Proton Dose Calculation with LSTM Networks in a Magnetic Field

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Background

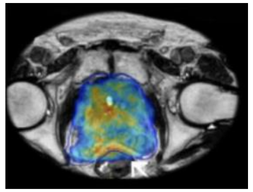
- Proton therapy:
  - Superior dose conformity compared with photon therapy
  - Limitations in achieving high-precision due to range uncertainty

Need for real-time image-guidance during PT

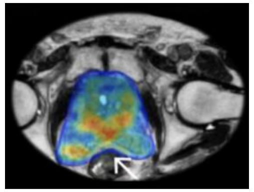
- MRI:
  - High soft tissue contrast, non-ionizing radiation, real-time imaging

Combination of MRI and PT

- Online MR-guided adaptive proton therapy:
  - Treatment plan can be **adapted or re-optimized** based on the latest patient geometry
  - Improve the target dose coverage and reduce the dose to surrounding normal tissues



Online plan re-optimization based on MRI

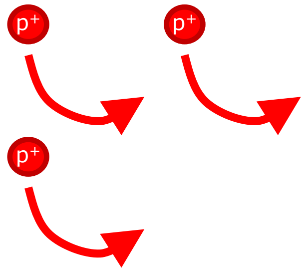


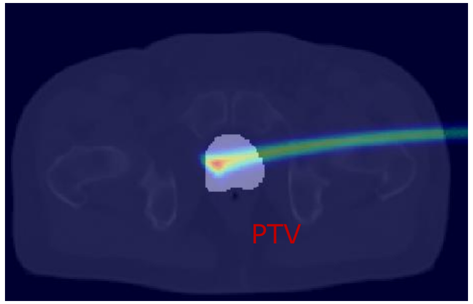
Images courtesy of Netherlands Cancer Institute, NKI

Online plan re-optimization needs accurate and fast dose calculation

Background

- Proton dose calculation in a **magnetic field**:
  - Lorentz force causes charged protons to be deflected
- Monte Carlo (MC) methods:
  - Accurate but speed is usually slow
  - GPU MC methods are still in the level of several seconds
- Analytical algorithms:
  - Speed can be closer to real-time
  - Lack the accuracy of MC methods, especially in inhomogeneous tissues





1.5T B field

Ultimate need for accurate real-time plan re-optimization is still unmet!

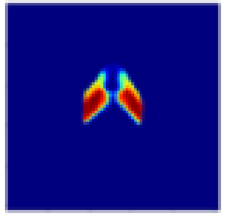
→ Dose calculation with MC accuracy at sub-second speeds

Background: DL dose calculation

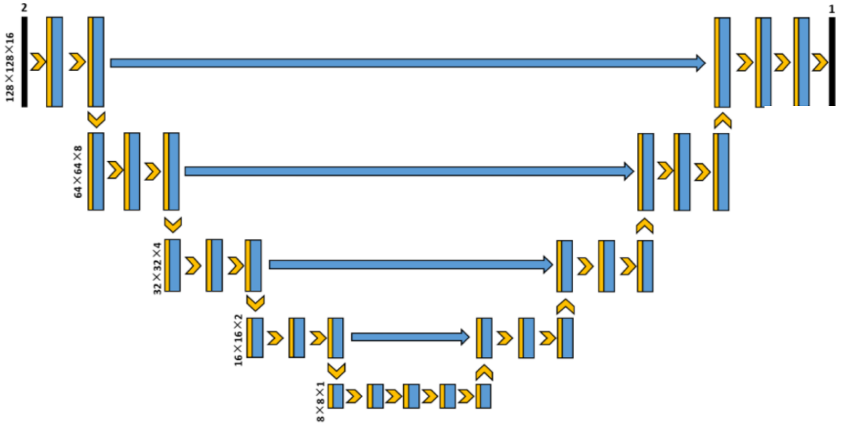
Category1: Convert low-cost physical inputs to MC dose

PB->MC[1]

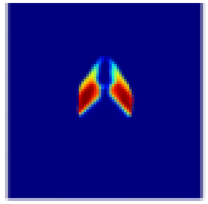
PB dose



CT

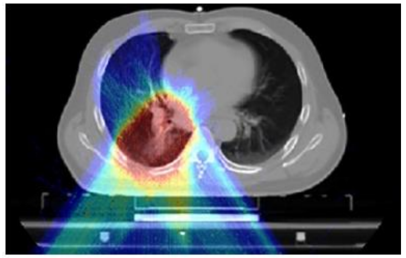


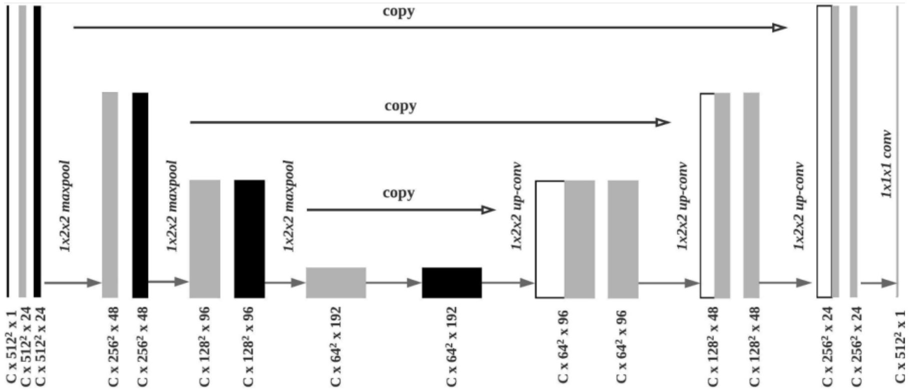
MC dose



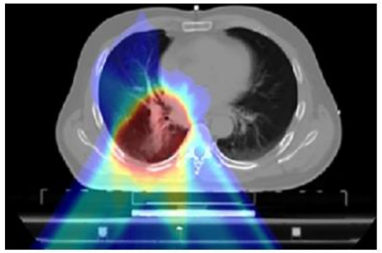
MC denoising[2]

Noisy MC dose





MC dose



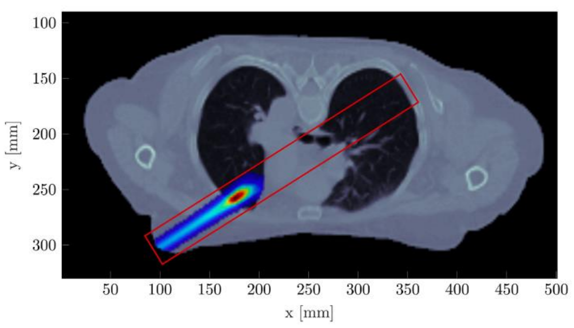
[1] Wu C 2021 Improving Proton Dose Calculation Accuracy by Using Deep Learning *Mach Learn Sci Technol*

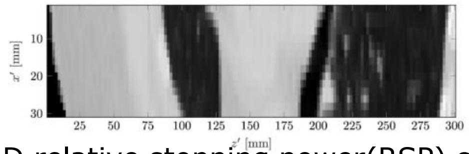
[2] Javaid U 2021 Denoising proton therapy Monte Carlo dose distributions in multiple tumor sites: A comparative neural networks architecture study *Phys Med*

Background: DL dose calculation
Category2: Slice sequence modelling from Beam's Eye View

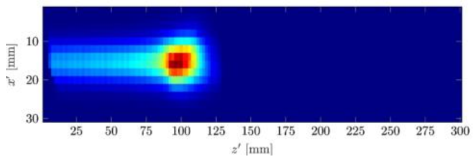
- Models focus on the individual beamlet from BEV
- Extract the beamlet and use LSTM or transformer models to process dose slice sequence modelling

LSTM method[3]

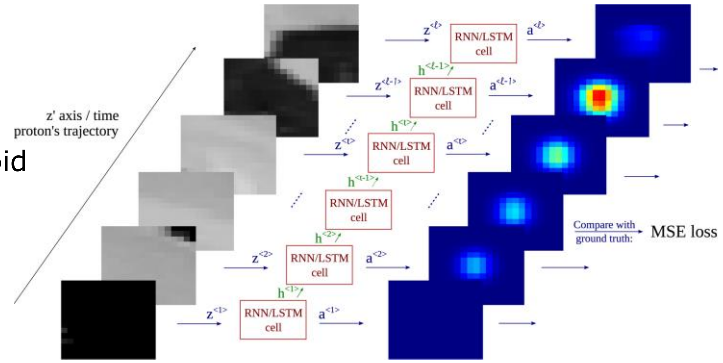




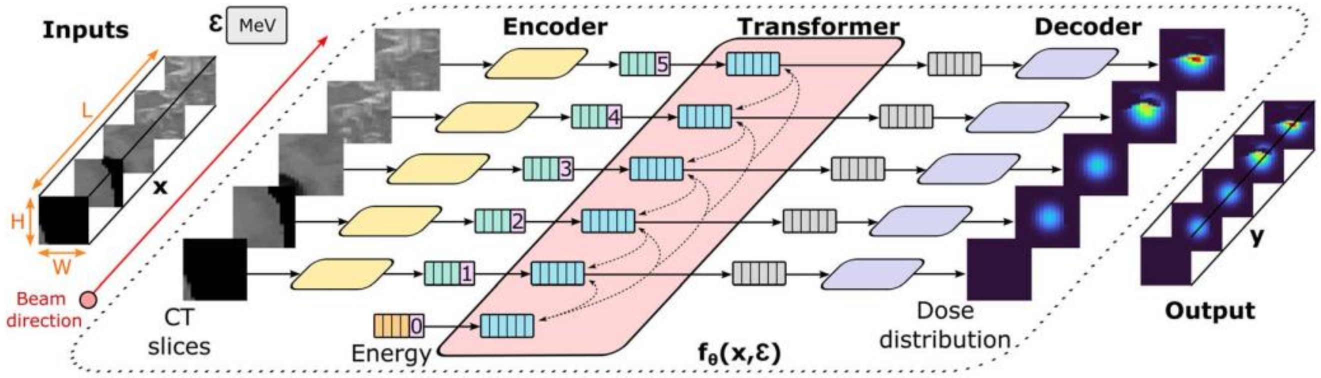
3D relative stopping power(RSP) cuboid



3D MC dose cuboid



Transformer method[4]

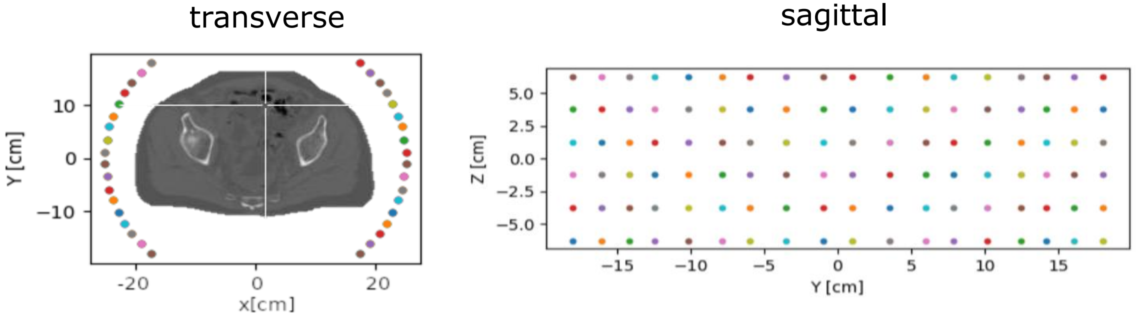


[3] Neishabouri A 2021 Long short-term memory networks for proton dose calculation in highly heterogeneous tissues *Med Phys*

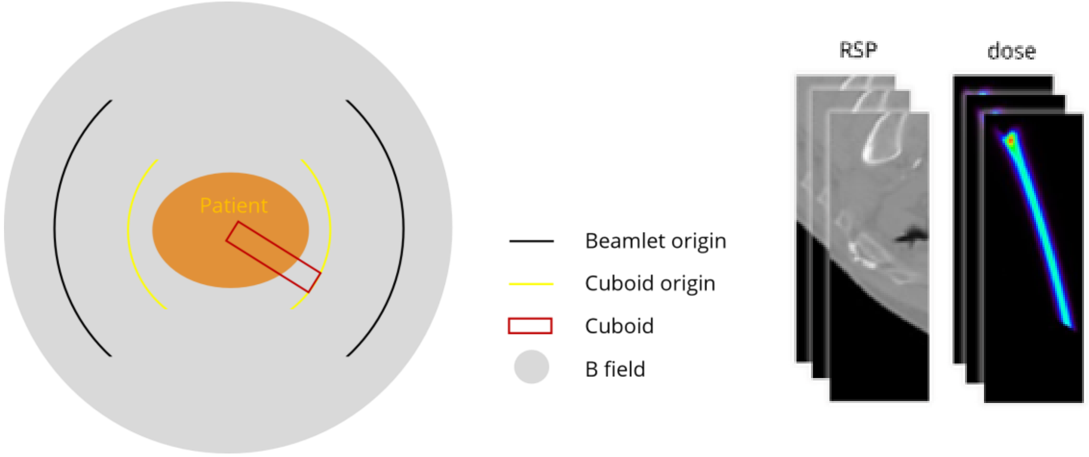
[4] Pastor-Serrano O 2022 Millisecond speed deep learning based proton dose calculation with Monte Carlo accuracy *Phys Med Biol*

Methods & Materials
Dataset

- Patients:
  - 35 prostate patients treated at MRIdian in LMU Hospital
  - Deformed CTs (from planning CT-MRI registration)
  - Resampled voxel size: 1.5x1.5x1.5mm^3
  - Dataset split: training/validation/testing=20/5/10



- Geant4 MC dose simulation:
  - Convert CTs to **RSP**s with respect to water using Geant4
  - **1.5T** B field within a cylinder of a 30 cm radius
  - Number of histories: 1M
  - Angular region: [40°, 140°]∪[220°, 320°], Δα=16.6°
  - 216 beamlets were simulated per patient
  - 3 beamlet datasets for 3 energies (**150/175/200 MeV**)
  - Cuboid extraction from a predefined distance before beamlet origin



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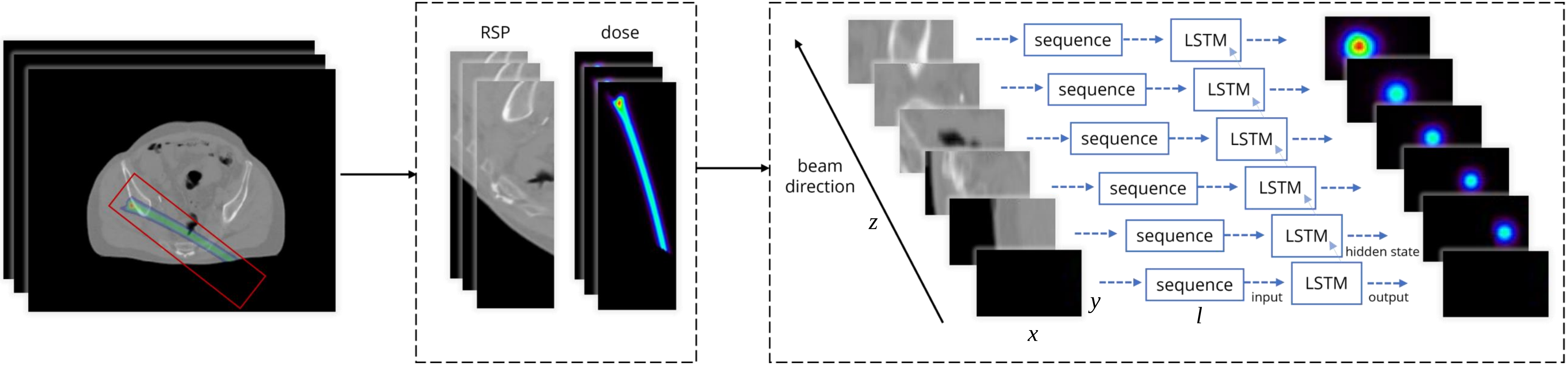
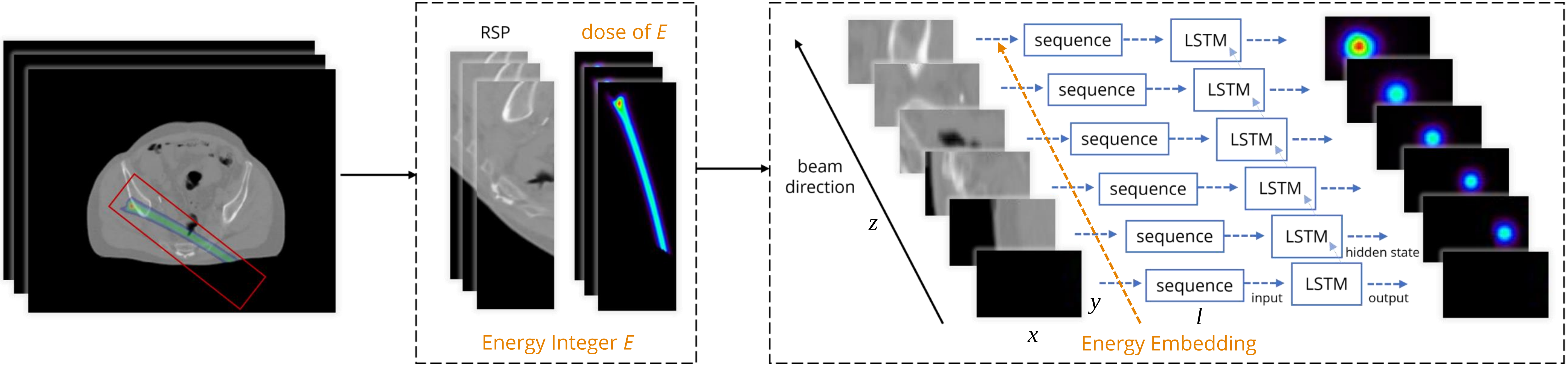
Methods & Materials
Single energy (SE) model

x/y/z: length/width/depth of cuboid, *l*: length of input sequence ($x \times y$)



Methods & Materials
Multi-energy (ME) model

$x/y/z$: length/width/depth of cuboid, l: length of input sequence ($x \times y$)



Energy Embedding layer

Energy integer: E → (One-hot encoding) → 1D one-hot encoded vector: V_{in} → (Full-connected layer) → 1D float vector: V_{out}

Flattened RSP sequences: F_{rsp}

$F_{rsp} \in M^{z \times l}$

$E \in \{150,175,200\}$

$V_{in} \in \{(1,0,0), (0,1,0), (0,0,1)\}$

$V_{out} \in M^{z \times 1}$

Methods & Materials
Model training

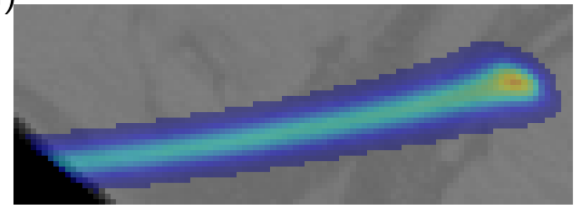
- Models
  - **3 single energy models** were trained **separately** on 150/175/200 MeV datasets
    - LSTM + two fully connected layers
  - **One multi-energy model** were trained on a **combined** 150/175/200 MeV dataset
    - Energy embedding layer + LSTM + two fully connected layers
- Training parameters
  - Optimizer: Adam, Loss: MSE, LR: 1e-5, batchsize: 8
  - Hardware: NVIDIA RTX A6000 GPU (48 GB)
  - Training GPU memory cost: within **1 GB**
  - Training time: 5 days

Methods & Materials
Metrics

- 10 test patients in 150/175/200 MeV datasets (216 beamlets per patient)
- 3D dose distribution comparison:
  - 3D global gamma passing rate $\boldsymbol{\gamma}_{\mathbf{PR}}$ (2%/2 mm, D>10%D_{max})
- Dose range comparison:
  - Laterally integrated **dose-depth profiles** of two doses with relative error $\boldsymbol{\varepsilon}_{\mathbf{rel}}$
  - Depth difference $\boldsymbol{\Delta R_{D80}}$ of the distal dose falloff to 80% of Bragg peak (mm&%)
- Magnetic dose deflection comparison:
  - Lateral profiles of two doses
  - Shift difference in the center of mass $\boldsymbol{F}_{\mathbf{COM}}$ at each depth of two doses (mm)

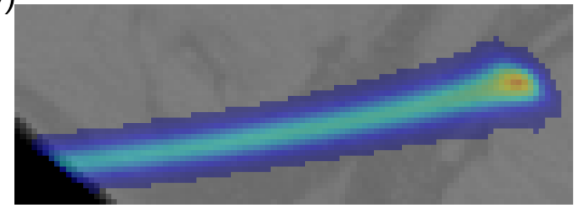
Geant4 simulated dose

a)

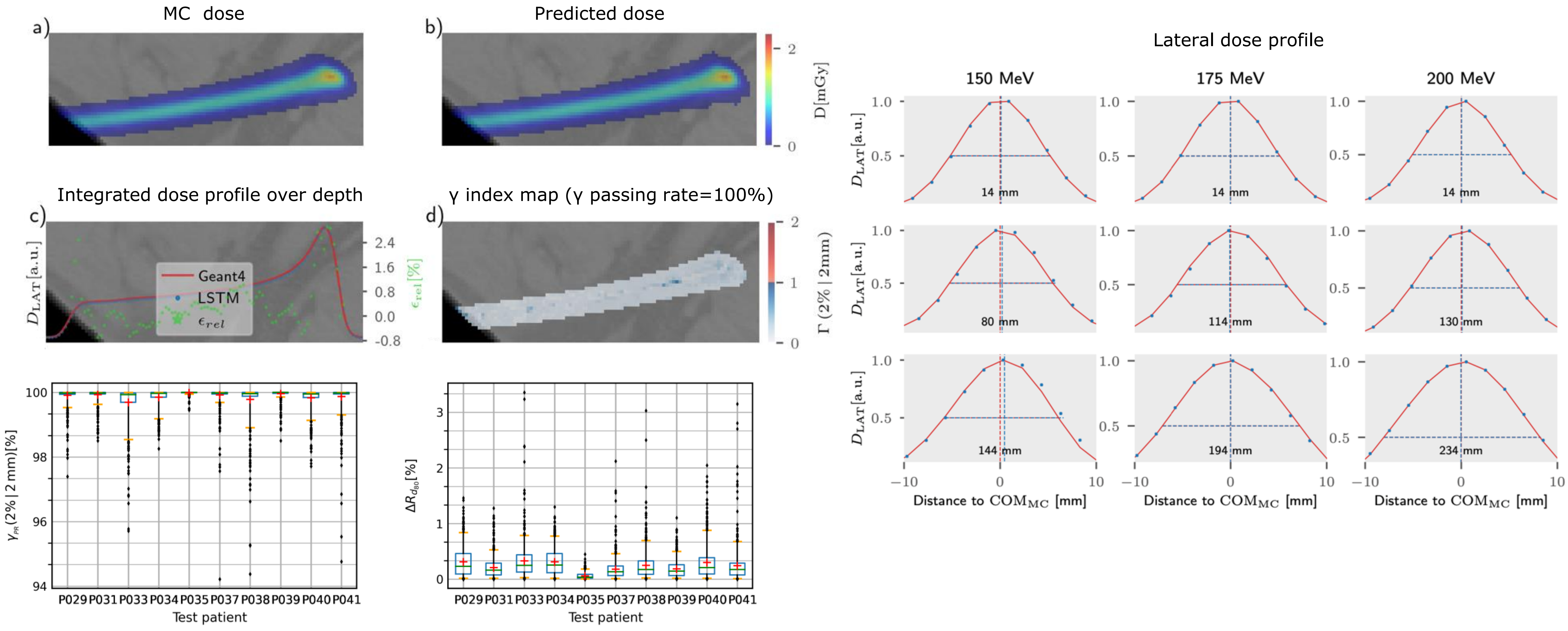


LSTM predicted dose

b)

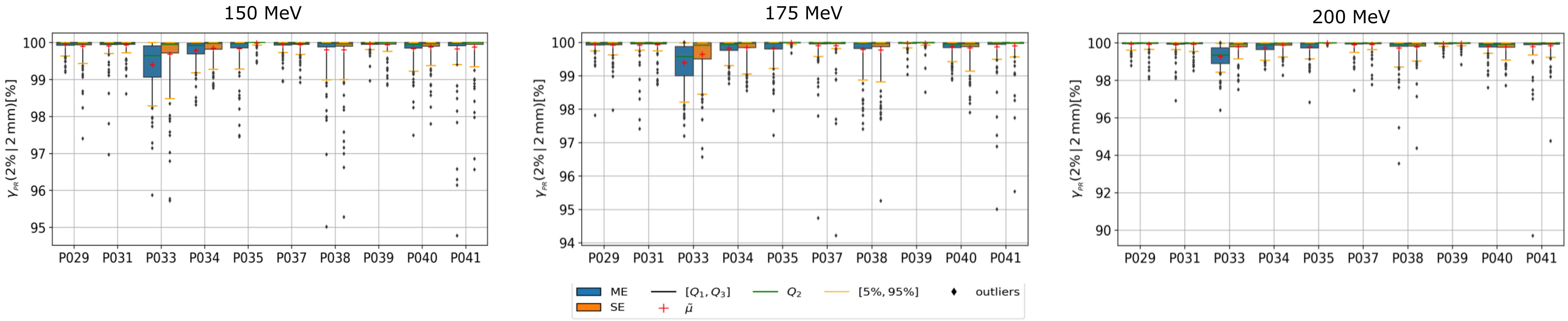


Results
Typical examples of SE models



Results

Metrics comparison between SE models and ME model



		γ_{PR} [%]		ΔR_{D80} [%]		F_{COM} [mm]	
Model	E[MeV]	min	mean	max	mean	max	mean
SE	150	95.28	99.88	2.70	**0.28**	**2.15**	**0.39**
	175	**94.21**	**99.87**	3.03	0.23	1.84	0.34
	200	94.38	99.88	**3.15**	0.19	2.03	0.30
ME	150	94.78	99.82	**4.59**	**0.29**	2.06	**0.45**
	175	94.74	99.83	3.68	0.22	2.09	0.37
	200	**89.69**	**99.78**	2.54	0.17	**5.36**	0.35

Results
Runtime

- Total runtime:
  - Measurement device:

    an Intel(R) Xeon(R) Gold 6354 3.00GHz CPU & an NVIDIA RTX A6000 GPU
  - Cuboid extraction time: 55ms
  - Model inference time:

Model	Mean (SD) [ms]
SE (150 MeV)	9 (1)
SE (175 MeV)	9 (1)
SE (200 MeV)	10 (1)
ME	10 (2)

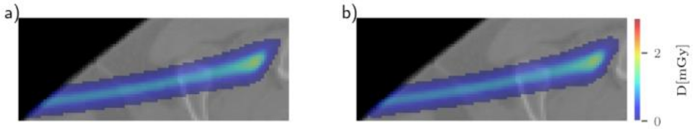
Appendix

Preliminary experiment for an energy range (ER) model

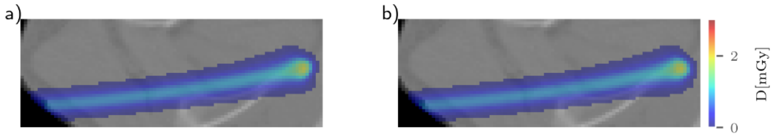
- The previous training/validation dataset for a single energy:
  - 216 beamlets per patient, the energy of each beamlet is fixed (e.g., 150 MeV)
- **A larger training/validation dataset for an energy range** (based on the same patients) **:**
  - 216**×4** beamlets for each patient, the energy of each beamlet is randomly selected from **125-200MeV** (76 integers)
  - Test results of the ER model on previous 150/175/200 MeV test datasets:

		γ_{PR} [%]		ΔR_{D80} [%]		F_{COM} [mm]	
Model	E[MeV]	min	mean	max	mean	max	mean
ME (ER)	150	93.32	99.76	**3.83**	**0.35**	2.73	0.53
	175	92.09	99.68	3.51	0.27	2.04	0.55
	200	**89.89**	**99.54**	3.62	0.28	**3.14**	**0.67**

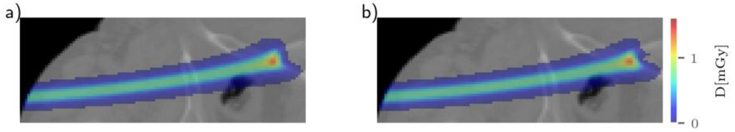
150 MeV



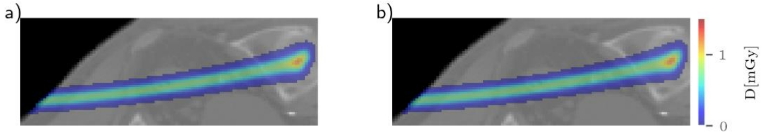
160 MeV



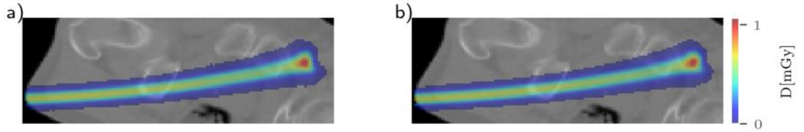
175MeV



185 MeV



200MeV



Conclusion

- We developed an LSTM-based method for proton dose calculation in a magnetic field
- An extended LSTM model for multi-energy dose calculation was proposed and showed its feasibility

Outlook

- Full plan test is ongoing
- Extend more sites and spot sizes
- Introduce uncertainties quantifying method into the model, e.g., Bayesian neural networks

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Gemeinsam. Fürsorglich. Wegweisend.

Thank you for your attention!

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