

# Geant4 Simulation of Y-90 Imaging: A Deep Learning Framework for 3D Image Enhancement

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**Abstract**—Accurate 3D imaging of radiopharmaceutical distribution is critical for personalized dosimetry and monitoring of malignant tumor characteristics. This study presents a comprehensive pipeline for simulating and reconstructing Yttrium-90 (Y-90) emissions using a one-stage Compton camera comprised of four crystal modules. We developed a Geant4-based Monte Carlo simulation of an isotropically distributed Y-90 source within a synthesized regular tumor, separated from the detector by an air gap. To emulate a tomographic scan, the simulated camera swept in a circular path, capturing the positions and energy depositions of gamma photons from 60 distinct orientations around both the X and Z axes of the centrally placed tumor. These readings were then reconstructed into 3D images using a kernel weighted back projection (KWBP) method. Because this physics-based reconstruction is limited by noise, blurring, and artifacts due to angular sampling restrictions, we developed an advanced 3D U-Net to denoise the reconstructed volumes. The model was trained using a hybrid loss function that combines mean squared error (MSE) and the structural similarity index measure (SSIM) to ensure both pixel-level accuracy and structural fidelity. We evaluated multiple network configurations, ultimately optimizing performance by integrating a dynamic learning rate, an additional residual U-Net block, and online data augmentation during training. Evaluated on a withheld test set, our best-performing configuration effectively mitigated reconstruction noise and arti-

facts, achieving a hybrid loss of 0.02730, an MSE of 0.00663, and an SSIM of 0.89002. These findings demonstrate that our two-step pipeline, combining physics-based KWBP reconstruction with optimized, data-driven 3D denoising, is an effective method for refining Compton camera images for clinical dosimetry and tumor monitoring applications.

**Index Terms**—Prompt-Gamma Imaging, Convolutional Neural Networks, 3D Image Reconstruction, Geant4 Simulation

## I. INTRODUCTION

Radiopharmaceutical therapy makes use of radioactive isotopes to kill malignant cells by delivering targeted radiation and trying to minimize damage to healthy tissues [1]–[3]. As an emerging technology for cancer treatment, this therapy has demonstrated its efficiency and is widely used for the treatment of neuroendocrine tumors, prostate cancer, and other malignancies [1], [3]–[5]. However, the precision of dosimetry, which is becoming more and more important due to the growing demand for patient-specific organ dosimetry, has become a challenge to optimize and alleviate adverse effects [1].

At present, single-photon emission computed tomography (SPECT) and positron emission tomography (PET) scanners are used in dosimetry protocols to retrieve the distribution of

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radiopharmaceuticals such as Yttrium-90 (Y-90) and Gallium-67 (Ga-67). This approach requires access to expensive scanners and is complex and tedious because the patient must repeat several imaging sessions over several days. As a result of the laborious requirements, this precise personalized dosimetry protocol has limited adoption in a clinical setting [1], [6], [7].

To improve the accuracy of dosimetry, a compact and economical imaging system has been developed by M3D, Inc. [8]. When placed beside the patient, it can capture the distribution of radiopharmaceuticals in real time. The system retrieves multiple 2D images from different angles and then reconstructs them into a 3D tracer uptake representation in the body. The reconstructed representation often lacks accuracy and contains noise and artifacts [1]. To address this problem, we take advantage of the power of the Deep Learning model to enhance reconstructed radiopharmaceutical images to improve dosimetry in radiopharmaceutical therapy. Y-90 imaging simulations were deployed in Geant4, and the Compton camera used in our simulation has a single-stage configuration consisting of only four crystal modules. We implemented Kernel Weighted Back Projection (KWBP) to reconstruct 3D images from detected events and converted a 2D U-Net to a 3D U-Net to train a specialized 3D deep learning neural network to eliminate back-projection noise and false coincidence artifacts [1], [8]. We also tested several modifications to this model to achieve the best performance.

A Geant4 model of the Polaris-J CC (H3D Inc., Ann Arbor, MI) with 4 crystals is used for prompt gamma imaging. Images from different camera positions were reconstructed and then denoised using a deep learning model. In our work, Monte Carlo simulation methods were adapted to model the imaging system, place a radiotracer source within a patient phantom, and reconstruct images to be applied to dosimetry analysis [1]. This work is adapted from an existing convolutional neural network to apply it to 3D data. The main components of this work include:

- A Geant4-based simulation model for a Compton camera system: We utilized Monte Carlo simulation to develop a simulation of a two-stage Compton camera and a radiopharmaceutical source. The simulation model we developed simulates gamma emissions from a Y-90 source, models their interactions with the proposed camera design (including scatter and absorber detector stages), and records the resulting energy deposition events [1].
- Application of 3D image reconstruction algorithms: We applied and evaluated the 3D image reconstruction algorithms (SBP, KWBP) to reconstruct the 3D source images of the gamma emissions [8], [9]. We also compared the reconstructed images with the ground truth images to assess their quality and accuracy [1].
- 3D U-Net-based image enhancement: We transformed the 2D U-Net to a 3D U-Net to reduce noise and artifacts in the reconstructed images. We also evaluated the reconstructed images against Monte Carlo ground truth to ensure improvements in accuracy for dosimetry analysis.

- Modifications to 3D U-Net: To exploit the power of the Deep Learning model, we implemented several modifications to our 3D U-Net and tested their effects on the accuracy of the output. Our modifications include a dynamic learning rate and online data augmentation. After comparison and evaluation, we only retained the modifications that helped the model produce better results.
- Framework for future experimental validation: We refined the pipeline of simulation and reconstruction with 3D U-Net, laying the basis to transition from simulation studies to experimental data collection in the future [10].

The rest of the paper is organized as follows. Section II provides background for Compton cameras, simulated data, and model inputs. Section III discusses related work. Section IV explains our methodology, including the Geant4 toolkit for data generation, the U-Net structure and how we trained it, and modifications to our model. Section V contains our results. Finally, Section VI presents our conclusions.

The code of this work is publicly available in a GitHub repository

## II. APPLICATION BACKGROUND

### A. Proton Beam Radiotherapy

Radiopharmaceutical imaging allows specific targeting and identification of tumors and malignant masses within biological tissue, improving patient care in oncology when systems are tuned to accurately identify and assess these tumors.

### B. Compton Cameras

In contrast to other imaging tools, Compton cameras are radiopharmaceutical devices that image tissue by emitting gamma rays and detecting the scattered photon particles as they are absorbed by a detector [11]. The Compton camera imaging process is best understood as two distinct stages in which a scatter detector measures the location and energy of the initial Compton scattering event by a front detector and then the absorber detector measures the same process when the proton hits this detector in the rear. Together, these events reveal a scattering angle ( $\theta$ ), providing us with a range of possible incident gamma-ray directions represented by the surface of a cone called the Compton cone. Compton cameras have incredible sensitivity to detecting emitted photons, resulting in higher detection efficiency and a potential higher spatial resolution than other gamma cameras, and offering to improve diagnostic accuracy for patients that undergo this imaging [12].

### C. Demand for Simulated Data

Images generated from this data are incredibly useful for clinicians to develop a treatment plan with patient-specific dosimetry for those in immediate need of this care, but specifying and developing a quantitative treatment plan for each patient can become exponentially more resource intensive as exclusive targeting of the malignant tissue increases in priority [1]. Standard dosimetry protocols are financially and temporally taxing for both patient and healthcare provider, and

there is a salient need for alternative techniques. 2D images of the area of interest can be acquired from a variety of angles and used to reconstruct a 3D image of radiotracer uptake, but these 2D images lack the resolution and clarity of 3D images. Machine learning techniques offer the capability to bridge this gap if an accurate and reliable model can be created, and this project seeks to do so by providing quantitative data that supports the validity and reliability of our model in reconstructing 3D Compton camera image data [13].

#### D. Model Inputs

In order to train and test a model for 3D image reconstruction, simulated detector data serves as the most functional dataset in this case where in-vivo medical imaging with human subjects is resource intensive and limited in capability to provide verifiable ground-truth images for validation of the model. The Geant4 C++ toolkit allows for the generation of such data on a large scale that can then be fed into training a machine learning model for 3D image reconstruction and prediction [14]. A convolutional neural network (U-Net) provides the means for suppression of noise and removal of image artifacts and can be adapted for 3D image reconstruction when trained on the Geant4 data in this case [15].

### III. RELATED WORK

Compton Cameras (CCs) have been extensively studied as an alternative to mainstream medical imaging devices. A two stage compact semiconductor CC was developed by Hirasawa et al. [16], which demonstrated its efficiency and advantage over collimated systems. The Polaris-series CC design has been applied to prompt-gamma imaging for proton therapy range verification, most notably by Panthi et al. [8], whose Geant4 model of Polaris-J CC forms the basis for the detector geometry adapted in this and related work. Wu et al. [12] proposed GPU accelerated 3D reconstruction method for CC-based radioisotope imaging, underscoring the computational demands of iterative cone-based reconstructions, while Kim and Lee [17] provide a broad review of CC image reconstruction techniques, including recent AI-driven approaches. Despite this body of work, the application of CCs remain comparatively unexplored in the realm of radiopharmaceutical therapy dose distributions.

This study draws on the work of Shakeri et al. [1], who developed Geant4-based Monte Carlo simulation of a two-stage POLARIS-J-style CC imaging a Tc-99m source and evaluated a simple back projection (SBP) against a kernel weighted back-projection (KWBP) algorithm for 3D construction. To address the noise and angular-sampling artifacts inherent to both methods, they trained RED-CNN and U-Net models as a post construction denoising stage finding that the U-Net trained with a hybrid MSE/SSIM loss outperformed RED-CNN in both quantitative metrics (MSE, PSNR) and qualitative preservation of source shape. Particularly they denoising step operated on a 2-D cross-sectional slices extracted from which reconstructed volume rather than volume itself. This

was a limitation that the authors attribute to difficulty of training a 3D network on their available dataset size, which was a priority direction for future work. The present study builds directly on this foundation, extending the reconstruction-plus-denoising pipeline of Shakeri et al. from single-slice 2D denoising to full volumetric 3D processing, applying a 3D U-Net directly to reconstructed voxel grid, rather than to extracted 2D cross-sections.

### IV. METHODOLOGY

#### A. Data Generation

Due to the difficulty of obtaining experimental data of a radioactive source in the tissue and the ethical considerations of obtaining this data using treatment methods that are still in development, our data is primarily composed of simulated data. For our data, we simulate both a 3-dimensional representation of a radioactive source as well as the Compton camera readings of the source.

For this simulation, we use the Geant4 toolkit, a platform for the simulation of particle movements through matter using Monte Carlo methods. We define an isotropic Yttrium-90 (Y-90) source in the shape of either a sphere with a radius which is a random value between 5 mm and 31.5 mm or an ellipsoid where all semi-axes have random lengths between 4 mm and 30 mm. Our image space is 64 mm x 64 mm x 64 mm, represented as a 3-dimensional array with a width, height, and depth of 64. The Y-90 source emits 100 million 140.5 keV gamma photons per orientation of the Compton camera. We simulate Compton camera readings at twelve positions 30 cm away from the Y-90 source, in 30 degree increments rotating around an axis. Using this method, we gathered data for sixty-seven cases rotating around the X-axis and the Z-axis of the Y-90 source. We also introduce more noise into the dataset by running the simulation with four different random seeds for each axial rotation. Finally, the data for all four seeds for each case is averaged together, and we take the average of the data for the X-axis rotation and the Z-axis rotation for each case to complete our final dataset. Our full pipeline for data generation and model application can be found in Figure 1.

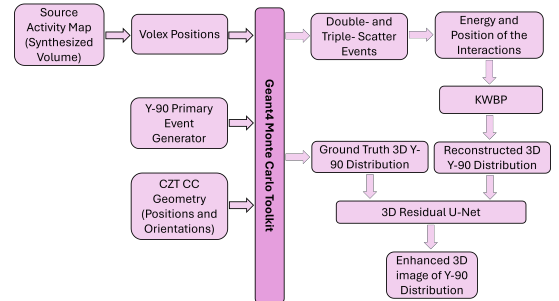


Fig. 1: Data Generation and Prediction Pipeline

## B. U-Net

For the task of denoising the data read by the Compton camera, we trained a Convolutional Neural Network (CNN) for 3D image denoising on our simulated dataset. We used the U-Net architecture for our model. The U-Net provided several advantages over a standard CNN. The U-Net more accurately preserved sharp edges and boundaries within images, and performed better on smaller datasets, working well with our more scarce data.

Our model is made up of four downsampling levels containing two repetitions of a  $3 \times 3 \times 3$  convolutional layer with BatchNorm and ReLU activation layers, a bottleneck block, and four upsampling levels, both with the same structure as the downsampling convolutional blocks. There is a final convolutional layer which produces the final denoised image. This image is passed through a Sigmoid activation function before it is outputted. Our U-Net architecture is shown in Figure 2.

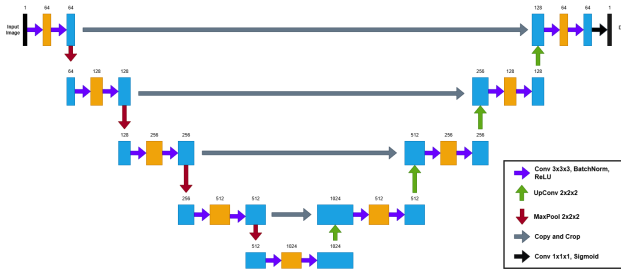


Fig. 2: Our U-Net Architecture

We trained it using 80% of our simulated data and used the remaining 20% for validation. Our loss function is a hybrid of Structural Similarity loss (SSIM) and Mean Squared Error loss (MSE). We weighted SSIM as 0.2 of our total loss and MSE as 0.8 of our total loss. In this way, MSE would ensure overall quality and conformity of the model's denoised images to the ground truth images, but SSIM would also improve the model's accuracy in determining boundaries and borders in the radiation sources. For our optimization function, we used the Adaptive Moment Estimation optimizer (Adam).

## C. Modifications

We ran many experiments testing different configurations of settings and parameters for the model.

First, we implemented a dynamic learning rate to combat overfitting on our limited dataset. Our implementation measured the validation loss each epoch and kept track of improvement. On fifteen epochs without improvement, the algorithm halved the learning rate of the model.

Next, we implemented online data augmentation to improve the variation in our dataset and artificially increase the effectiveness of our limited data. Every epoch, we applied random transformations to the image data, including random flipping along each axis, adding Gaussian noise, and Gaussian blur, and random scaling of intensity.

## V. RESULTS

For each of our model configurations, we recorded loss values on a held-out test set and also recorded case-specific metrics for two cases of our data generation, case 18 and case 50. The loss values we recorded were Mean Squared Error loss (MSE), Structural Similarity Measure (SSIM), and our hybrid MSE/SSIM loss. For our case-specific results, we generated visualizations of the middle XY slice, XZ slice, and YZ slice for the ground truth data, the reconstructed image data after the simulation, and our model's de-noised output. We also generated 3D visualizations of the ground truth, reconstructed data, and the model's de-noised output image to compare them visually. The metrics we recorded for our case-specific results were SSIM, Peak Signal-to-Noise Ratio (PSNR), and Normalized Root Mean Squared Error (NRMSE). For each metric, we recorded both a masked value and a global value. The global value used the entire image in its calculation, while the masked value only used the parts of the image that included the 3D shape, leaving out the empty space in its calculation.

### A. Baseline Model Results

Our baseline model with no additional modifications or settings achieved a hybrid loss of 0.037328, an MSE loss of 0.011108, and an SSIM of 0.857791. The results for case 18 are shown in Figure 3, and the results for Case 50 are shown in Figure 4. The 2D slices for case 18 are shown in Figure 5, and the 2D slices for case 50 are shown in Figure 6.

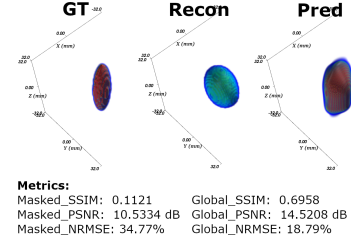


Fig. 3: Baseline Results for Case 18

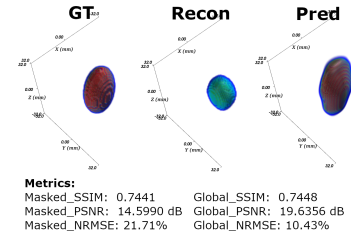


Fig. 4: Baseline Results for Case 50

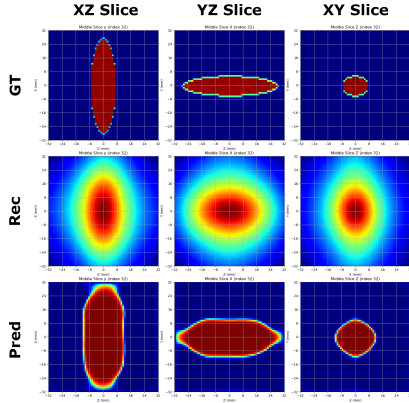


Fig. 5: 2D Slices for Case 18

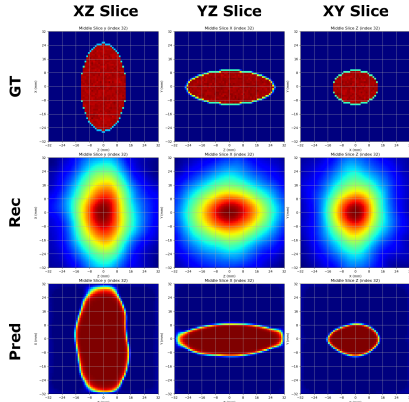


Fig. 6: 2D Slices for Case 50

### B. Dynamic Learning Rate

Next, we implemented a dynamic learning rate. Our model began with a learning rate of 0.001; then, if the validation loss did not improve for a set number of epochs determined by a patience value, the learning rate would be halved. The patience value we used was 15 epochs. This configuration achieved a hybrid loss of 0.036018, an MSE loss of 0.009679, and an SSIM of 0.858626. The results for case 18 are shown in Figure 7, and the results for Case 50 are shown in Figure 8. The 2D slices for case 18 are shown in Figure 9, and the 2D slices for case 50 are shown in Figure 10. This model showed a small improvement over baseline performance.

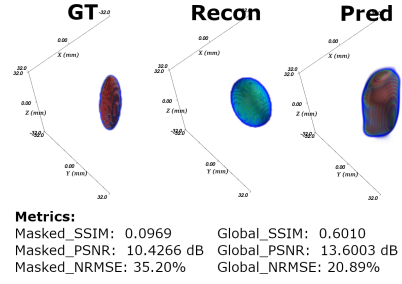


Fig. 7: Results for Case 18 for a Dynamic Learning Rate

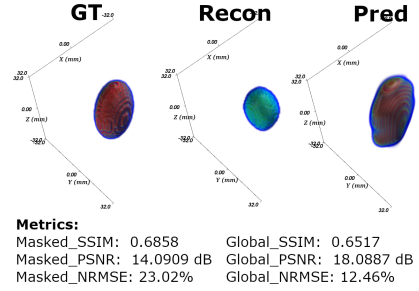


Fig. 8: Results for Case 50 for a Dynamic Learning Rate

### C. Residual Block + Data Augmentation

Combining the residual block with online data augmentation produced mixed results across our two test cases. On Case 18, the model correctly captured the overall elongated shape of the source, but the boundary extended somewhat beyond the true extent along one axis, which is reflected in a relatively modest Masked SSIM of 0.2208 and shown in Figures 11 and 12. Case 50 performed noticeably better under this configuration, with a Masked SSIM of 0.6729, and the predicted boundaries aligned more closely with ground truth across all three orthogonal views as seen in Figures 13 and 14. As with our other configurations, the gap between Masked and Global SSIM values remained large, showing that most of the reconstruction volume is easy background that any model can get right.

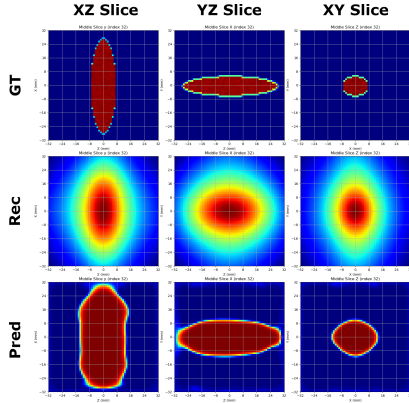


Fig. 9: 2D Slices for Case 18 for a Dynamic Learning Rate

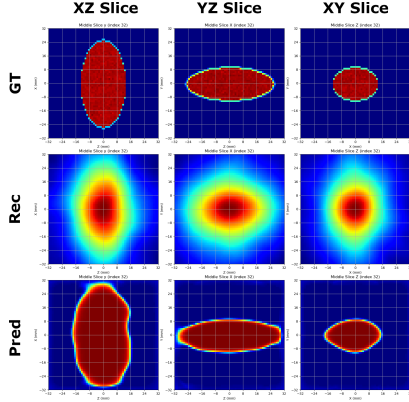


Fig. 10: 2D Slices for Case 50 for a Dynamic Learning Rate

#### D. Online Data Augmentation

Due to our limited dataset, we implemented online data augmentation. For this, the model would apply random transformations to the data as it is passed into the model during the training loop. We applied a random flip, intensity scaling, Gaussian noise, and Gaussian blur. The data augmentation greatly improved our model's performance, with our best configuration achieving a hybrid loss of 0.0273, an MSE loss of 0.00663, and an SSIM of 0.890. Our results are in Table I. Visualizations for specific cases can be found in Figures 15–18.

TABLE I: Results with Online Data Augmentation

| Model Configuration | Hybrid Loss | MSE Loss | SSIM     |
|---------------------|-------------|----------|----------|
| Baseline            | 0.036377    | 0.009822 | 0.857402 |
| Dynamic LR          | 0.027300    | 0.006631 | 0.890023 |
| Residual Block      | 0.033251    | 0.008252 | 0.866753 |

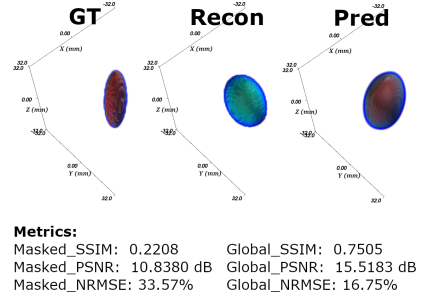


Fig. 11: Results for Case 18 for a Residual Block with Online Data Augmentation

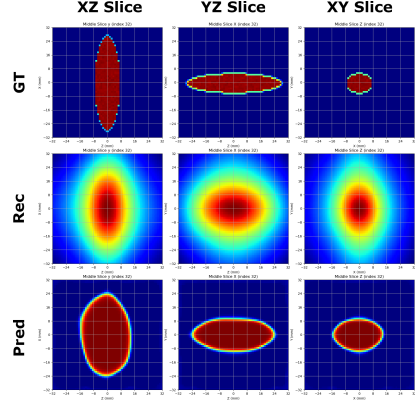


Fig. 12: 2D Slices for Case 18 for a Residual Block with Online Data Augmentation

#### E. Hyperparameter Study

In order to optimize for the best parameters among learning rate, patience value, and inclusion of the residual block, a hyperparameter test was established to identify the values of these variables that produced the lowest loss values across the hybrid, MSE, and SSIM loss categories.

Tables II and III detail the best parameters and the loss values across the board for those parameters, respectively. SSIM/MSE weights were most effective for all permutations of dynamic learning rate and residual block combinations at 0.2/0.8. The best patience value was 15 epochs for dynamic learning rate alone and 30 epochs for dynamic learning rate and residual block together. The dynamic learning rate alone produced the best hybrid loss value at 0.027490 and the best MSE loss value at 0.006283, while the dynamic learning rate and residual block in tandem yielded the best SSIM loss value of 0.867055.

TABLE II: Best Hyperparameter Setting Per Model Configuration

| Model Configuration         | Base LR | SSIM/MSE Weights | Patience |
|-----------------------------|---------|------------------|----------|
| Dynamic LR Alone            | 0.01    | 0.2 / 0.8        | 15       |
| Residual Block Alone        | 0.001   | 0.2 / 0.8        | N/A      |
| Dynamic LR + Residual Block | 0.001   | 0.2 / 0.8        | 30       |

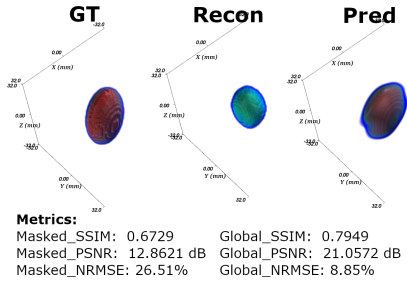


Fig. 13: Results for Case 50 for a Residual Block with Online Data Augmentation

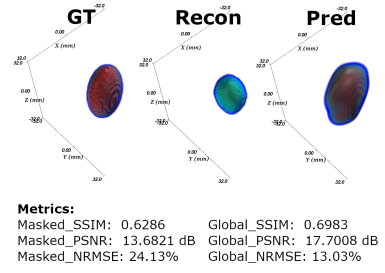


Fig. 16: Results for Case 50 for a Dynamic Learning Rate with Online Data Augmentation

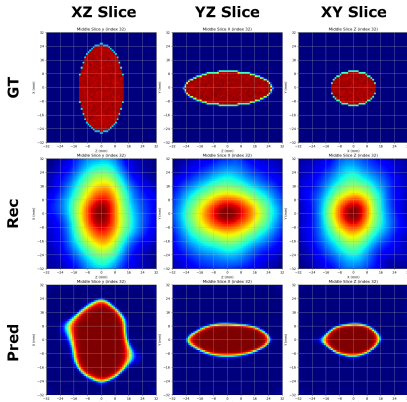


Fig. 14: 2D Slices for Case 50 for a Residual Block with Online Data Augmentation

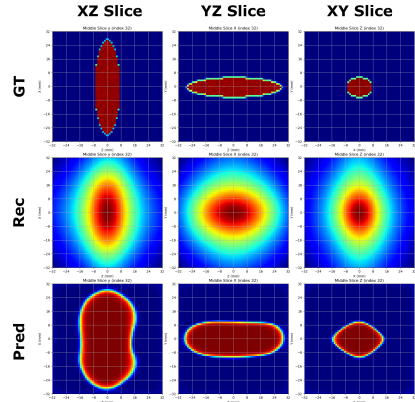


Fig. 17: 2D Slices for Case 18 for a Dynamic Learning Rate with Online Data Augmentation

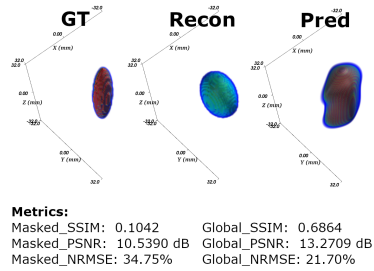


Fig. 15: Results for Case 18 for a Dynamic Learning Rate with Online Data Augmentation

TABLE III: Hyperparameter Study Results

| Model Configuration  | Hybrid Loss | MSE Loss | SSIM     |
|----------------------|-------------|----------|----------|
| Dynamic LR Alone     | 0.027490    | 0.006283 | 0.887681 |
| Residual Block Alone | 0.030970    | 0.008069 | 0.877424 |
| Dynamic LR + RB      | 0.034148    | 0.009449 | 0.867055 |

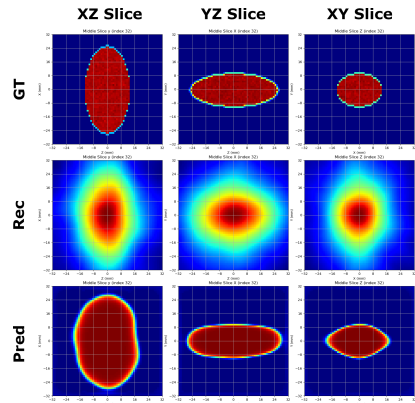


Fig. 18: 2D Slices for Case 50 for a Dynamic Learning Rate with Online Data Augmentation

## VI. CONCLUSIONS

In conclusion, a two-step pipeline of physics-based Kernel-Weighted Back Projection reconstruction and data-driven 3D denoising is an effective method of refining Compton Camera images for clinical dosimetry.

Our experiments showed that a 3D U-Net architecture is a useful method of denoising Compton Camera image data. The use of a hybrid loss function in training, comprising the weighted sum of Mean Squared Error loss and Structural Similarity Metric, was effective in improving the model's accuracy in preserving the shapes and edges of images during denoising. Additional experiments showed that the incorporation of a dynamic learning rate based on validation loss during training, an additional residual U-Net block, and online data augmentation within the training loop significantly improved the performance of the U-Net for the denoising task.

Future steps to improve the model pipeline for application in clinical dosimetry tasks include modifying the simulated training data to improve accuracy. The simple tumor sphere could be replaced by more advanced and accurate patient-specific CT anatomy, which would help to test the pipeline for more real-world applications.

Finally, while our experiment focused on denoising Compton Camera image data, the proposed methodology is more broadly applicable for other denoising and clinical imaging tasks.

Information on our experiments and results was originally reported on in our technical report [18].

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