a model for pelvic male. Once the ROIs have been generated, they can be edited with the tools available in the structure definition section of the patient modeling module, just as any other ROI in RayStation.

Deep-learning segmentation can also be accessed via scripting which allows for batch processing of patients during off-hours.

> *“We collaborated on a model for male pelvis segmentation, of organs at risk, as well as target volumes. It was great to work with RaySearch and the results were very good from the start. We believe this exciting new application will lead to significant time-savings for our clinicians and technologists and result in an automated workflow for delineation and planning of our prostate cancer treatments.”*
>
> ***Piet Dirix,** MD, PhD, Radiation Oncologist,*
> *Iridium Kankernetwerk, Antwerp, Belgium*

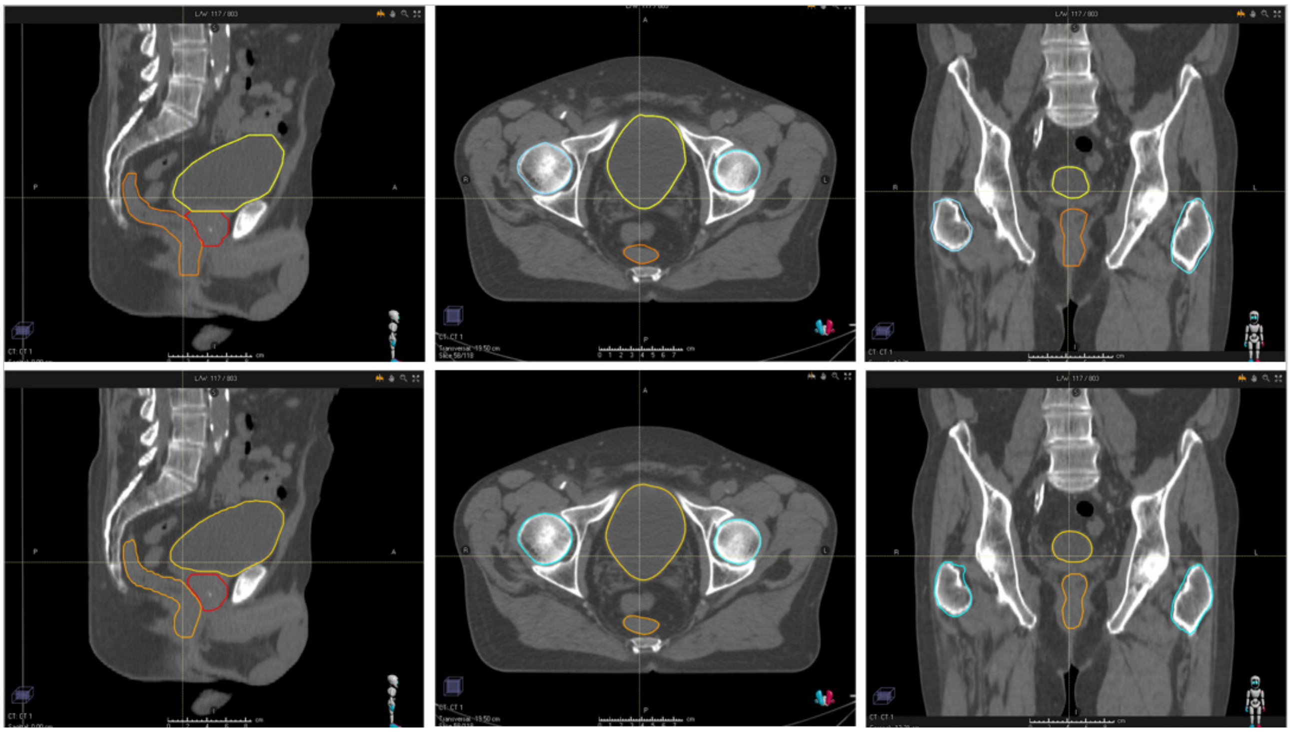


Figure 2. *Results from model trained in collaboration with the Iridium Kankernetwerk in Belgium. The three upper images are ground-truth segmentations, and lower images show contours generated using the deep-learning segmentation tool.*

THE METHOD

The actual algorithm is a powerful and versatile voxel classifier called a neural network, where each voxel in the image is classified as belonging either to unspecified tissue or to a specific structure. To learn how to classify voxels, the algorithm is trained on a large number of previously segmented image sets. The trained network can be thought of as a non-linear function taking a three-dimensional image as input and producing a labelled (segmented) image as output. The specific network used is a 3D-convolutional neural network of U-net architecture [1]. This type of network can combine image features on different levels of abstraction to generate a segmentation map, as illustrated in Figure 3. While the number of features available to the algorithm is predefined, the features themselves are not. Instead, the algorithm will learn the most important features from the training data set when the model is trained. Since the number of features is constant, the algorithm is able to learn from an unlimited number of training cases without affecting the size or runtime of the model. This provides an edge over atlas-based techniques, for which structure sets of hundreds of cases are not feasible.

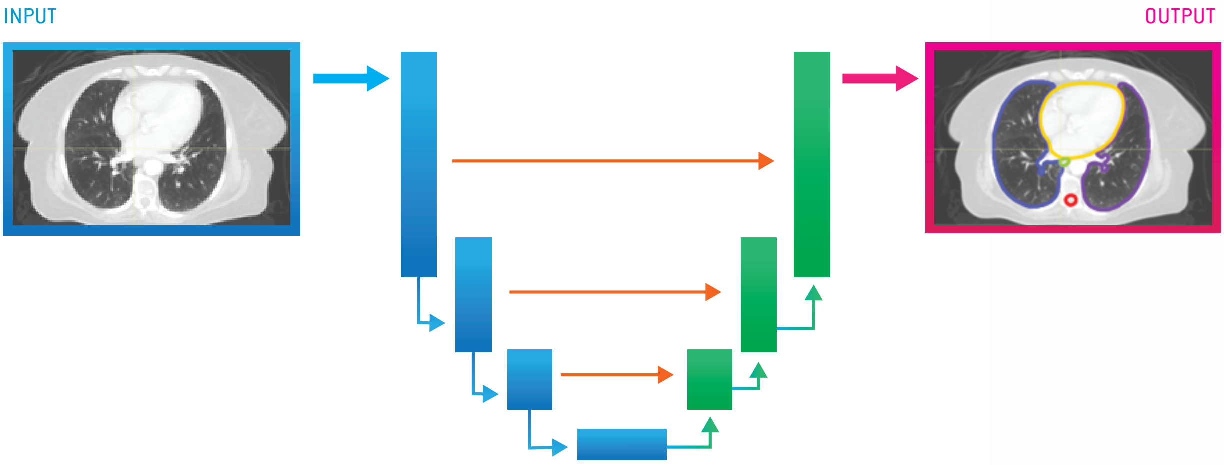


Figure 3. *Convolutional neural network of U-net architecture. Each block represents a set of consecutive convolutional layers. The output of the blocks is downsampled on the left side of the network and upsampled on the right side, which allows the network to work with features at different resolutions.*

TRAINING

Deep-learning segmentation in RayStation comes with pre-trained models from leading cancer clinics. The models are based on data selected by the clinics and are then trained and evaluated by RaySearch in collaboration with them. Clinics can also train their own models and therefore take responsibility for selecting training data and evaluating performance. A trained model does not contain any image data from the training data set. This makes sharing models between clinics more convenient, since no patient data is included within the models.

If a systematic change to contouring procedures are introduced, clinics can update their own models by retraining them on data that holds the new contours and then approve the models for clinical use.

The models are trained using a stochastic gradient descent method, where the weights of the models are tuned to achieve high accuracy measured on the training data set. It's an iterative process with many small gradual improvements of the model, stopping when updates of the model no longer yield lower loss function values. An example of a loss function from a model training is shown in Figure 4, where the model has converged after 250 epochs. The training process is computationally intensive and may take as long as 50 hours to complete on a single GPU.

Selecting the training data is a crucial part of the training and there is often a trade-off between the size and quality of the data. Training data of 100 image sets or more is preferable, even though smaller training sets can perform well in some situations. A model that can handle a large variability in patient anatomy and image quality will require more training data compared to a model where the requirement for such variability is lower. For instance, if delineations of both full and empty bladders are expected, examples of both should be include in the training data, making the data set larger. In order to get the most out of available data, the algorithm implements several data augmentation techniques to artificially increase the size of the training data set. These augmentations consist of image transformations, such as small random rotations and translations, which are performed during training so that the model is presented with a slightly different version of the images for each training iteration.

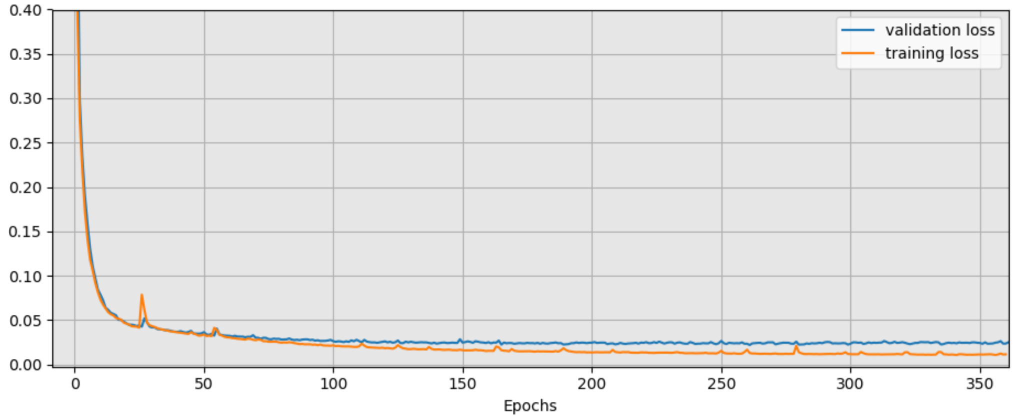


Figure 4. *Loss function history from a model training, where the model seems to have converged after approximately 250 epochs.*

ACKNOWLEDGEMENT

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REFERENCES

[1] Olaf Ronneberger, Philipp Fischer and Thomas Brox. *U-Net: Convolutional Networks for Biomedical Image Segmentation,* Medical. Image Computing and Computer-Assisted Intervention – MICCAI 2015 Vol. 9351, 234-241, 2015

* Subject to regulatory clearance in some markets.

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