

Deep Learning Generation of Attenuation Maps for a CT-less Dual Flat-Panel PET Scanner

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Abstract—Positron Emission Tomography (PET) imaging has seen transformative advancements through the development of long axial field-of-view (LAFOV) systems, enabling higher sensitivity and shorter scan durations. However, widespread adoption remains limited due to the prohibitive costs of cylindrical LAFOV PET scanners. The Walk-Through PET (WT-PET) system, under development at Ghent University by the MEDISIP group, presents a cost-effective alternative with a novel dual flat-panel geometry designed for upright patient imaging. Given that the first prototype of the WT-PET system does not include an integrated CT component, this thesis explores a deep learning-based approach to predict attenuation maps directly from non-attenuation corrected (NAC) PET images to enable CT-less attenuation correction (AC) of PET images. A clinical dataset of 32 high-quality PET/CT scans acquired on a Siemens Biograph Vision Quadra scanner was used for Monte Carlo simulations to model WT-PET acquisitions, and both NAC and CT-based AC PET images were reconstructed to serve as input and reference for evaluation, respectively. Combining a pixel-wise (MSE and MAE) and a perceptual loss function, a 2D U-Net was trained on axial, sagittal and coronal image slices to capture multi-view contextual information, and augment the number of training data. Results showed that the predicted attenuation maps demonstrated sufficient structural consistency to be used for AC, but lacked the anatomical fidelity required for diagnostic or anatomical localization purposes. When applied to PET image reconstruction, these synthetic attenuation maps produced AC images closely matching those obtained using ground truth CT-derived attenuation maps. Quantitative evaluation across four test patients revealed relative SUV differences below 8% for regional volumes-of-interest analysis placed in the liver, lung, and heart. Global voxel-wise comparison, averaged across the entire 3D patient volume (excluding air) yielded a mean absolute relative error of $12.18\% \pm 2.84\%$. These results suggest that the proposed deep learning-based attenuation map prediction from NAC PET data is a viable approach for AC for the WT-PET system.

Index Terms—Positron Emission Tomography, Attenuation Correction, Deep Learning, Image Generation, CT-less PET

I. INTRODUCTION

POSITRON Emission Tomography (PET) has over the past decades become a standard molecular imaging technique with applications in oncology, neurology, and cardiology. Recent advancements in PET instrumentation have led to the development of long axial field-of-view (LAFOV) PET systems with an axial coverage ranging from 70 cm to 195 cm. The increase in axial lengths provide significant sensitivity increases, which can be used to decrease radiotracer dose to patients and allows for shorter scans while achieving similar or higher image quality [1]. However, the high acquisition and maintenance costs of these systems, estimated at 8-12 million euros compared to 2-3 million euros for short AFOV PET-CT scanners, pose significant challenges for widespread adoption in routine nuclear medicine departments [2]. The cost scaling almost linearly with detector length due to expensive detector components, limits their accessibility primarily to research

centers with substantial instrumentation grants. In addition to financial barriers, conventional LAFOV PET systems often face throughput limitations, as significant time is spent on patient positioning and table movement within the scanner, which reduces the number of patients that can be scanned per day.

To address these cost and throughput limitations, the Walk-Through PET (WT-PET) system is currently under development by the MEDISIP group at Ghent University as an innovative, patient-centric approach to LAFOV imaging [2]. The WT-PET introduces a paradigm shift by replacing the traditional cylindrical ring design with two flat panels (71 cm wide and 106 cm high) separated by a 50 cm gap, allowing patients to stand upright rather than lie on a bed. [3]. This design aims to achieve image quality and AFOV comparable to high-cost cylindrical LAFOV systems, while significantly reducing detector costs and enabling faster patient throughput [4].

Accurate PET quantification requires attenuation correction (AC) to compensate for the loss of photon counts due to interactions with tissues in the patient's body. One common and highly effective method for obtaining attenuation information is through CT-based AC, which provides accurate linear attenuation coefficients and facilitates anatomical localization (AL). However, using a CT scan introduces several challenges, including additional radiation exposure and the need for image registration due to potential misalignment caused by patient motion between the PET and CT acquisitions.

For standalone PET scanners, alternative AC methods are commonly used, such as Maximum-Likelihood reconstruction of Attenuation and Activity, the use of external transmission sources, or leveraging intrinsic radiation from the scanner's detectors. These approaches aim to overcome the limitations posed by the lack of integrated CT but often come with trade-offs in complexity, scan time, or accuracy. Due to its open, dual flat-panel geometry designed for upright patient imaging, the WT-PET presents significant challenges for integrating a conventional CT component. Unlike standard PET/CT systems that rely on a rotating CT component, the flat configuration of the WT-PET limits the feasibility of such integration.

As an alternative to CT-based AC, this thesis explores a deep learning-based approach to generate attenuation maps directly from non-attenuation corrected (NAC) PET images. This data-driven approach not only eliminates the need for a CT scan but also ensures inherently coregistered attenuation maps, potentially improving workflow efficiency, reducing radiation dose, and enhancing patient comfort. While deep learning-based generation of attenuation maps from NAC PET has been previously studied [5]–[7], research into its application beyond cylindrical systems is very limited. The central research goal of the thesis is therefore to evaluate

whether deep learning can produce qualitatively accurate attenuation maps from NAC PET data specifically for the WT-PET system. While the generated maps may not provide sufficient anatomical detail for standalone diagnostic imaging or AL, they may hold strong potential for AC in scenarios such as repeat scans, pediatric imaging where minimizing radiation dose is critical, or in cases where the CT component is unavailable or malfunctioning.

II. MATERIALS AND METHODS

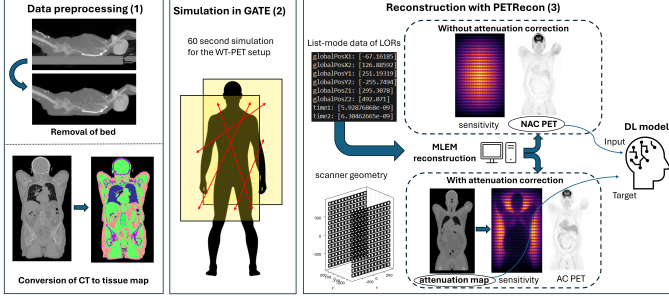


Fig. 1. Schematic of Materials and Methods for (1) PET/CT data preprocessing, (2) data simulation and (3) reconstruction. The NAC PET image and attenuation map serve as the input/target for the deep learning model.

A. Data Generation

The development of deep learning models for attenuation map prediction required the preparation and generation of suitable training/target data, specifically paired images of NAC PET and attenuation maps. As the WT-PET scanner is still under development, no real patient data acquired directly on the WT-PET system were available. To overcome this limitation, a Monte Carlo simulation was employed in GATE [8]. To generate a realistic and diverse database of simulated WT-PET images, a structured approach was developed making use of high-quality PET/CT scans acquired on a state-of-the-art LAFOV PET/CT scanner as phantoms.

1) *Data Collection*: A comprehensive dataset of ^{18}F -FDG PET/CT images was collected, which were acquired on the Siemens Biograph Vision Quadra scanner [9]. The entire dataset consists of 32 patients with diverse demographics and clinical characteristics. The demographic and clinical characteristics of the patient population are summarized in Table I.

TABLE I
DESCRIPTIVE STATISTICS OF THE PET/CT DATASET

Variable	Mean	Std Dev	Min	Max
Weight (Kg)	78.81	21.86	46	121
Injected Dose (MBq)	156.71	45.45	84.0	249.5
Injected Dose per Weight (MBq/kg)	1.99	0.19	1.53	2.47
Scan Duration (sec)	506.67	118.66	360	600
BMI (kg/m ²)	26.71	7.04	16.0	48.3
Age (years)	62.60	15.34	26.3	85.1

Prior to simulation, the acquired PET/CT datasets underwent preprocessing including bed removal, rigid coregistration and conversion of units. As the WT-PET scanner

takes standup scans, scanner beds were removed using custom Python algorithms with threshold-based contour detection to separate patient from bed. To avoid any spatial mismatch between PET and CT data, rigid coregistration was performed using PMOD V4.4 (PMOD Technologies LLC, Zurich, Switzerland).

2) *Simulation of the WT-PET in GATE*: A 60-second WT-PET acquisition was simulated in GATE for each patient. The high quality PET image was used as activity map, and the CT image was converted to a tissue map based on Schneider's stoichiometric conversion [10]. These tissue maps contained the anatomical information (composition and density) needed for the simulation. A new ground truth attenuation map was calculated by assigning GATE derived attenuation values for each tissue type. Each detector panel ($71 \times 106 \text{ cm}^2$) consisted of a 12×14 array of $50 \times 50 \times 16 \text{ mm}^3$ monolithic LYSO detectors with a lateral and depth resolution of 1.14 mm and 2.67 mm, respectively, and a coincidence timing resolution of 300 ps. The energy resolution of the panels was set to 11% FWHM and the detector dead time was set to 370 ns based on LYSO scintillator properties [11] (Figure 2). The simulation output consisted of list-mode data containing the 3D interaction coordinates, timing and interaction information. Postprocessing focused on selecting true coincidence events by filtering for photon pairs with matching source identification and no prior scattering interactions within the patient volume. The data preparation and simulation of the WT-PET scan can be seen in Figure 1.

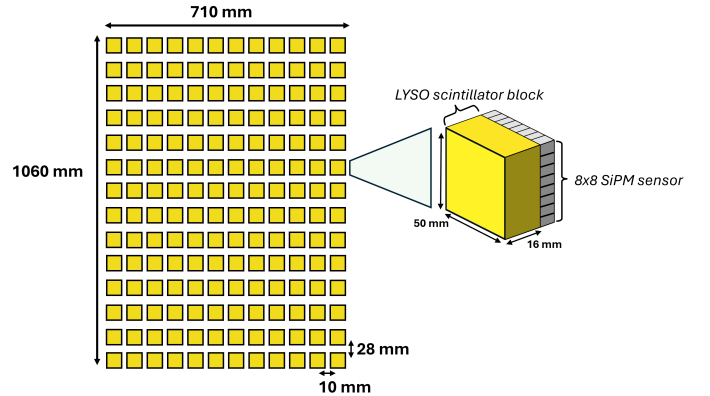


Fig. 2. GATE simulation setup of the WT-PET scanner. The configuration includes two flat-panel detector arrays simulating the upright PET acquisition geometry. The simulation includes accurate modeling of detector dimensions, interaction probabilities, and timing and spatial resolution characteristics.

3) *Reconstruction of PET images*: The simulated list-mode PET data were reconstructed using the in-house PETRecon framework [12], tailored to the flat-panel geometry of the WT-PET system. A time-of-flight MLEM algorithm with 300 ps resolution was used, incorporating patient-specific attenuation and sensitivity maps. Reconstructions were performed for NAC PET images, which serve as the model input. The fifth MLEM iteration was selected for analysis due to its

optimal trade-off between image sharpness and noise. The reconstruction of the NAC PET image is visualized in Figure 1.

B. Generating Synthetic Attenuation Maps

To generate attenuation maps from NAC PET images, a deep learning-based framework was developed. This framework is based on a 2D convolutional U-Net architecture and trained using the simulated PET data described earlier. The thesis work involved data preparation, architecture design, training with both pixel-based and perceptual loss functions, and multi-directional inference to reconstruct full 3D attenuation maps.

1) *Data Preparation and Normalization*: The coregistered PET images and attenuation maps were resampled from a voxel size of (1.52, 1.52, 1.65) mm³ to (3, 3, 3) mm³ to reduce memory consumption during training. The NAC PET images were converted to SUV units to account for variations in body weight and injected dose between patients, while attenuation maps (in cm⁻¹) already had comparable intensity ranges across patients. A bilinear normalization function was applied to the NAC PET images, stretching low-intensity SUV values to enhance contrast in anatomical regions critical for attenuation map prediction. Based on visual inspection and empirical evaluation, an optimal SUV threshold of 0.15 and a stretch factor of 50 were selected.

2) *Model Architecture*: The model is a 2D U-Net implemented in PyTorch [13], with five encoding and decoding layers, skip connections, and a total of 19 convolutional layers comprising 44,133,911 trainable parameters (Figure 3). Each encoder level included two convolutional layers (kernel size of 3 and a stride of 1), followed by batch normalization (BN) and a parametric rectified linear unit (PReLU) activation function. Max-pooling (a stride of 2) was used to reduce spatial dimensions and double the number of feature channels at each level, reaching 1028 channels at the bottleneck. The decoder performed bilinear upsampling, halving the number of feature maps at each stage. Decoder features were concatenated with encoder features via skip connections and processed through convolution-BN-PReLU blocks. A final convolution layer (kernel size of 1) generated the single-channel output slice, representing the predicted attenuation map.

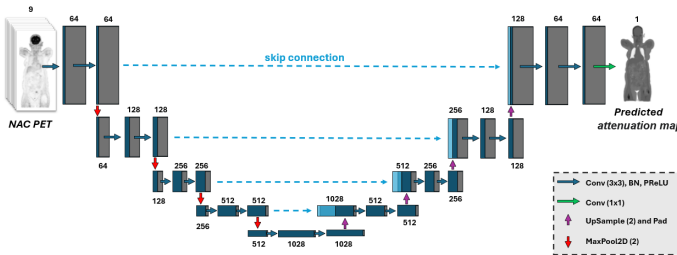


Fig. 3. Schematic of the 2D U-Net architecture used for attenuation map prediction. The network takes as input a stack of 9 consecutive NAC PET slices and predicts the central attenuation map slice. It consists of five encoding and decoding levels with skip connections, convolutional layers, batch normalization, and PReLU activations.

3) *Data Encoding*: Training was performed on 2D slices in all three anatomical orientations: transverse, coronal, and sagittal. From the 32-patient dataset, 24 were used for training, 4 for validation, and 4 for testing. Slices containing only background were excluded, and inputs were cropped to valid anatomical regions, padded to the largest image in the batch, and processed in batches of four. The slice stack for each input was composed of 9 slices (central slice plus 4 on either side). Random horizontal and vertical flips were used for data augmentation. In total, 13,389 2D slices were used for training and validation, split as follows: 7,841 transverse, 3,449 coronal, and 2,099 sagittal slices. Each orientation was cycled through sequentially in every training epoch to ensure uniform exposure across views.

4) *Training Parameters and Loss Strategy*: Training was performed on a NVIDIA Tesla V100 GPU (32 GB VRAM) provided by the Flemish Supercomputing Center. The model was trained using the Adam optimizer with a base learning rate of $1E^{-5}$ and a two-phase loss function strategy:

Phase 1: Pixel-Wise Loss: The model was initially trained using a loss function combining Mean Absolute Error (L_1 -loss) and Mean Squared Error (L_2 -loss) to promote voxel-level accuracy and stable convergence based on pixel-wise differences. Various ratios between L_1/L_2 were tested, with the 50/50 MAE-MSE ratio showing the best qualitative results. The first training phase reached its optimal validation performance after 22 hours and 51 epochs.

Phase 2: Perceptual Loss Fine-Tuning: After convergence with the pixel-wise loss, the model weights were transferred for a second training phase using a perceptual loss function based on a pre-trained VGG16 model [14]. This computed L_1 -loss on the output of intermediate feature layers (layers 3, 8, and 15) between predicted and ground truth attenuation maps. Perceptual loss emphasizes structural and anatomical features rather than pixel-level accuracy. This phase converged after 19 hours and 45 epochs, resulting in a total training time of 41 hours with a total of 96 epochs.

5) *Model Inference and 3D Reconstruction*: Inference was performed on four test patients whose data were excluded from both training and validation. The model, trained using mixed anatomical orientations (coronal, sagittal, and transverse), was applied separately to stacks of 9 consecutive NAC PET slices from each of these directions, producing three distinct 3D attenuation maps. These are referred to as the coronally-, sagittally-, and transversely-inferred predictions, respectively. A fourth attenuation map, denoted as the averaged prediction (μ_{DL} -average), was obtained by performing a voxel-wise average of the three orientation-specific predictions.

C. Evaluation

To evaluate the feasibility of using the predicted attenuation maps for both AL and AC, several metrics were employed to assess their quality. First, we evaluated the structural accuracy

and consistency of the predicted attenuation maps using the Structural Similarity Index Measure (SSIM) and normalized Root Mean Square Error (nRMSE), comparing them against the ground truth CT-derived attenuation maps. In addition, difference images, line profiles, and summed attenuation profiles were analyzed. Next, a subsequent evaluation of the AC PET images was performed. AC PET images were reconstructed using both the predicted attenuation maps and the ground truth CT-based attenuation maps, at a final voxel resolution of (6, 6, 6) mm³. The reconstructed PET images were subsequently evaluated using difference image analysis and regional volume-of-interest (VOI) analysis in key anatomical regions, including the heart, lungs, and liver.

III. RESULTS AND DISCUSSION

A. Quality Evaluation of Attenuation Maps

The four predicted attenuation maps were evaluated to determine which yielded the highest quality to be used for AC. As shown in Figure 4, visual inspection of a sagittal slice highlights systematic errors in the trachea and esophagus, where alternating bands in the difference images indicate model hallucinations. These artifacts appear consistently across all inference directions, indicating a shared limitation of the model in reconstructing air-filled regions where NAC PET provides insufficient structural information. Notably, the arrows in the coronally-inferred prediction ($\mu_{DL-coronal}$) reveal that limited-angle artifacts present in the WT-PET images are propagated into the corresponding attenuation map—an issue less observed in the transversely-inferred or sagittally-inferred predicted attenuation maps.

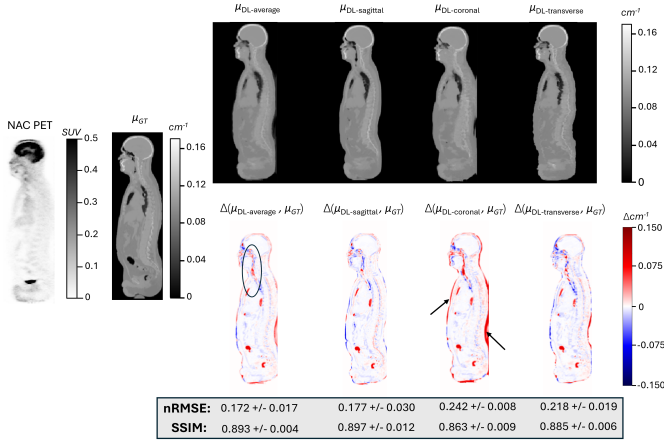


Fig. 4. Comparison between the different predicted attenuation maps visualized for a sagittal slice. The NAC PET slice shown corresponds anatomically to the displayed CT slice and is provided for visual reference only; the model input consists of a stack of 9 adjacent NAC PET slices along each inference direction. Absolute difference images are shown between the predicted attenuation maps and the ground truth attenuation map. The grey table on the bottom shows the nRMSE and SSIM values between the ground truth and the deep learning-predicted attenuation maps for this specific image slice. The ellipse highlights the errors around the esophagus and trachea and the arrows show errors due to the limited angle artifact.

Among all views, the averaged attenuation map $\mu_{DL-average}$ showed the clearest anatomical delineation and fewest artifacts. This was consistently supported by the lowest nRMSE

and highest SSIM across different slices of the test subjects. By integrating structural information from all three anatomical planes, the averaged prediction effectively mitigated orientation-specific artifacts and was therefore selected for all subsequent evaluations.

TABLE II
NRMSE AND SSIM COMPARISON BETWEEN PREDICTED ATTENUATION MAPS AND GROUND TRUTH ACROSS FOUR PATIENTS.

Test Patient	nRMSE	SSIM
Male, 66 Kg, 129.4 MBq	0.1662	0.9599
Female, 70 Kg, 132 MBq	0.1401	0.9665
Male, 98 Kg, 203 MBq	0.1503	0.9564
Female, 89 Kg, 172.9 MBq	0.1814	0.9545
Mean $\pm$ Std	0.1595 $\pm$ 0.0181	0.9593 $\pm$ 0.0053

As shown in Table II, the averaged attenuation map achieved a mean nRMSE of **0.159** and SSIM of **0.959**, indicating high fidelity to the CT-based reference. These results were further supported by line profiles and cumulative attenuation comparisons, discussed below.

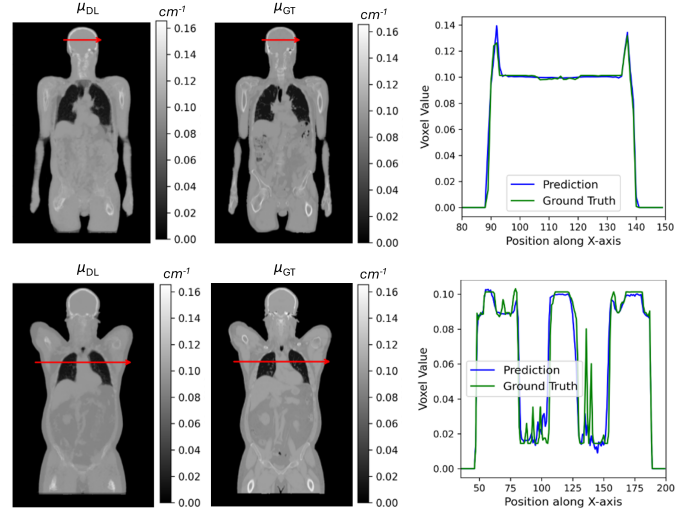


Fig. 5. Line profiles comparing the predicted attenuation map and the ground truth attenuation map. The upper profile spans the head region, while the lower profile traverses the thorax, including the lungs.

Figure 5 shows line profile comparisons for coronal slices in two patients. The top line traverses the brain laterally, revealing that the model accurately reconstructs the homogeneous attenuation of brain tissue and captures bone transitions, despite the NAC PET input being highly noisy and dominated by intense metabolic activity in the brain. The discrete plateaus observed in the ground truth profile result from the stoichiometric conversion of CT images into a finite set of attenuation values. The second profile spans the thoracic region, crossing the lungs and mediastinum. While the model aligns well with the reference in soft tissue regions, localized underestimations are observed in the lungs, where the model fails to represent finer air-tissue transitions such as airway branches. These errors stem from the limited structural contrast in NAC PET for such features.

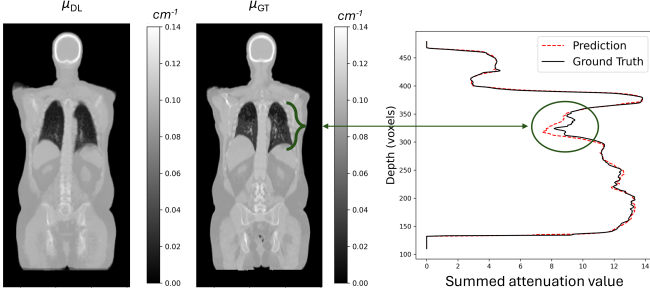


Fig. 6. Summed attenuation profile along the axial direction for a coronal slice of a test patient. The offset due to the misestimation of the lung boundary is highlighted in green.

Figure 6 illustrates attenuation profiles summed along the axial direction in the coronal plane. The predicted and ground truth curves show strong alignment across most anatomical regions, especially in dense soft tissues such as the brain and liver. However, deviations are visible in the lungs, where predicted attenuation tends to overestimate lung volume. These discrepancies likely stem from the limited anatomical detail available in the NAC PET input, as well as potential blurring from respiratory motion during the original 6-minute PET acquisition. This makes it difficult for the model to accurately delineate the true extent of the lung boundaries, often resulting in blurred or inflated lung contours.

Overall, the summed attenuation profile confirms that while the model lacks complete anatomical specificity—particularly in air-filled or low-density regions—it captures global attenuation trends with sufficient accuracy for AC. The promising performance of the predicted attenuation maps will be further validated in the following PET reconstruction experiments.

B. Assessment of Attenuation Correction Performance

PET images were reconstructed using the averaged prediction ($\mu_{DL\text{-average}}$) and compared to ground truth reconstructions based on CT-derived attenuation maps.

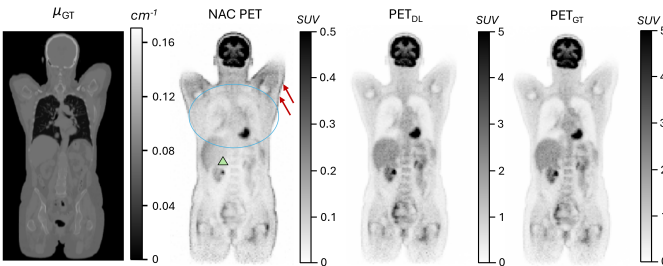


Fig. 7. Comparison of AC PET images reconstructed using the DL-predicted attenuation map and the ground truth attenuation map, shown in a coronal view. For reference, the NAC PET image is also included, along with pointers towards some expected image characteristics for NAC PET images.

Visualization of AC PET: As shown in Figure 7, the NAC PET image displays expected characteristics such as overestimated lung activity (blue ellipse), non-uniform liver uptake (light green triangle), and edge over-enhancement of the skin (red arrows). These issues are substantially corrected

in PET_{DL}, which closely resembles the CT-based PET_{GT}, particularly in soft tissue and organ boundaries.

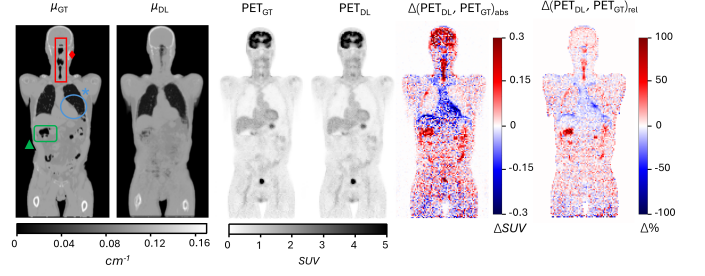


Fig. 8. Absolute and relative difference images between PET_{DL} and PET_{GT} for a representative coronal slice. The corresponding DL-predicted and ground truth attenuation maps are shown on the left to aid interpretation. Colored shapes highlight regions where discrepancies in the attenuation maps likely contributed to PET reconstruction errors.

Difference Images of AC PET: Difference image analysis (Figure 8) includes both absolute and relative error maps to offer complementary insights. Absolute difference maps reveal the magnitude of discrepancies, while relative difference maps normalize these differences to the ground truth, highlighting meaningful errors in low-uptake areas. Including both allows for a more balanced evaluation of AC performance. The esophagus and vocal tract (red box) show consistent overestimation of activity, attributed to the model's inability to reconstruct narrow air-filled cavities. Just below the liver (green box), cavities in the ground truth are missed by the model, again leading to overestimation. The nasal and oral cavities also show mixed over- and under-estimations due to poor air-tissue differentiation. Elsewhere, the difference images exhibit mostly white or lightly colored regions, indicating close agreement without systematic bias. This suggests that the overall anatomical delineation and patient contour are well preserved, despite the presence of limited-angle artifacts throughout the body. With global voxel-wise comparison across the entire 3D image volumes yielding a mean absolute relative error of $12.18\% \pm 2.84\%$. Importantly, taking the absolute value ensures that local over- and underestimations do not cancel each other out.

Volume-of-Interest Comparison: To quantify regional AC PET accuracy, spherical VOIs (diameter of 30 mm) were placed in the heart, lung, and liver for all four test patients. The relative bias between PET_{DL} and PET_{GT} was computed.

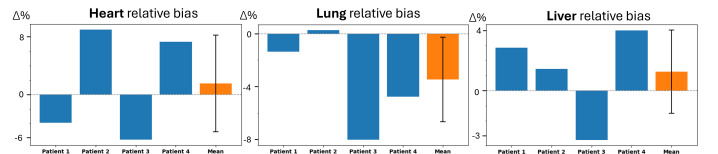


Fig. 9. VOI analyses (30 mm diameter) comparing the relative bias of PET_{DL} and PET_{GT} for the heart, lung, and liver.

As seen in Figure 9—the liver VOIs showed minimal bias with a mean of $+1.25\% (\pm 2.76\%)$, indicating consistent performance in this region. Heart VOIs exhibited greater variability, with a mean bias of $+1.54\% (\pm 6.70\%)$, ranging from -6.25%

to +9.01%, potentially reflecting heterogeneous uptake. Lung VOIs revealed a general underestimation, averaging -3.47% ($\pm 3.19\%$), as the model struggled to delineate the lung volume. Notably, the largest deviations were observed in patients with the highest BMI (Patients 3 and 4), who exhibited both the highest positive and negative biases, likely due to increased photon attenuation and variability in body morphology, which pose additional challenges for the DL model.

General Reflection on the Model Performance: This thesis demonstrates that attenuation maps predicted from NAC WT-PET images (with an unconventional dual-panel geometry) are suitable for AC but lack the fine detail needed for diagnostic interpretation or precise anatomical localization. While the overall anatomical layout is reasonably preserved (despite limited angle artifacts), boundaries of air cavities and fine tissue structures remain challenging to delineate due to low resolution and noise. Nevertheless, the predicted attenuation maps enable accurate AC, as shown by strong agreement with CT-based reconstructions and quantitative metrics.

Approximately 33% of CT usage is for AC, another 33% for anatomical localization, and the remainder for diagnostic imaging [15]. Based on a systematic review and meta-analysis, low-dose CT scans for AC/AL deliver an average dose of 4.3 mGy, which can accumulate over repeated scans [16]. In cases where CT is performed solely for AC, this dose could potentially be avoided by using this model. In addition to dose reduction, the method developed in this thesis is particularly relevant for PET systems that lack a CT component altogether (like the WT-PET), or in cases where the CT is unavailable due to hardware malfunction or yields severely misaligned images. In such scenarios, conventional CT-based AC is compromised or entirely infeasible. The model developed in this thesis provides a robust, coregistered solution for AC by generating attenuation maps directly from NAC PET data, eliminating the dependence on an additional anatomical imaging modality and mitigating the problems associated with misregistration.

The choice to input nine consecutive NAC PET slices allows the model to leverage 3D anatomical context, improving its ability to infer attenuation from structures not fully visible in a single slice, as attenuation occurs in 3D. Training on simulated data from high-quality PET/CT scans further enhanced its robustness across diverse patient anatomies. Resampling the input to a lower resolution increased the signal-to-noise ratio, aiding the recovery of anatomical boundaries.

IV. CONCLUSIONS

This thesis presented a deep learning method for generating attenuation maps directly from NAC PET, enabling CT-free attenuation correction for the WT-PET. Although not suitable for diagnostic interpretation, the predicted attenuation maps were accurate enough for attenuation correction, with relative SUV differences below 8% for regional VOI analyses and global voxel-wise comparisons yielding a mean absolute relative error of $12.18\% \pm 2.84\%$ for the PET reconstructions. The approach also ensured spatial coregistration, offering clinical value in reducing dose and addressing scenarios without CT. Future work could focus on combining the model with CT reconstruction to help fill in sparse-view gaps, potentially enabling

lower-dose CT imaging without compromising image quality. Additionally, incorporating multi-view histo-projections, which preserve directional emission information that is lost in reconstructed NAC PET, may offer richer input for attenuation prediction and enhance performance beyond using NAC PET alone.

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