

## INTRODUCTION

Accurate segmentation of medical images is a key step in medical image processing. As the amount of medical images obtained in diagnostics, clinical studies and treatment planning increases, automatic segmentation algorithms become increasingly more important. Therefore, we plan to develop an automatic segmentation approach for the urinary bladder in computed tomography (CT) images using deep learning.

**Segmentation algorithms are of big interest in medical image analysis. Applications include the quantification of tissue volume, localization of pathologies, treatment planning and computer-integrated surgery. To this day, delineation is often still done manually. This is a tedious task, since it is time-consuming and requires a lot of experience. Furthermore, manual segmentation is prone to errors and, since it is highly operator-dependent, not reproducible.**

For training a neural network, a large amount of labeled training data is needed. However, public data sets of medical images with segmented ground truth are scarce. We overcome this problem by generating binary masks of images of the  $^{18}\text{F}$ -FDG enhanced urinary bladder obtained from a multi-modal scanner delivering registered CT and Positron Emission Tomography (PET) image pairs. Since PET images offer good contrast, a simple thresholding algorithm suffices for segmentation. We apply data augmentation to these datasets to increase the amount of available training data. In this contribution, we present algorithms developed with the medical image processing and visualization platform MeVisLab to achieve our goals. With the proposed methods, accurate segmentation masks of the urinary bladder could be generated, and given datasets could be enlarged by a factor of up to 2500.

**PET imaging is based on measuring radiation emitted by a radiotracer injected into the patient. Fluorine-18-labelled fluorodeoxyglucose ( $^{18}\text{F}$ -FDG) is the most commonly used radiotracer in PET imaging. It always accumulates in the urinary bladder.**

## METHODS

The software application was developed using the medical imaging and visualization platform MeVisLab, which is a modular framework for developing via visual programming using preexisting modules and macro-module creation via Python scripting. Figure 1 shows the internal network of the *DataPreparation* macro-module which performs all main processing steps. The *Reformat* module transforms the PET dataset to the local coordinate system of the CT dataset using trilinear interpolation. The *SubImage* module allows the selection of individual transversal slices. PET slices are segmented by the application of the *Threshold* module, where the threshold is calculated for each dataset in the Python script. Data augmentation is performed using the *AffineTransformation2D* module. For this macro module, rotation and scaling is enabled. Further, the *AddNoise* module enables the addition of noise from various distributions to CT slices. The *Scale* module allows scaling and conversion of the image file type. The contrast for soft tissue in CT images is adjusted by applying windowing using the *Window* module. At last, the produced slices are saved in TIFF format using the *ImageSave* module. Interactions between these modules and with inputs and outputs, as well as module parameters, were realized via Python scripting.

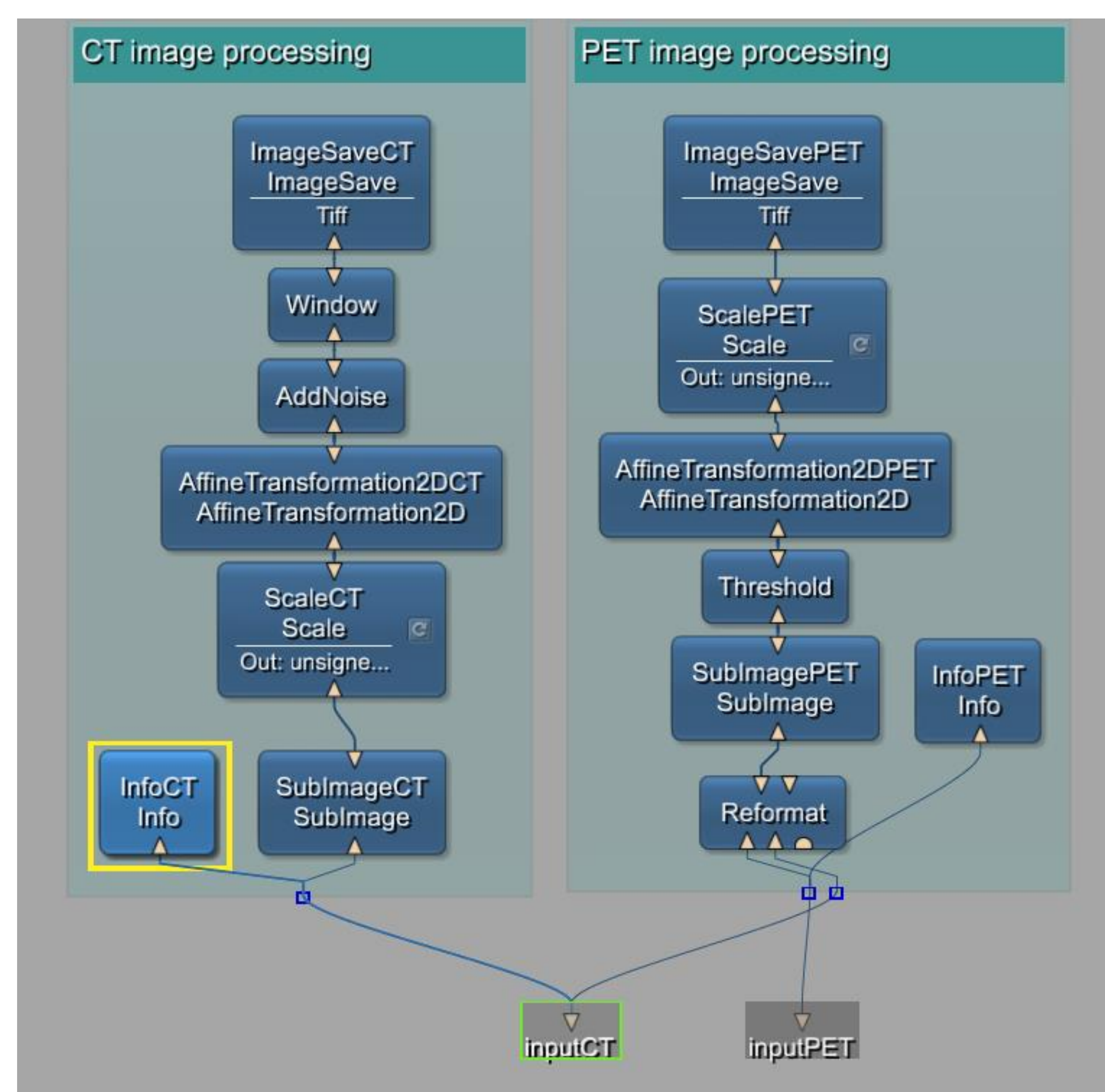


Fig. 1 The internal network of the *DataPreparation* macro module.

## RESULTS

Figure 2 shows overlays of CT slices (in grayscale) and their corresponding binary masks of the urinary bladder generated from the respective PET datasets (in red). Representative datasets were chosen for illustration.

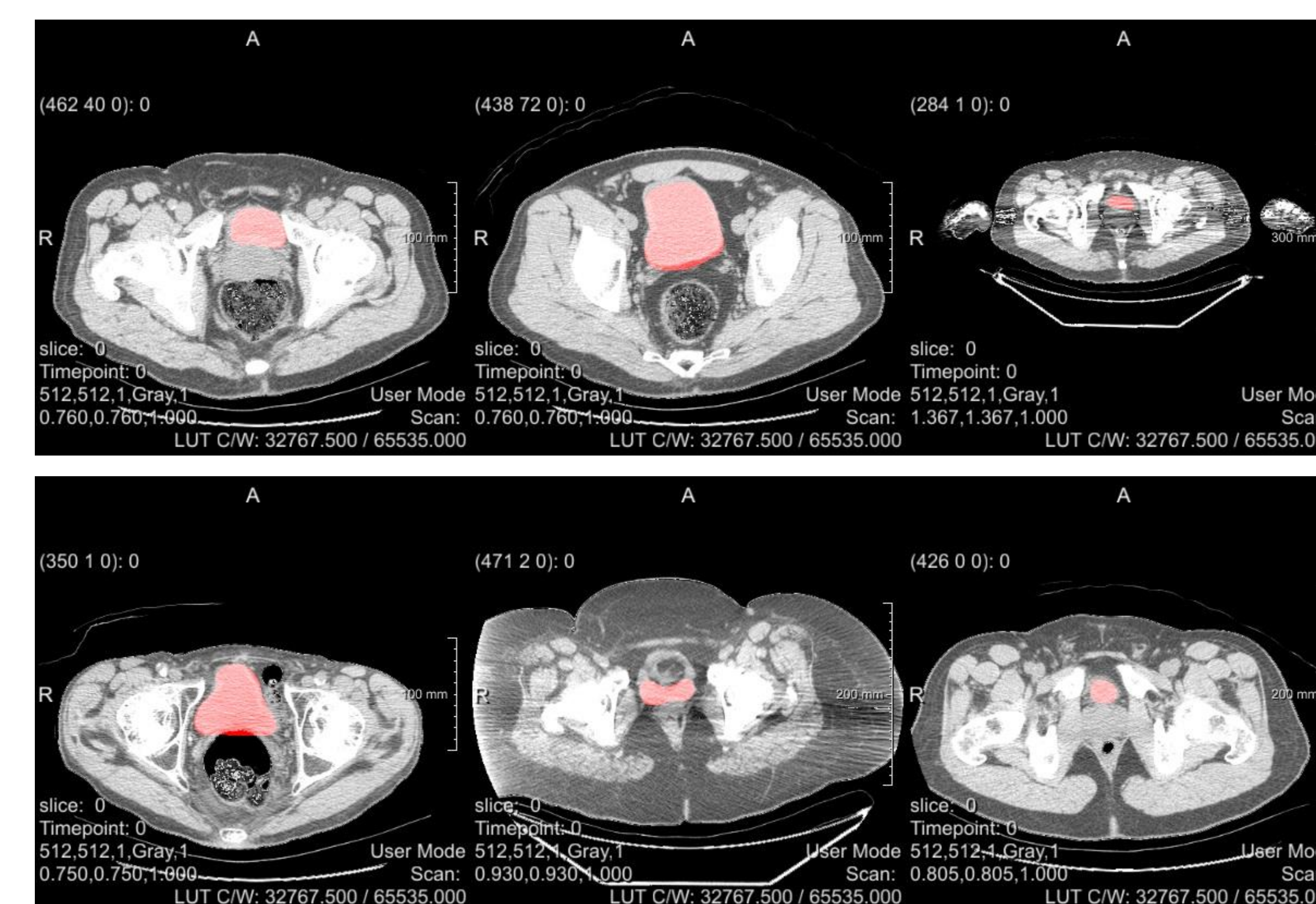


Fig. 2 Overlays of CT data and generated binary masks.

## CONCLUSIONS

1. We provide a macro-module in MeVisLab for the preparation of training data for a deep neural network to segment the urinary bladder;
2. PET data is segmented using thresholding to generate ground truths for training;
3. Data augmentation is used to enlarge data sets;
4. Agreement between ground truth labels and CT data is overall good;
5. A data set can be enlarged by a factor of 2500 using the presented software application;

There are several areas left for future work, in particular the evaluation of the generated data with an actual deep neural network in terms of accuracy of the obtained ground truth labels as well as the meaningfulness of our data augmentation approach.

## REFERENCES

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