Evaluating convolutional neural networks for image upsampling of anisotropic Magnetic Resonance Images in radiation oncology

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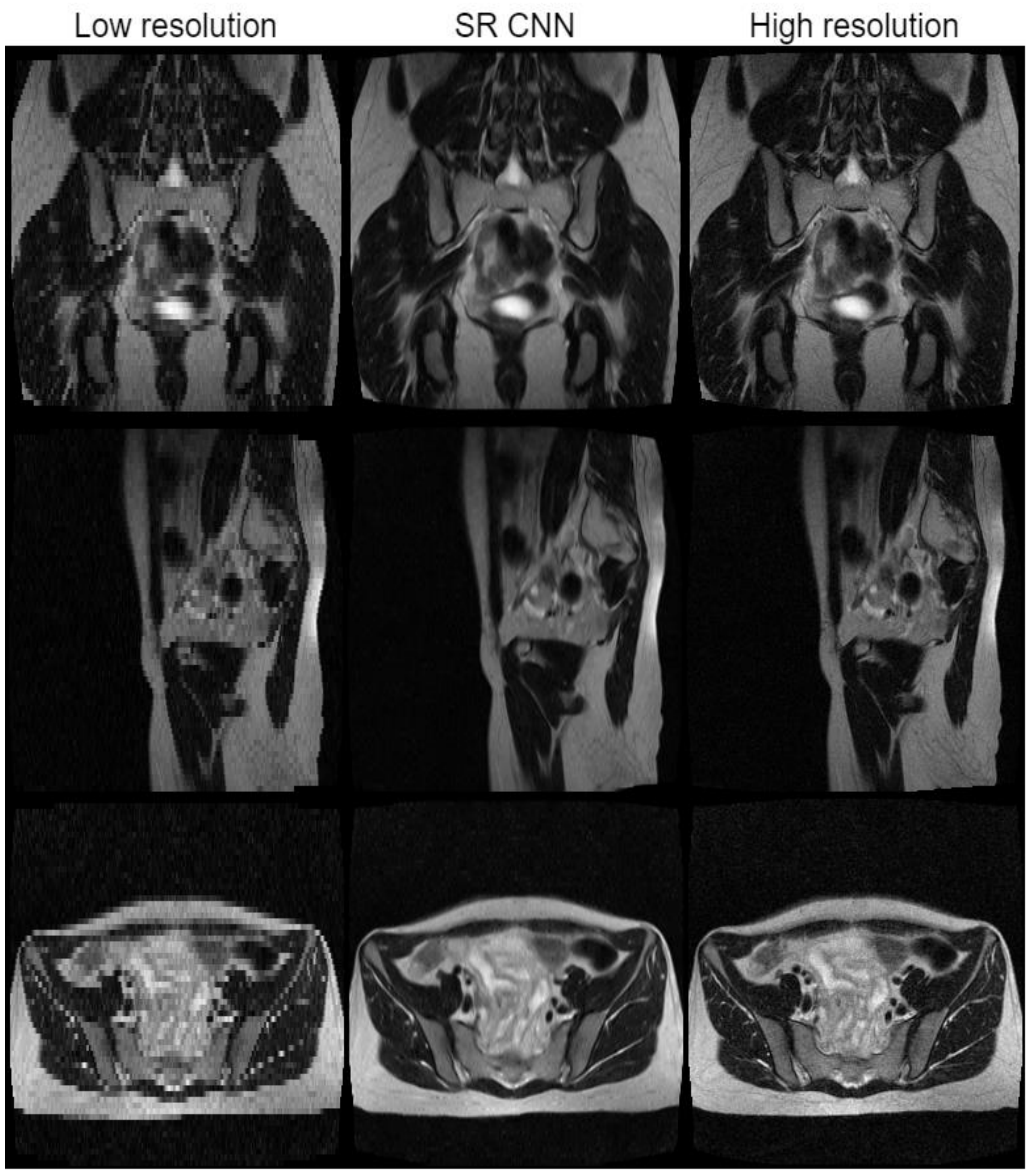

Figure 1: Comparison of low resolution (left), original high resolution (right) and generated MR-images by our network (middle). Low resolution images were created for training by anisotropic downsampling of original images.

Objective

Magnetic resonance imaging (MRI) for brachytherapy treatment of locally advanced cervical cancer (LACC) is regarded as gold standard [1]. While imaging resolution in the imaging plane is isotropic, slice resolution is lower to reduce imaging time. The resulting voxelised representation of the 3D volume reduces delineation accuracy and requires the acquisition of additional scans in the other planes.

In this work the potential of convolutional neural networks (CNNs) to upsample these anisotropic volumes is investigated.

Materials and Methods

At the Medical University of Vienna an open MR scanner (0.35T) for treatment of LACC is used. Images are acquired for each patient in para-transversal, sagittal and coronal direction (256x256, 1.17mm pixel spacing, 5mm slice thickness) for planning and control.

A CNN was used with anisotropic transpose convolution layers to increase the image dimensions by a factor of four in one direction (Figure 2). The optimal model was defined by a hyperparameter search including:

- normalization layers (instance, group and batch norm)
- batch size (8-14), and
- objective metric (feature loss, spatial profile loss [2], mean absolute error loss).

For optimization AdamW with decoupled weight decay factor of 10^{-2} was used with a learning rate schedule following the one cycle learning policy.

The image quality was measured with peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) on the validation dataset. The test data set conversions were compared to a bicubic interpolation. An overview of dataset sizes is shown in Table 1.

Table 1: Overview of used training and test datasets for CNN training and evaluation. Images include para-transversal, sagittal and coronal direction for control and planning

	Patients (n)	Images (n)
Training set	30	19409
Test set	13	7963
Total	43	27372

Results

The results of the hyperparameter search are given in Table 2. The best results were achieved with

- the mean absolute error loss,
- group normalization and
- a batch size of 12 images.

The SSIM and PSNR of the test data set was 0.87±0.02/0.75±0.05 and 32.1±1.6/27.3±1.8 for the SRCNN model and bicubic interpolation, respectively.

The final images demonstrated a high quality, and the CNN had an additional denoising ability which can be observed in Figure 1.

Table 2: Best hyperparameter search results in terms of PSNR and SSIM for each loss function. (MAE: Mean absolute error, Feature: Feature loss, SPL: Spatial Profile Loss). Results based on training set.

Loss function	Batch size	Normalization	Learning Rate	Runtime	PSNR	SSIM
MAE	12	group	4.3e-9	9h 14m	33.5	0.904
Feature	12	batch	5.6e-9	6h 13m	33.0	0.892
SPL	12	batch	5.6e-9	7h 33m	27.2	0.894

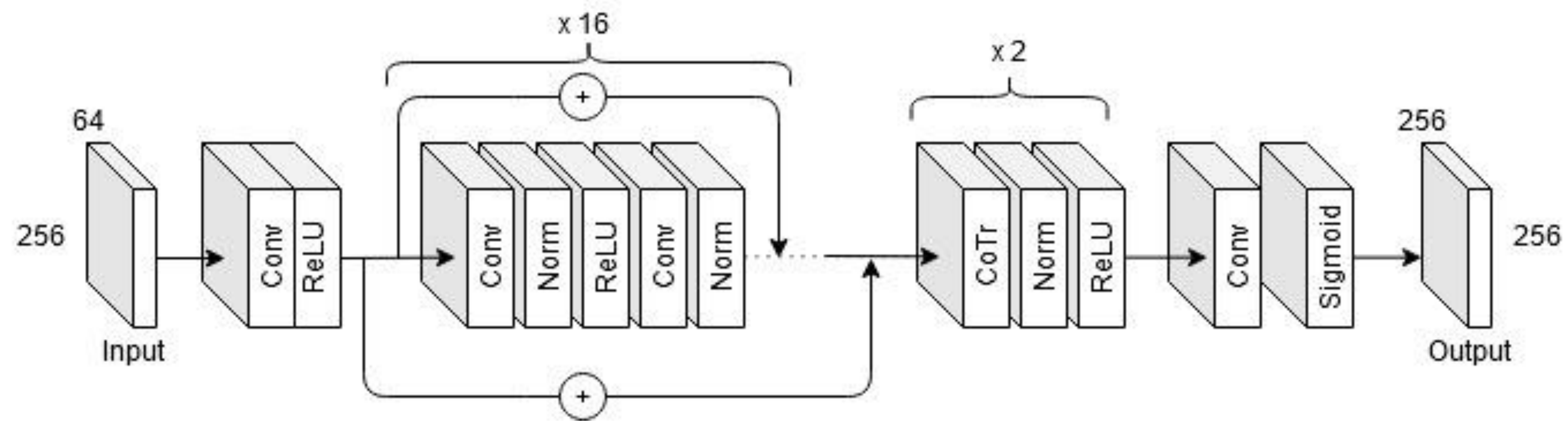

Figure 2: Architecture of the used CNN. (Conv: 2D convolution, ReLU: PReLU activation function, Norm: normalization layer, CoTr: 2D transposed convolution). Image input dimensions 64x256 pixels. Image output dimensions 256x256 pixels.

Conclusion

A CNN was successfully trained to increase the resolution of anisotropic voxels. The output could enable several applications in the clinical workflow, like enhanced image registration quality. The acquisition of all images series currently takes 30 minutes. Using the upsampled volumes it would be possible to study inter- and intra-acquisition motion of organs at risk during this time and help reduce dosimetric uncertainties of radiotherapy applications.

References

[1] Tanderup, K., J.C. Lindegaard, C. Kirisits, C. Haie-Meder, K. Kirchheiner, A. de Leeuw, I. Jurgenliemk-Schulz, E. Van Limbergen, and R. Potter, Image Guided Adaptive Brachytherapy in cervix cancer: A new paradigm changing clinical practice and outcome. Radiother Oncol, 2016. 120(3): p. 365-369.

[2] Sarfraz et al., Content and Colour Distillation for Learning Image Translations with the Spatial Profile Loss (2019)

Acknowledgements

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