Up-scaling for measuring the spatial distribution of radiation dose for applications in the preparation of individual patient treatment plans

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Scope and Motivation

Figure 1: The experimental setup at the Linac facility of the Maria Sklodowska-Curie National Research Institute of Oncology, Krakow Branch, with a spatial dose detector phantom placed in the beam path. The phantom, featuring a 1 cm³ active volume for measuring radiation dose distribution, is also modeled for Monte Carlo (MC) simulation [1].

Developing a system to monitor real-time 3D dose deposition can improve the safety and efficiency of radiotherapy treatments. This advancement could possibly enable hospitals to treat more patients effectively while potentially reducing the side effects associated with radiation therapy. To achieve this, our team Dose3D-Future (D3D-F) has created a scalable detection system for assessing dose distributions in a reconfigurable 3D phantom used in photon radiotherapy treatment planning [1]. A key project objective is to ensure compliance with medical standards, particularly regarding Digital Imaging and Communications in Medicine (DICOM) format and accuracy. Currently, our detector has a resolution of 1 cm³, determined by the size of the cubic units in the phantom (depicted in Fig. 1). By utilizing Machine Learning (ML) techniques, we aim to enhance the dose measurement resolution to 1 mm³.

The high-level software stack was developed to ensure compatibility with existing market software. Figure 2 illustrates the D3DF system within the Treatment Planning System (TPS) procedure and outlines future detector validation. The system's integration with TPS is facilitated by the use of the DICOM data format. An in-house Geant4 Radiotherapy (G4RT) simulation platform, based on the Geant4 Software Toolkit, is being developed. This tool has been validated against simulations from widely used software, such as PRIMO, and through actual measurements using a water phantom.

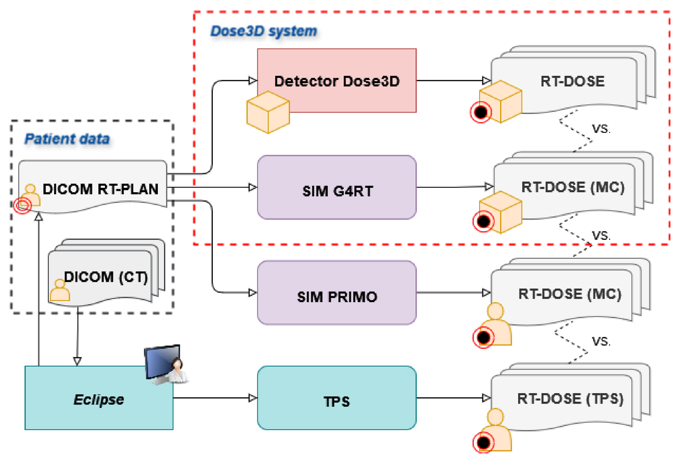


Figure 2: The D3DF system within the tele-radiotherapy treatment procedure data flow, ultimately generated RT-Dose for the patient plan, can subsequently be used for further analysis.

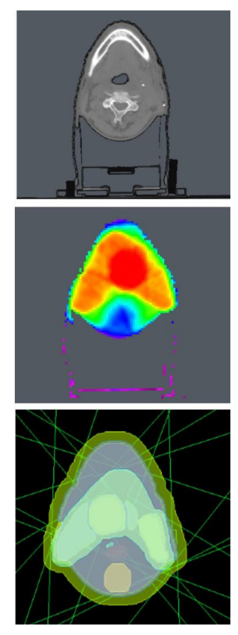


Figure 3: The successive steps in the radiotherapy imaging chain use of DICOM formats like CT, RT-Dose, and RT-Struct.

In both medical imaging and radiation therapy, precise spatial resolution is crucial for delivering effective treatment while ensuring patient safety.

Medical images, such as CT scans and radiation therapy dose data (RT-Dose), are stored in the standardized DICOM format. Additionally, anatomical structures, including the tumor, are defined in RT-Struct files, which provide essential segmentation data for treatment planning (Fig.3). While the CT image resolution:

- Axial Plane (slice thickness): Typically around 2 mm,
- In-plane resolution (pixel/voxel size): About 1 mm x 1 mm,

the resolution of RT-Dose Data:

- Voxel size for RT-Dose data: Commonly ~2.5 mm per side.

When dose calculations are performed at relatively coarse resolutions, several techniques can enhance the precision of dose distribution, including interpolation, resampling, subdivision, and advanced dose calculation algorithms. These refinements are crucial because RT-Struct data is used alongside RT-Dose data to compute key metrics like the Dose Volume Histogram (DVH), an essential tool for evaluating dose distribution across different tissues and volumes.

Improving imaging and dose resolution directly affects the accuracy of dose delivery to the Gross Tumor Volume, which represents the tumor as seen in imaging studies. Precise targeting of this volume, along with careful consideration of other patient volumes, is essential for effective and personalized treatment planning.

Dose 3D Super Resolution Pipeline

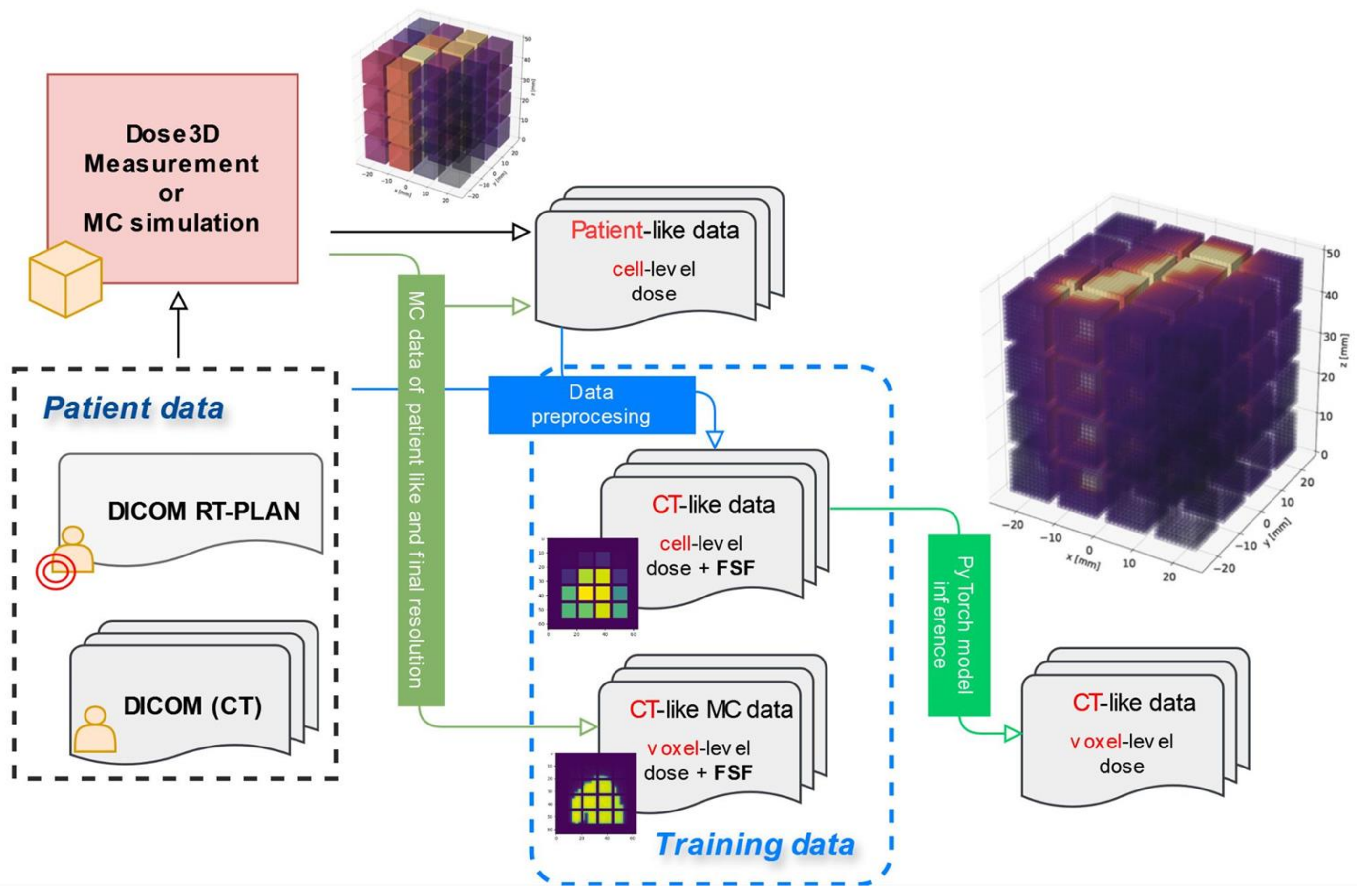


Figure 4: The patient data, including CT scans and the RT-Plan, is used both for real-data acquisition setup and Monte Carlo (MC) simulations. Additionally, this data is used as input for preprocessing measured cell-level data, preparing it for the final up-scaling inference (here en extra Field Scaling Factor is being calculate for each voxel, see Beam Aided Learning section). Independently, the MC-produced cell-level and voxel-level data serve as a comprehensive set of physics **input** and **target** information for model training.

Training Dataset

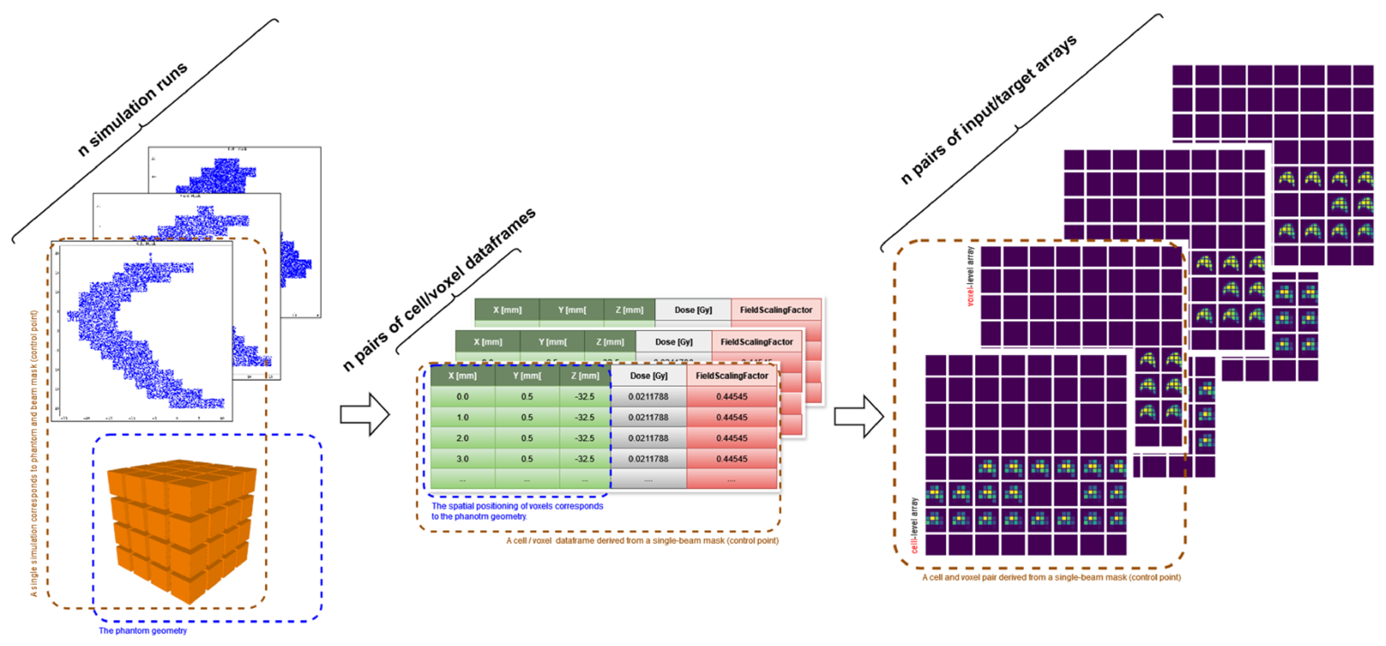


Figure 5: The information regarding geometry from the detector, along with dose values and the configuration of MLC leaves (i.e. the beam mask) are combined and then saved in the form of a Data Frame in CSV format. The final step involves transforming the data from the table-like into a 3D arrays (a stack of 2D slices).

By adjusting the parameters of the photon therapeutic beam, a variety of dose distribution patterns can be generated in Monte Carlo simulations. Ensuring a varied dataset is crucial for Machine Learning since it helps models to generalize better and reduces the risk of overfitting. Data from simulations are stored in the form of Data Frames with columns: *X, Y, Z* defining the point of voxel's location in 3D space, *Dose [Gy]* standing for dose distribution per voxel and *FieldScalingFactor*, which is a scaling parameter . During the data preprocessing, the final observable is calculated, transformed into 3D arrays and therefore prepared to be passed to the Machine Learning model. The dataset of 80 input-target pairs was splitted into training, validation and test sub-datasets in proportions of 6:3:1.

Treatment plan - Beam Aided Learning - GPR Figure of Merit

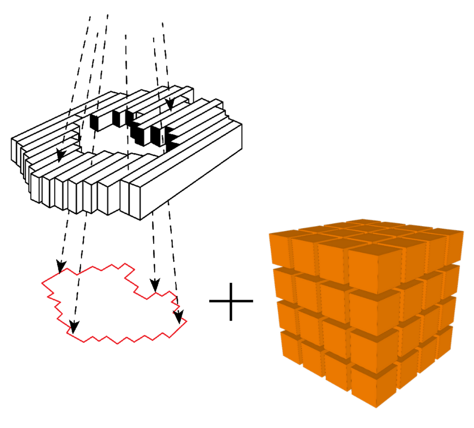
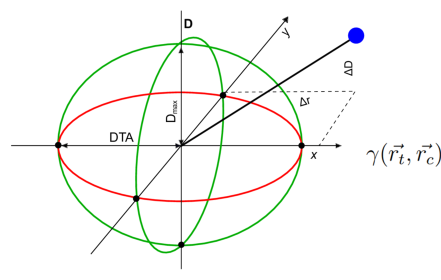


Figure 6: The Field Scaling Factor (FSF) is calculated for each voxel, utilizing information from the RT-Plan, which contains the positioning of each leaf of the Multi-Leaf Collimator (MLC) to shape the beam for the current control point. By referencing the voxel position against the positions of all MLC leaves, the FSF allows for an intricate connection between the beam's influence and the resulting dose spatial distribution within the patient.

Entanglement of the treatment plan with the physical dose distribution in the patient

- **Control Point (RT-Plan):** In an RT-plan, control points provide detailed information for each step in a radiation treatment delivery sequence. Each control point specifies the amount of dose to be delivered to the patient, along with other parameters. The realization of the control point configuration is achieved through the precise positioning of the Multi-Leaf Collimator (MLC), which shapes the radiation beam during delivery.
- **Field Scaling Factor (FSF):** The FSF is a parameter used to link the beam mask at a specific control point to the patient's voxelization. Each voxel in the patient's body is assigned an FSF value, which enables the model to accurately follow the treatment plan information during inference for super-resolution calculations.



$$\gamma(\vec{r_t},\vec{r_c}) = \sqrt{\frac{|\vec{r_t},\vec{r_c}|^2}{DTA^2}+\frac{|D(\vec{r_c})-D(\vec{r_t}))|^2}{D^2_{max}}}$$

Figure 7: The gamma index assess the agreement between a measured dose distribution and a planned (reference) dose distribution [3]. It evaluates both the dose difference and spatial accuracy by combining two criteria:

- Dose Difference: the relative difference in dose between the measured and planned distributions at a specific point, typically expressed as a percentage.
- Distance to Agreement (DTA): Evaluation how closely the spatial positions of corresponding dose points match between the two distributions, usually defined in terms of a distance (e.g., in millimeters).

Gamma index Passing Rate (GPR)

- The **Gamma Index** is a metric used in radiation therapy to compare the delivered dose distribution with the planned dose. See Figure 6
- In our case: model results vs. simulation for spatial dose distribution at voxel-level.
- **The Gamma Index Passing Rate** is the percentage of points in a dose distribution that meet the predefined gamma index criteria: **X% / Y mm**:
  - X % represents the percentage dose difference allowed between the calculated and measured doses at corresponding points.
  - Y mm indicates the maximum distance-to-agreement (DTA) allowed between the calculated and measured positions.
- GPR of 95% or higher is often considered acceptable with a 3%/2 mm.

Machine Learning Model

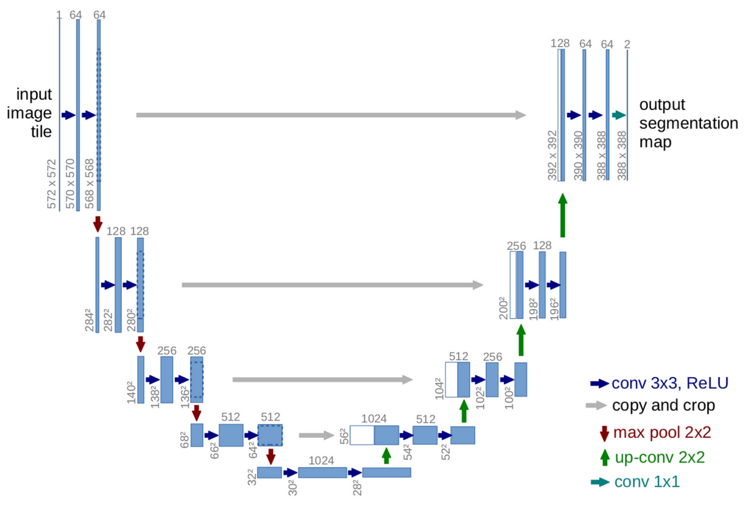


Figure 8: U-Net [2] is an encoder-decoder architecture.

A 3D U-Net neural network was utilized for 3D dose Super Resolution. U-Net [2] is an encoder-decoder architecture commonly used for image segmentation, capturing multi-scale contextual information. The 3D adaptation of this model (Unet3D) was implemented in PyTorch and trained with Mean Squared Error (MSE) as the loss function.

Peak Signal-to-Noise Ratio (PSNR) was used as the evaluation metric, which measures image reconstruction quality by comparing the maximum possible signal to the noise. PSNR is particularly suitable for this task as it quantifies the accuracy of values at the voxel level. PSNR is defined via the maximum pixel value (denoted as L) and the mean squared error (MSE) between images. Given the ground truth image I with N pixels and the reconstruction Î, the PSNR between I and are defined as follows [4]:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{L^2}{\frac{1}{N}\sum_{i=1}^{N}(I(i)-\hat{I}(i))^2}\right)$$

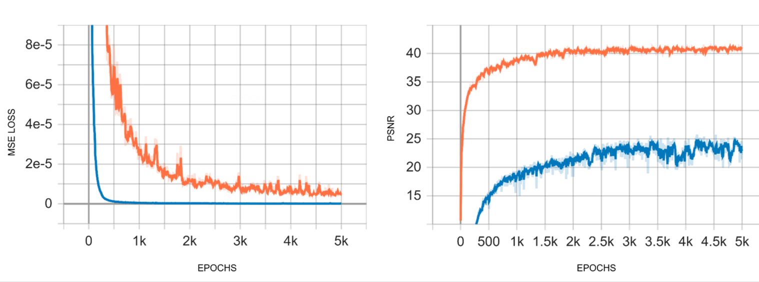


Figure 9: The plot presents loss MSE (left one) and PSNR (right one) versus training epochs. The blue line represents training on raw dose values whereas orange line shows training using the Field Scaling Factor (FSF). The orange line consistently reaches higher PSNR values, demonstrating a clear improvement in super resolution quality and indicating that FSF is a crucial achievement in our research.

Results on Test Dataset

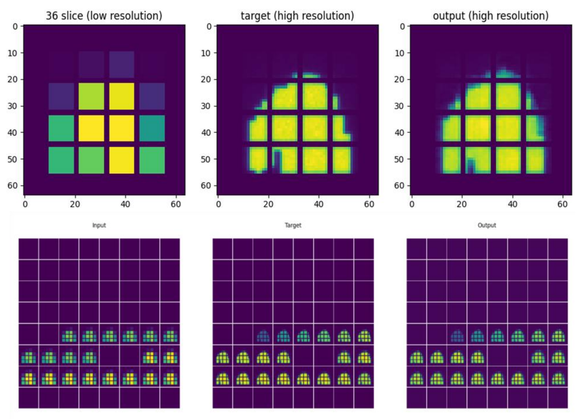


Figure 10: The results on test data are presented, both for a single slice (upper) and for the all slices (bottom). From left to right: input, target, and model output.

The final evaluation of the model is performed by converting the predicted values back to dose units, followed by normalization within each cell, and the gamma passing rate is calculated.
A promising 79% is achieved so far.

Gamma Index Passing Rate 3%/3 mm: 79 %

Summary and prospects

- The Dose3D-F detector system has been designed and is currently being utilized in test-beam campaigns.
- A Monte Carlo simulation platform is being developed as a digital twin of Dose3D-F.
- Machine learning algorithms are being created to enhance the resolution of future measurement data to match CT resolution.
- Comparing the results of model training on raw dose vs. on FSF data showed that preprocessing using this transformation is a crucial achievement in our research.
- The use of a basic ML model leaves considerable room for further experimentation and potential improvement of the results.
- The current size of the training dataset will also be increased and enriched with more variations in patient geometry and mask field shapes.
- Standard gamma analyses of 3%/3 mm were conducted on the spatial dose distributions predicted by the Unet3D model and the simulated samples in the test dataset, yielding promising gamma pass rates.
- Preliminary results highlight the significant potential of deep learning methods for upscaling the dose delivered to Dose3D-like phantoms in radiotherapy treatments.

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