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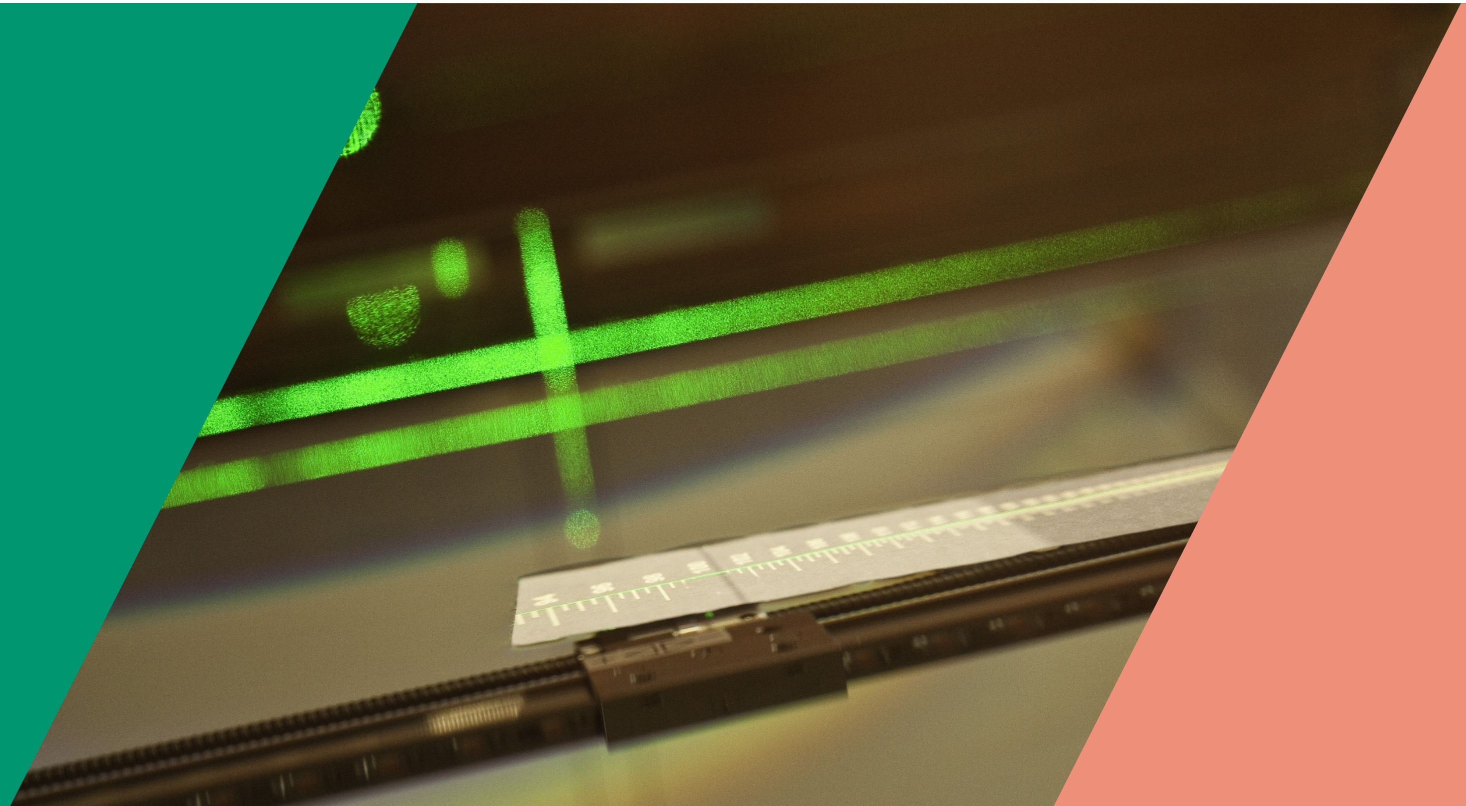
Deep-learning powered denoising of Monte Carlo dose distributions

H.A. Loebner, R. Joost, J. Bertholet, S. Mougiakakou, M.K. Fix & P. Manser

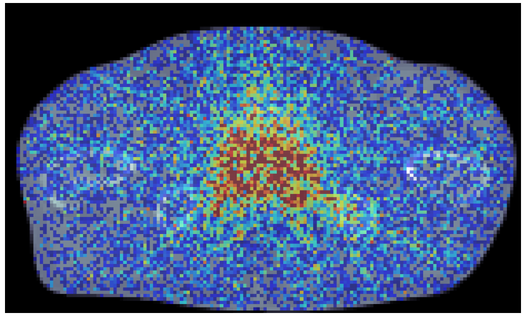


Background

Monte Carlo (MC) dose calculation is widely considered as a gold-standard in radiotherapy [1]

- Accurate in inhomogeneous media
- Accurate simulation of physical processes

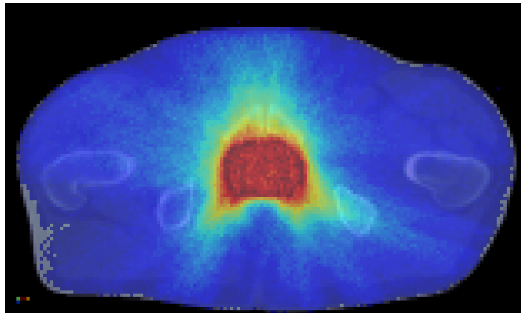
MC-DD with high SU



BUT

- **Large** number of particle histories needed for reasonable statistical uncertainty
- **Long calculation times** for simulation of large number of particle histories [2]

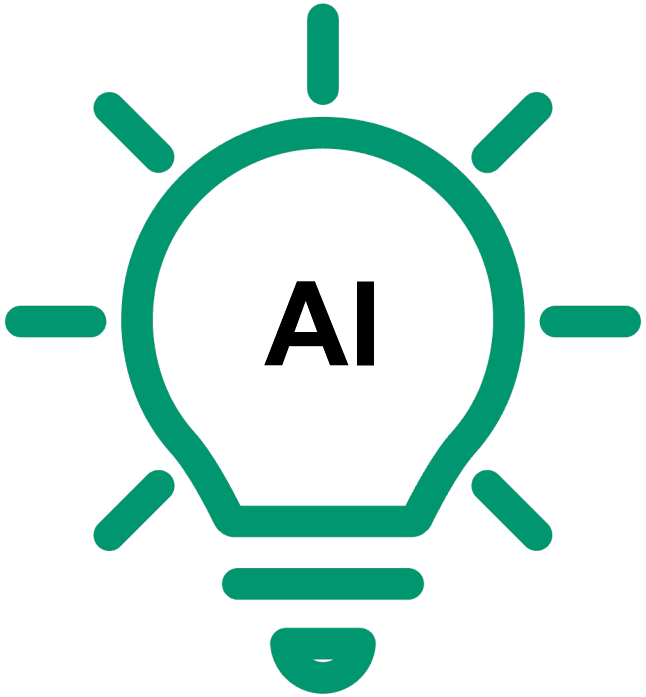
MC-DD with low SU



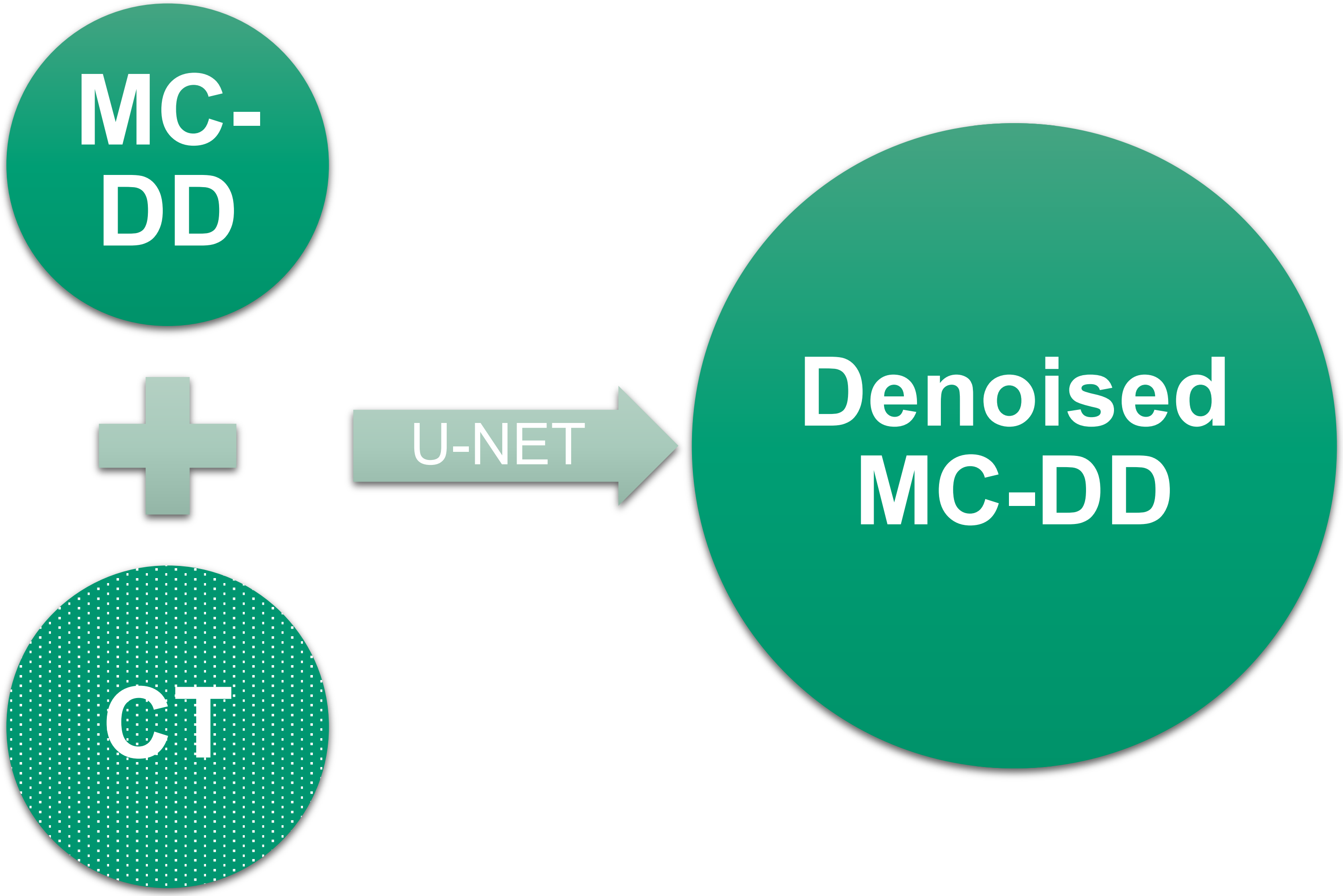
[1] Fauzi et al.: Monte Carlo- versus pencil-beam-/collapsed-cone-dose calculation in a heterogeneous multi-layer phantom. *Phys Med Biol.* 2005

[2] Chetty et al. Report of the AAPM Task Group No. 105: Issues associated with clinical implementation of Monte Carlo-based photon and electron external beam treatment planning. Med Phys. 2007

Idea



Idea



[3] Fornander H. Denoising Monte Carlo Dose Calculations Using a Deep Neural Network (2019).

Methods

1 Generation of Training Data

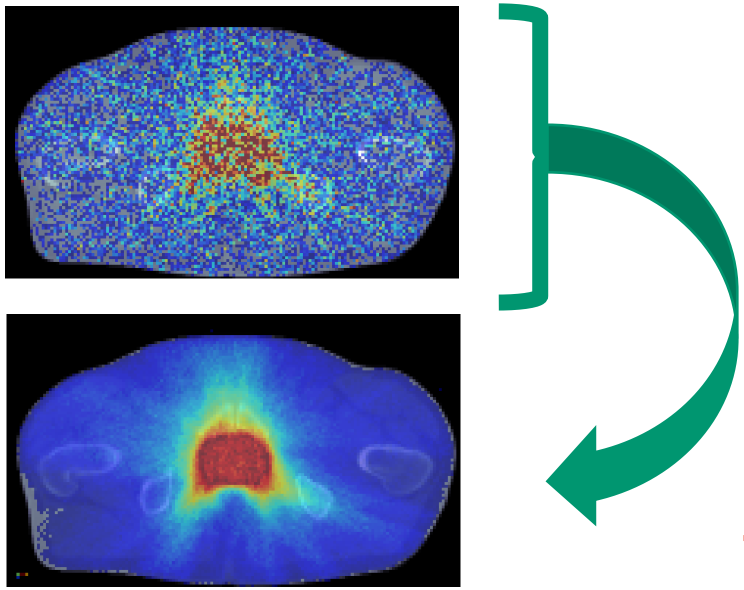
- Using Swiss Monte Carlo Plan (SMCP) [4]
- **5346 dose distributions** of randomly generated VMAT plans for **447 CTs**

Input

- MC-DD with high statistical uncertainty (SU)
  - $1.5 * 10^6$ particle histories→ *noisy*
- CT

Target

- MC-DD with low SU
  - $3.0 * 10^8$ particle histories



[4] Fix et al.: Efficient photon treatment planning by the use of Swiss Monte Carlo Plan. J Phys Conf Ser. 2007

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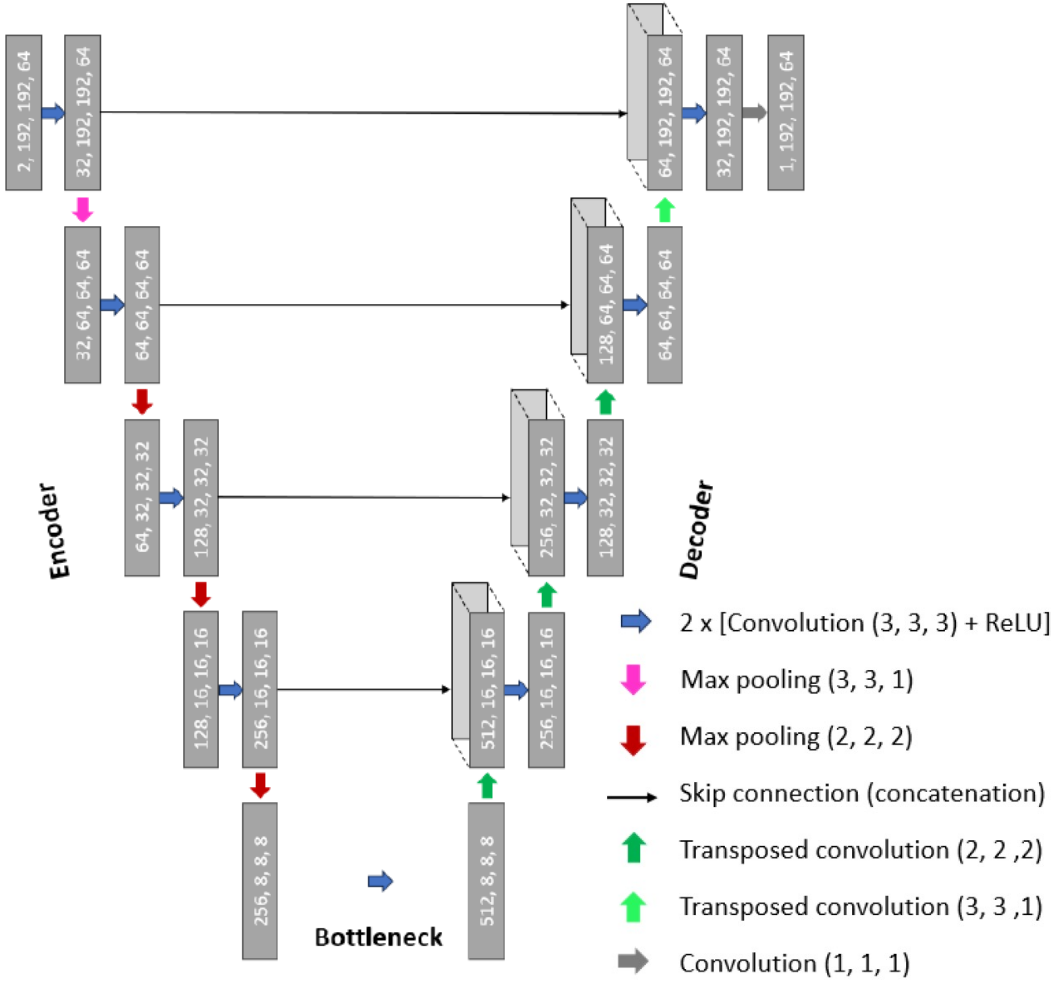
2 Base Model



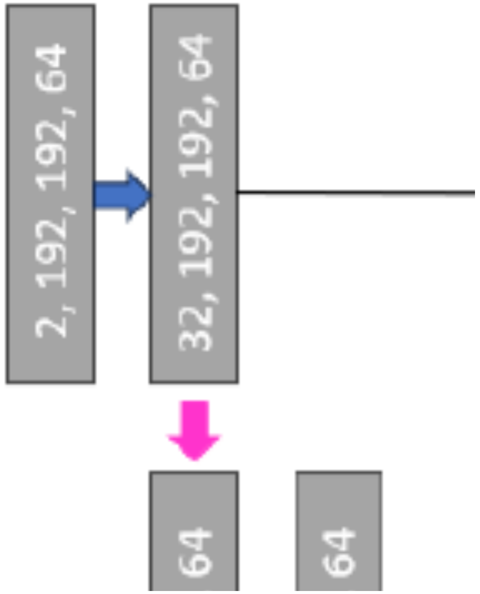
[4] Fix et al.: Efficient photon treatment planning by the use of Swiss Monte Carlo Plan. J Phys Conf Ser. 2007

Methods

2 Model variations

X, Y, Z
#voxels

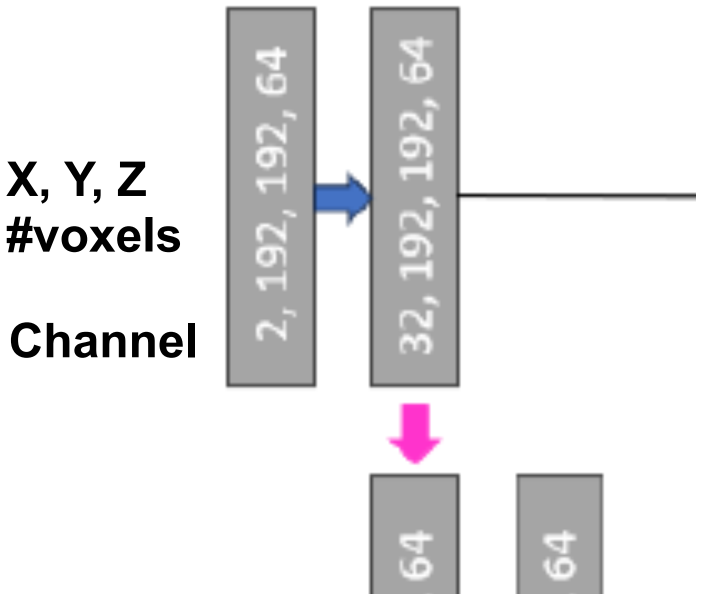
Channel



Model	#slices	CT	Batch normalization
1	32	yes	no
2	64	yes	no
3	96	yes	no
4	64	no	no
5	64	yes	yes

Methods

2 Model variations



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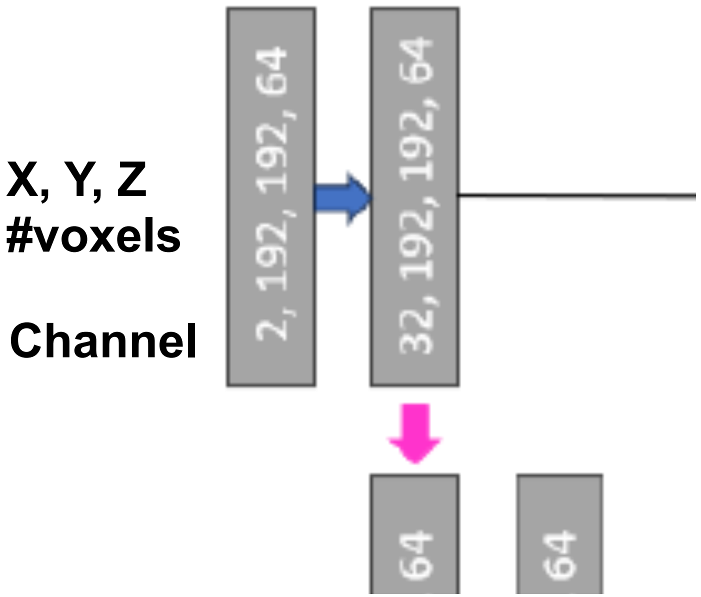

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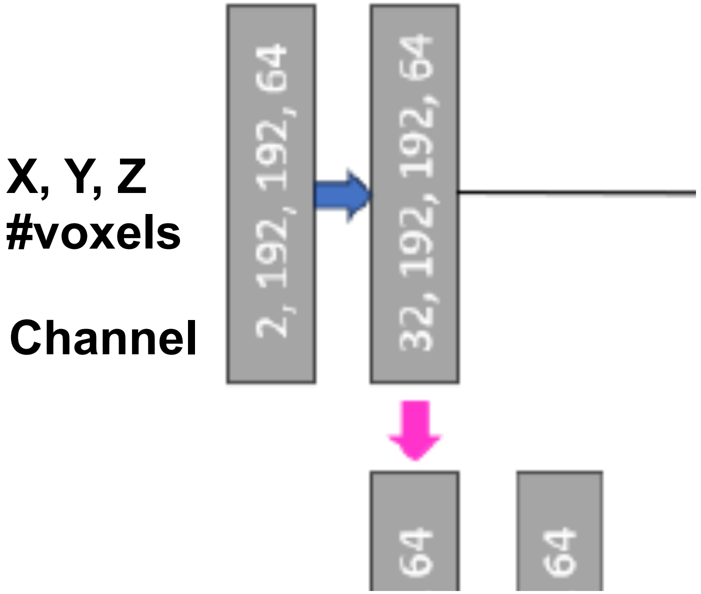

Model	#slices	CT	Batch normalization
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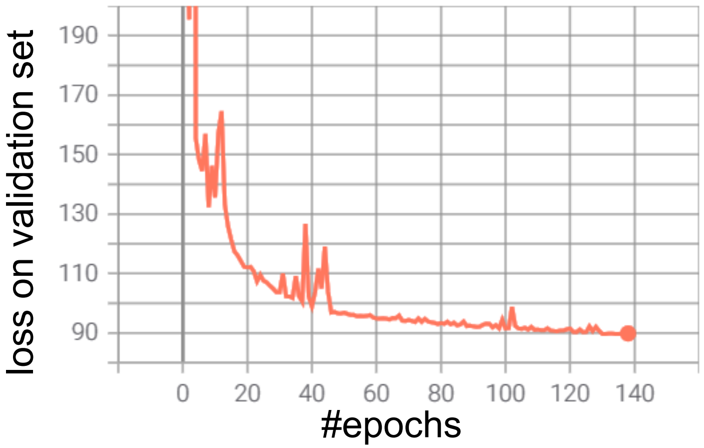
Methods

3 Training

- Mean squared error loss function
- ADAM optimizer with adaptive learning rate
- 149 Epochs
  - ~28 h on GeForce RTX 3090



- Patch based approach
  - TorchIO [5]
- Larger geometries:
  - Averaging of overlapping voxels
  - → multiple predictions
- Smaller geometries:
  - Add “empty” voxels

[5] Pérez-Garcia et al.: TorchIO: A python library for efficient loading, preprocessing, augmentation and patch-based sampling of medical images in deep learning, EESS 2020

Methods

4 Evaluation and selection of best performing model

- Gamma passing rate
  - **gamma-2** (2%/2 mm, 10% threshold)
  - **gamma-3** (3%/3 mm, 10% threshold)
- Root-mean-square error (**RMSE**) in $[10^{-4}$Gy/MU]

→ Selected best performing model

5 Retraining

- Augmentation of 106 clinically motivated VMAT arcs for 29 CTs to a total of **3074 DD** (80/10/10 split)

6 Application

- *Accuracy:* RMSE, gamma-2 & -3
- *Performance*: Calculation time
- *Application*: Dose distribution of entire treatment plans of different cases

Results

1 Model evaluation

Model	Average gamma-2 [%]	Average gamma-3 [%]	RMSE [10^{-4}Gy/MU]
1	89.16 ± 3.99	97.30 ± 1.69	1.21 ± 0.22
2	**89.74 ± 4.00**	**97.50 ± 1.66**	**1.16 ± 0.20**
3	89.72 ± 3.92	97.48 ± 1.61	1.15 ± 0.20
4	89.23 ± 4.16	97.30 ± 1.78	1.16 ± 0.20
5	83.54 ± 4.77	94.50 ± 2.55	1.26 ± 0.27

Model	#slices	CT	Batch norm.
1	32	yes	no
2	64	yes	no
3	96	yes	no
4	64	no	no
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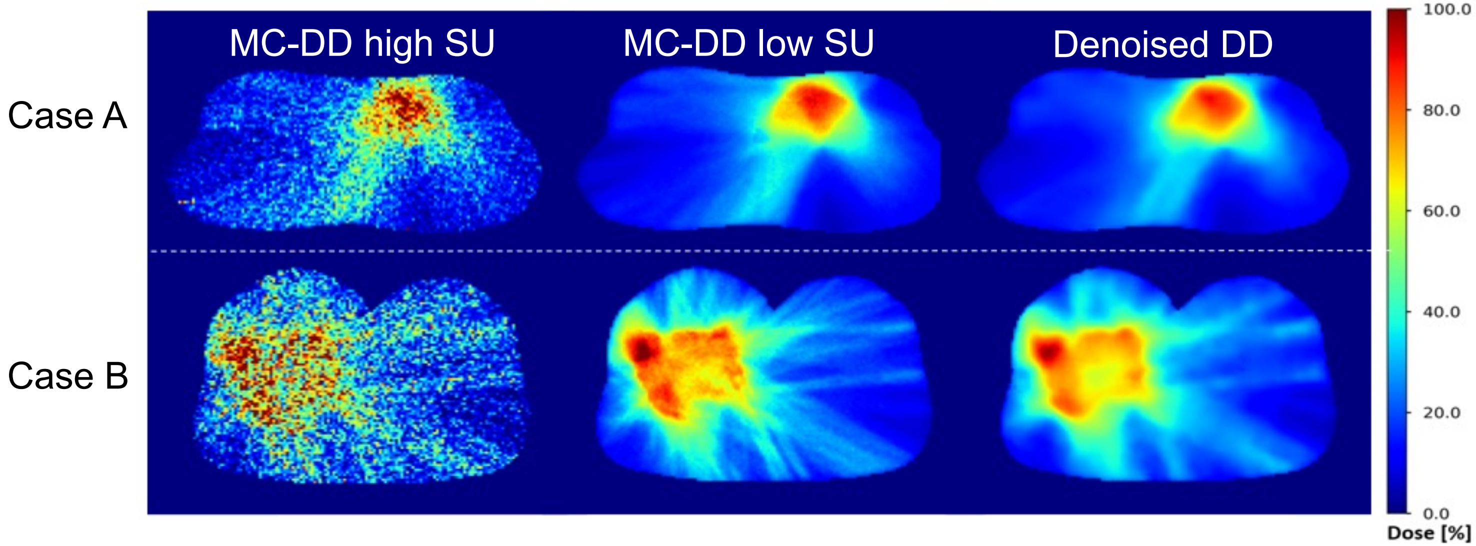
Results

2 Application: test set

- *Accuracy*
  - Gamma-3: **94.0** ± 2.3%
  - RMSE: $\mathbf{1.2} \pm 0.2 * 10^{-4}$ Gy/MU

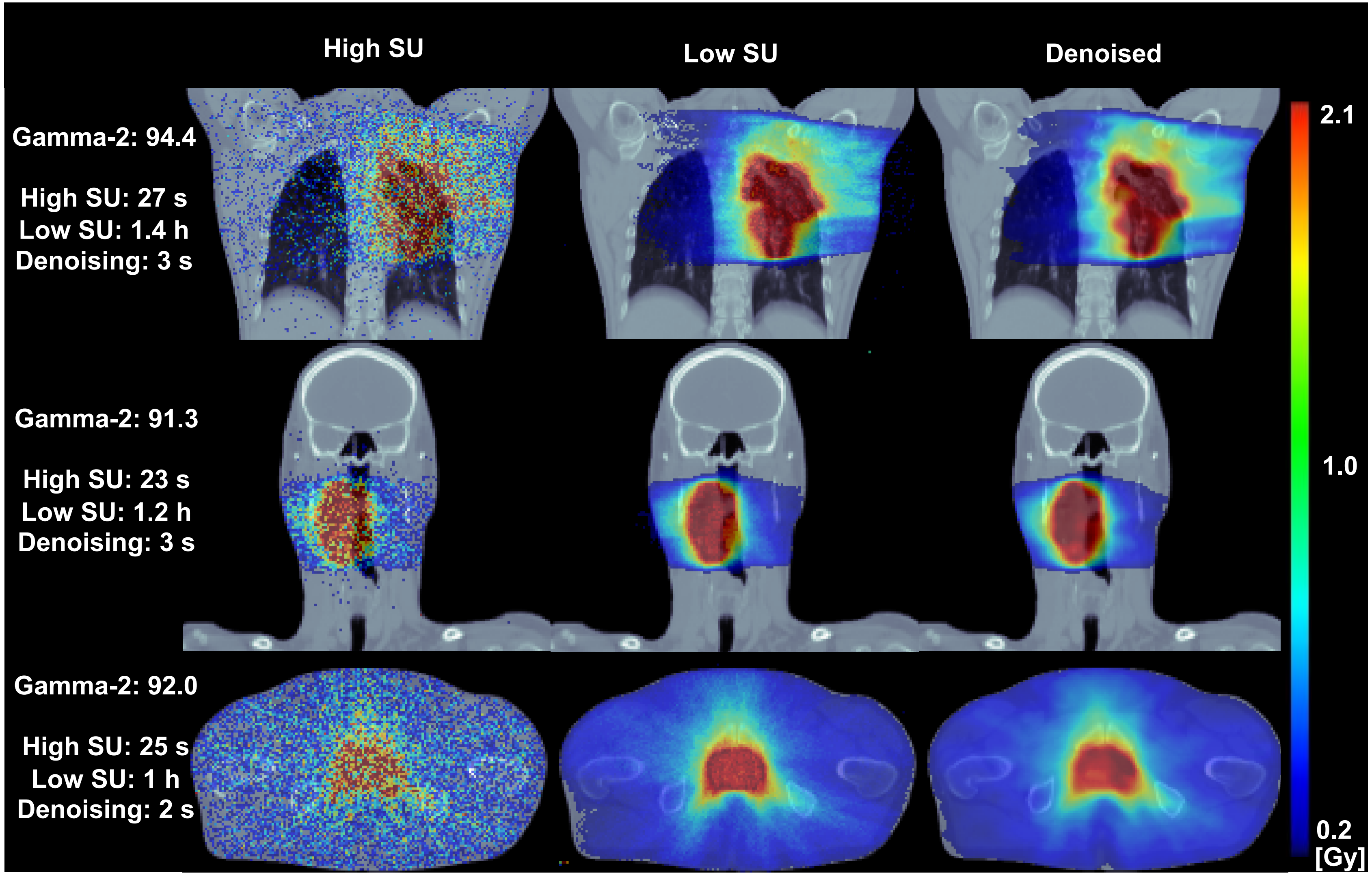
- *Performance*
  - Dose distribution with high SU: **32.7** ± 7.5 s
  - Denoising: **2.6** ± 0.3 s
  - Dose distribution with low SU: **3.2** ± 0.7 h



Results

3 Application realistic cases

- *Accuracy*
  - Gamma-3: **~97.5%**
  - RMSE: $\mathbf{1.1 * 10^{-4}}$ **Gy/MU**
- *Performance*
  - Dose distribution with high SU: **~32.0 s**
  - Denoising: **~4.0 s**
  - Dose distribution with low SU: **~2 h**



Conclusion

1. **Training data can be easily generated**

   → applicable on real data

2. **Little impact of number of slices on performance & accuracy**

   → Select model according to specifications of GPU model

3. **No substantial improvement by additional CT input**

   → Can be beneficial in the context of “explainable results”

4. **Batch normalization substantially degraded accuracy**

   → Information about absolute dose values can be lost

   → Effect is amplified when using patching

Developed a denoising model of promising accuracy with impressive efficiency gain (factor 340)

→ Denoised MC dose distributions within <1 min

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