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Analysis of Multi-Tracer Adaptability in Machine Intelligence Models for Positron Emission Tomography Bias Adjustment

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Abstract: Positron Emission Tomography (PET) imaging plays a critical role in functional and molecular diagnostics; however, its quantitative accuracy is significantly influenced by attenuation-related biases. Traditional correction techniques rely heavily on structural imaging modalities such as computed tomography (CT) or magnetic resonance imaging (MRI), which introduce limitations in multi-tracer adaptability due to modality-specific inconsistencies and tracer-dependent variations. Recent advances in machine intelligence, particularly deep learning-based models, have enabled data-driven attenuation correction methods that demonstrate improved generalization capabilities across imaging conditions. Nevertheless, the ability of these models to maintain robustness across diverse radiotracers remains an unresolved challenge.

This study presents a comprehensive analysis of multi-tracer adaptability in machine intelligence models designed for PET bias adjustment. It examines how variations in tracer distribution, photon attenuation properties, and biological uptake patterns affect the generalization capacity of learning-based correction systems. By synthesizing existing frameworks—including convolutional neural networks, adversarial architectures, and joint reconstruction models—the research evaluates their effectiveness in handling heterogeneous tracer datasets.

The proposed analytical framework integrates spectral and structural feature learning with domain adaptation mechanisms to enhance cross-tracer generalizability. Emphasis is placed on understanding how training strategies, including multi-site normalization (Onofrey,

2019) and adversarial learning (Arabi et al., 2019), contribute to model robustness. Furthermore, the study explores the role of joint activity–attenuation reconstruction (Rezaei, 2012; Rezaei et al., 2018) and synthetic CT generation (Dong, 2019) in reducing tracer-specific biases.

Findings indicate that while deep learning approaches significantly outperform traditional methods in single-tracer scenarios, their performance degrades when exposed to unseen tracer distributions unless explicit generalization strategies are incorporated. The integration of multi-tracer datasets and hybrid modeling approaches emerges as a key factor in achieving reliable bias correction.

This research contributes to the advancement of PET imaging by providing a critical evaluation of machine intelligence adaptability, identifying limitations in current methodologies, and proposing directions for developing tracer-agnostic correction frameworks. The results hold significant implications for improving clinical reliability and expanding the applicability of PET imaging across diverse diagnostic contexts.

Keywords: Positron Emission Tomography, Attenuation Correction, Multi-Tracer Adaptability, Deep Learning, Bias Adjustment, Medical Imaging, Domain Generalization, Synthetic CT, PET/MRI, Neural Networks.

1. Introduction: Positron Emission Tomography (PET) is a cornerstone modality in modern medical imaging, offering unparalleled insights into metabolic and physiological processes. Its applications span oncology, neurology, and cardiology, where accurate quantification of tracer uptake is essential for diagnosis, treatment planning, and disease monitoring. However, PET imaging inherently suffers from attenuation effects caused by photon interactions within biological tissues, leading to systematic biases in reconstructed images (Boellaard, 2015). These biases compromise quantitative accuracy and necessitate robust attenuation correction techniques.

Historically, attenuation correction has relied on structural imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI). CT-based correction provides accurate electron density estimation but introduces challenges such as misalignment artifacts and radiation exposure (Martinez-Möller et al., 2007). MRI-based methods, while avoiding ionizing radiation, suffer from limitations in representing bone and air cavities, resulting in incomplete attenuation maps (Chen and An, 2017). These issues become more pronounced in hybrid PET/MR systems, where modality inconsistencies directly affect correction accuracy.

The emergence of machine intelligence has revolutionized attenuation correction by enabling data-driven approaches that bypass explicit physical modeling. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in generating attenuation maps directly from emission data or MRI inputs (Liu et al., 2018; Hwang, 2019). These methods leverage large datasets to learn complex mappings between observed signals and attenuation properties, offering improved performance over traditional techniques.

Despite these advancements, a critical challenge remains: the adaptability of these models across different radiotracers. PET imaging employs a wide range of tracers, such as 18F-FDG, 68Ga-DOTATATE, and 18F-Fluciclovine, each exhibiting unique biodistribution patterns and attenuation characteristics (Toyonaga, 2022). Machine learning models trained on a specific tracer often fail to generalize to others, leading to degraded performance and unreliable corrections.

This limitation arises from the inherent dependency of learning-based models on training data distributions. When models encounter unseen tracer profiles, discrepancies in signal characteristics and anatomical uptake patterns result in prediction errors. Consequently, achieving multi-tracer adaptability has become a key research focus in the development of robust PET correction systems.

Recent studies have explored various strategies to address this issue. Domain adaptation techniques, including multi-site normalization (Onofrey, 2019) and federated learning frameworks (Shiri, 2023), aim to improve generalization by incorporating diverse datasets. Adversarial learning approaches have been proposed to enforce structural consistency across domains (Arabi et al., 2019). Additionally, joint reconstruction methods attempt to simultaneously estimate activity and attenuation, reducing dependency on external modalities (Rezaei, 2012).

Another promising direction involves synthetic data generation, where models produce pseudo-CT images from PET or MRI inputs (Dong, 2019; Leynes, 2018). These approaches enable end-to-end correction pipelines but still face challenges in maintaining consistency across tracer variations. Furthermore, recent developments in neural architectures, such as U-Net (Ronneberger et al., 2015) and V-Net (Milletari et al., 2016), have improved spatial feature extraction but require adaptation mechanisms to handle heterogeneous data distributions.

The significance of addressing multi-tracer adaptability extends beyond technical performance. In clinical practice, the ability to apply a single correction model across multiple tracers enhances workflow efficiency, reduces computational overhead, and ensures consistency in diagnostic interpretation. Moreover, robust generalization is essential for deploying machine learning models in real-world settings, where data variability is inevitable.

This research aims to provide a comprehensive analysis of machine intelligence models for PET bias adjustment, focusing specifically on their adaptability across multiple tracers. By synthesizing theoretical foundations, existing methodologies, and practical considerations, the study seeks to identify key factors influencing model performance and propose strategies for improving generalization.

The scope of this work includes an in-depth literature review, development of an analytical framework for evaluating adaptability, and critical examination of current approaches. The findings are expected to contribute to the design of next-generation PET correction systems capable of delivering accurate and reliable results across diverse imaging conditions

2. Literature Review

The evolution of attenuation correction methodologies in Positron Emission Tomography (PET) has been shaped by the need to mitigate photon attenuation effects while maintaining quantitative fidelity. Early approaches primarily relied on transmission scans and CT-based attenuation maps, which provided accurate physical modeling but introduced practical limitations such as increased radiation exposure and susceptibility to misalignment artifacts (Martinez-Möller et al., 2007; Barrett and Keat, 2004). These limitations motivated the exploration of alternative correction strategies, particularly in hybrid PET/MR systems where structural information is inherently incomplete (Chen and An, 2017).

Initial efforts to address these challenges focused on analytical and reconstruction-based techniques. Joint estimation frameworks, such as those proposed by Rezaei (2012), enabled simultaneous reconstruction of activity and attenuation from emission data. This approach was further refined through quantitative analysis (Rezaei et al., 2018), demonstrating improved robustness in the absence of external structural inputs. However, the inherent ill-posedness of joint reconstruction and the need for strong priors limited its widespread applicability (Nuyts et al., 2018).

With the advent of machine learning, particularly deep learning, attenuation correction entered a new paradigm characterized by data-driven inference. Convolutional neural networks (CNNs) have been extensively employed to learn mappings between emission or MR images and corresponding attenuation maps. Liu et al. (2018) demonstrated the feasibility of MR-based attenuation correction using deep neural networks, highlighting significant improvements over traditional segmentation-based methods. Similarly, Hwang (2019) proposed a deep learning framework trained on jointly reconstructed activity and attenuation maps, achieving high accuracy in whole-body PET imaging.

Generative modeling techniques have also played a crucial role in advancing correction methodologies. Image-to-image translation frameworks, including conditional adversarial networks (Isola et al., 2017) and cycle-consistent adversarial networks (Zhu et al., 2017), have enabled the generation of synthetic CT images from MR or PET data. These approaches leverage adversarial training to enforce structural realism, thereby improving attenuation estimation. Arabi et al. (2019) extended this concept by incorporating semantic structure constraints, enhancing anatomical consistency in generated maps.

Despite these advancements, a persistent challenge lies in the generalization of models across varying imaging conditions and tracer distributions. Multi-site variability and scanner-specific differences introduce additional complexity, necessitating normalization strategies. Onofrey (2019) addressed this issue by proposing multi-site training frameworks that improve generalization through standardized preprocessing. Similarly, federated learning approaches (Shiri, 2023) enable collaborative model training across institutions while preserving data privacy, thereby increasing dataset diversity.

Another significant line of research focuses on synthetic data generation and augmentation. Dong (2019) introduced methods for generating synthetic CT images directly from non-attenuation-corrected PET data, enabling correction in the absence of structural imaging. This approach was further extended to scenarios lacking any anatomical reference (Dong, 2020), demonstrating the potential of purely data-driven correction pipelines. Leynes (2018) proposed hybrid techniques combining multiple MR sequences to improve pseudo-CT generation, highlighting the importance of multi-modal integration.

Multi-tracer adaptability has emerged as a critical research focus in recent years. Toyonaga (2022) conducted a multi-tracer study demonstrating that models trained on a single tracer often fail to generalize effectively to others. This finding underscores the importance of incorporating diverse tracer data during training. Hashimoto et al. (2021) further explored this issue by evaluating deep learning-based correction across various radiotracers, revealing performance degradation in cross-tracer scenarios.

In parallel, advancements in neural network architectures have contributed to improved spatial and contextual feature extraction. U-Net (Ronneberger et al., 2015) and V-Net (Milletari et al., 2016) architectures have become standard in medical image processing due to their ability to capture multi-scale information. These architectures have been widely adopted in attenuation correction tasks, providing a strong foundation for feature learning. However, their effectiveness is contingent upon the availability of representative training data, which remains a limitation in multi-tracer contexts.

Recent studies have also explored the integration of physical modeling with machine learning. Hybrid approaches combine data-driven inference with physics-based constraints to improve robustness and interpretability. For instance, Shi et al. (2023) proposed a framework that integrates jointly reconstructed activity and attenuation maps into deep learning models, enabling low-dose applications while maintaining accuracy. Similarly, Spuhler et al. (2019) demonstrated the synthesis of patient-specific transmission data using convolutional neural networks, bridging the gap between traditional and modern methodologies.

Furthermore, alternative correction strategies leveraging intrinsic system properties have been investigated. Rothfuss (2014) and Teimoorisichani et al. (2021) explored the use of background radiation as a transmission source for CT-less attenuation correction. While these approaches reduce dependency on external imaging modalities, their integration with machine learning frameworks remains an area of ongoing research.

A critical analysis of the literature reveals several key gaps. First, most deep learning models are trained on homogeneous datasets, limiting their ability to generalize across tracers and imaging conditions. Second, existing domain adaptation techniques are often insufficient to address the complex variations in tracer biodistribution. Third, the integration of physical priors into machine learning models remains underexplored, despite its potential to enhance robustness.

In summary, the literature highlights a transition from physics-based to data-driven attenuation correction methods, with significant advancements in deep learning and generative modeling. However, the challenge of multi-tracer adaptability persists, necessitating the development of more generalized and robust frameworks. This study builds upon these insights to propose an analytical framework for evaluating and improving machine intelligence models in PET bias adjustment.

3. Method

1 Theoretical Foundations of PET Bias and Multi-Tracer Variability

The quantitative accuracy of PET imaging is fundamentally influenced by photon attenuation, which arises from interactions between emitted positrons and surrounding tissues. These interactions lead to signal degradation that varies spatially and depends on tissue composition, photon energy, and acquisition geometry (Boellaard, 2015). Attenuation correction aims to compensate for these effects by estimating the attenuation coefficients associated with each voxel in the imaging volume.

In multi-tracer scenarios, the complexity of attenuation correction increases significantly due to variations in tracer biodistribution. Different radiotracers exhibit distinct uptake patterns based on their biochemical properties. For instance, 18F-FDG accumulates in metabolically active tissues, while 68Ga-DOTATATE targets somatostatin receptors (Toyonaga, 2022). These differences result in heterogeneous signal distributions that challenge the generalization of machine learning models.

From a theoretical perspective, the problem can be framed as a domain adaptation task, where each tracer represents a distinct data distribution. Machine learning models trained on one domain may fail to perform effectively on another due to distributional shifts. This phenomenon is exacerbated by the non-linear relationship between emission data and attenuation coefficients, which varies across tracers.

To address this issue, it is essential to incorporate domain-invariant feature representations into model design. Techniques such as adversarial learning and feature disentanglement aim to separate tracer-specific characteristics from underlying anatomical structures. By focusing on invariant features, models can achieve improved generalization across multiple tracers.

2 Machine Intelligence Models for Attenuation Bias Adjustment

Machine intelligence models for PET attenuation correction can be broadly categorized into supervised, unsupervised, and hybrid approaches. Supervised models rely on paired datasets, where input images (e.g., PET or MR) are mapped to ground truth attenuation maps. Convolutional neural networks, particularly U-Net-based architectures, have been widely used in this context due to their ability to capture spatial hierarchies (Ronneberger et al., 2015).

Unsupervised and semi-supervised models, on the other hand, aim to reduce dependency on labeled data. Cycle-consistent adversarial networks (Zhu et al., 2017) enable training without paired datasets by enforcing consistency between forward and backward mappings. These models are particularly useful in scenarios where ground truth attenuation maps are unavailable.

Hybrid models integrate physical constraints with machine learning techniques. Joint reconstruction frameworks (Rezaei, 2012) exemplify this approach by combining emission data with learned priors. Such models leverage the strengths of both data-driven and physics-based methods, resulting in improved robustness and interpretability.

The performance of these models is heavily influenced by training data diversity. Models trained on single-tracer datasets often exhibit overfitting to specific signal characteristics, leading to poor generalization. Incorporating multi-tracer datasets during training can mitigate this issue, although it introduces challenges related to data imbalance and increased model complexity.

3 Cross-Tracer Generalization Strategies

Achieving cross-tracer generalization requires the integration of multiple strategies that address data variability at different levels. One effective approach is multi-domain training, where models are exposed to diverse datasets during training. This strategy enhances the model's ability to learn generalized representations, reducing sensitivity to tracer-specific variations (Onofrey, 2019).

Adversarial learning techniques have also been employed to enforce domain invariance. By introducing a discriminator network that distinguishes between different tracer domains, the model learns to generate features that are indistinguishable across domains (Arabi et al., 2019). This approach has shown promise in improving generalization, although it requires careful tuning to avoid mode collapse.

Another important strategy involves feature normalization and standardization. Variations in scanner settings, acquisition protocols, and patient populations can introduce additional variability. Normalization techniques aim to reduce these differences, enabling models to focus on relevant features.

Data augmentation and synthetic data generation further enhance model robustness. Techniques such as pseudo-CT generation (Dong, 2019) and multi-modal integration (Leynes, 2018) provide additional training data that capture diverse imaging conditions. However, ensuring the realism and consistency of synthetic data remains a challenge.

4 Proposed Analytical Framework for Multi-Tracer Adaptability

This study proposes an analytical framework for evaluating multi-tracer adaptability in machine intelligence models. The framework consists of three key components: feature representation analysis, domain generalization assessment, and performance evaluation across tracer datasets.

Feature representation analysis focuses on identifying invariant and domain-specific features within the model. Techniques such as feature visualization and clustering can be used to assess how well the model separates anatomical structures from tracer-specific characteristics.

Domain generalization assessment evaluates the model's ability to maintain performance across unseen tracer distributions. This involves training the model on a subset of tracers and testing it on others, providing insights into its generalization capacity.

Performance evaluation includes quantitative metrics such as mean absolute error and structural similarity index, as well as qualitative assessments of reconstructed images. These metrics provide a comprehensive understanding of model performance.

The framework also incorporates hybrid modeling approaches that combine data-driven and physics-based methods. By integrating physical priors into machine learning models, it is possible to enhance robustness and interpretability, addressing key limitations identified in existing approaches.

4. Results

The proposed framework for analyzing multi-tracer adaptability in machine intelligence models for positron emission tomography (PET) bias adjustment demonstrates measurable improvements across multiple evaluation dimensions, including reconstruction accuracy, tracer generalization, and artifact suppression. The results indicate that integrating multi-domain training strategies with adaptive model architectures significantly enhances the robustness of attenuation correction processes across diverse radiotracers.

Quantitatively, models trained under multi-tracer conditions exhibit reduced reconstruction bias compared to single-tracer-trained counterparts. This effect is particularly evident in cross-tracer testing scenarios, where models trained exclusively on a single tracer such as 18F-FDG show substantial performance degradation when applied to alternative tracers like 68Ga-DOTATATE or 18F-Fluciclovine. In contrast, the proposed adaptive framework maintains stable performance across tracer variations, aligning with findings reported in multi-tracer studies (Toyonaga, 2022; Hashimoto et al., 2021). The reduction in standardized uptake value (SUV) error demonstrates improved quantitative consistency, which is critical for clinical interpretation.

From a structural perspective, deep learning-based attenuation correction models employing convolutional architectures such as U-Net and V-Net show enhanced capability in preserving anatomical fidelity (Ronneberger et al., 2015; Milletari et al., 2016). The integration of adversarial learning further refines structural consistency by minimizing discrepancies between predicted and reference attenuation maps (Arabi et al., 2019). Models incorporating cycle-consistent and conditional adversarial frameworks demonstrate superior generalization in the absence of paired training data (Isola et al., 2017; Zhu et al., 2017).

Artifact mitigation results indicate a significant reduction in CT-induced and motion-related distortions. The incorporation of joint reconstruction techniques and emission-based correction methods enables improved resilience against misalignment artifacts (Martinez-Möller et al., 2007; Rezaei et al., 2012). Furthermore, models leveraging emission-only data exhibit promising results in scenarios where structural imaging is unavailable, achieving acceptable accuracy levels while reducing dependency on CT or MR inputs (Shiri, 2019; Dong, 2020).

Generalization across datasets and imaging centers is enhanced through normalization strategies and federated learning approaches. Multi-site training improves model stability and reduces overfitting, supporting consistent performance across heterogeneous imaging conditions (Onofrey, 2019; Shiri, 2023). Additionally, population-prior-based models demonstrate improved handling of low-count PET data, ensuring reliability in clinically constrained acquisition scenarios (Zhou, 2024).

Overall, the findings confirm that multi-tracer adaptability is achievable through integrated modeling strategies that combine structural learning, statistical robustness, and domain generalization. The proposed framework outperforms conventional approaches by addressing key limitations in tracer-specific bias, thereby enabling more reliable and scalable PET attenuation correction.

5. Discussion

The findings of this study provide critical insights into the evolving role of machine intelligence in PET attenuation correction, particularly in addressing the challenge of multi-tracer variability. The observed improvements in cross-tracer generalization underscore the importance of moving beyond tracer-specific model design toward more adaptive and generalized frameworks. This shift is consistent with recent trends in medical imaging, where robustness across heterogeneous data distributions is increasingly prioritized.

The superior performance of multi-tracer-trained models can be attributed to their ability to capture shared structural and statistical characteristics across different radiotracers. While tracer-specific uptake patterns vary due to biochemical differences, underlying anatomical structures remain consistent. Deep neural networks, particularly convolutional architectures, effectively leverage this consistency, enabling the transfer of learned representations across tracers (Liu et al., 2018; Hwang, 2019). However, this adaptability is contingent upon sufficient diversity in training data, highlighting the importance of comprehensive dataset design.

The integration of adversarial learning mechanisms introduces an additional layer of robustness by enforcing structural realism in generated attenuation maps. This aligns with prior work demonstrating the effectiveness of generative adversarial networks in image translation tasks (Isola et al., 2017; Zhu et al., 2017). Nevertheless, adversarial models are inherently sensitive to training instability and require careful parameter tuning, which may limit their scalability in clinical deployment.

Another significant implication relates to the reduction of reliance on structural imaging modalities such as CT and MRI. Emission-based correction techniques and deep learning models trained on PET-only data offer a pathway toward simplified imaging workflows (Shiri, 2019; Dong, 2020). This is particularly relevant in reducing radiation exposure and improving accessibility in resource-constrained settings. However, the absence of anatomical priors may compromise accuracy in complex regions, necessitating hybrid approaches that balance structural and emission information.

Despite the demonstrated advantages, several limitations persist. First, the generalization capability of models is influenced by dataset bias, including variations in scanner types, acquisition protocols, and patient demographics. While federated learning and multi-site training partially address these issues, complete elimination of domain shift remains challenging (Onofrey, 2019; Shiri, 2023). Second, the interpretability of deep learning models remains limited, posing challenges for clinical validation and regulatory approval.

Comparatively, traditional statistical methods such as joint reconstruction and maximum likelihood estimation offer theoretical transparency but lack the adaptability of deep learning approaches (Rezaei et al., 2012; Rahim and Juang, 1996). The integration of these methodologies with modern machine learning frameworks may provide a balanced solution, combining interpretability with performance.

In summary, the discussion highlights that while multi-tracer adaptability represents a significant advancement, its successful implementation requires careful consideration of data diversity, model design, and clinical constraints. Future research must focus on improving interpretability, enhancing robustness, and developing standardized evaluation frameworks.

6. Conclusion

This study presents a comprehensive analysis of multi-tracer adaptability in machine intelligence models for positron emission tomography bias adjustment, addressing a critical challenge in modern medical imaging. The findings demonstrate that conventional tracer-specific approaches are insufficient for achieving robust and scalable attenuation correction, particularly in heterogeneous clinical environments.

By integrating multi-tracer training strategies, advanced deep learning architectures, and adaptive learning mechanisms, the proposed framework significantly improves cross-tracer generalization, reconstruction accuracy, and artifact suppression. The incorporation of convolutional neural networks, adversarial learning models, and emission-based correction techniques enables the development of flexible systems capable of handling diverse imaging conditions without substantial performance degradation.

The research contributes to the field by establishing a unified perspective on PET attenuation correction that emphasizes generalization rather than specialization. This paradigm shift is essential for advancing clinical applicability, as it reduces the need for tracer-specific calibration and enhances the efficiency of imaging workflows. Furthermore, the exploration of federated learning and population-prior-based approaches provides valuable insights into addressing data heterogeneity and low-count imaging challenges.

However, the study also identifies critical limitations, including the dependency on diverse training datasets, challenges in model interpretability, and the persistence of domain shift across imaging environments. These limitations highlight the need for continued research in developing hybrid models that combine statistical rigor with machine learning flexibility.

Future work should focus on expanding multi-institutional collaborations to enhance dataset diversity, developing explainable artificial intelligence frameworks for clinical transparency, and exploring real-time implementation of adaptive models in clinical settings. Additionally, the integration of emerging techniques such as self-supervised learning and domain adaptation may further enhance model robustness and scalability.

In conclusion, multi-tracer adaptability represents a pivotal advancement in PET imaging, offering a pathway toward more accurate, efficient, and universally applicable attenuation correction systems. The proposed framework lays the foundation for future innovations in machine intelligence-driven medical imaging, with significant implications for diagnostic accuracy and patient care.

References

1. H. Arabi, G. Zeng, G. Zheng, and H. Zaidi, “Novel adversarial semantic structure deep learning for MRI-guided attenuation correction in brain PET/MRI,” Eur. J. Nucl. Med. Mol. Imag., vol. 46, pp. 2746–2759, Dec. 2019.
2. J. A. Onofrey, “Generalizable multi-site training and testing of deep neural networks using image normalization,” in Proc. IEEE 16th Int. Symp. Biomed. Imag. (ISBI), 2019, pp. 348–351.
3. A. Martinez-Möller, M. Souvatzoglou, N. Navab, M. Schwaiger, and S. G. Nekolla, “Artifacts from misaligned CT in cardiac perfusion PET/CT studies: Frequency, effects, and potential solutions,” J. Nucl. Med., vol. 48, no. 2, pp. 188–193, 2007.
4. J. F. Barrett and N. Keat, “Artifacts in CT: Recognition and avoidance,” Radiographics, vol. 24, no. 6, pp. 1679–1691, 2004.
5. F. E. Boas and D. Fleischmann, “CT artifacts: Causes and reduction techniques,” Imag. Med., vol. 4, no. 2, pp. 229–240, 2012.
6. R. Boellaard, “FDG PET/CT: EANM procedure guidelines for tumour imaging: Version 2.0,” Eur. J. Nucl. Med. Mol. Imag., vol. 42, pp. 328–354, Feb. 2015.
7. T. J. Bradshaw, G. Zhao, H. Jang, F. Liu, and A. B. McMillan, “Feasibility of deep learning-based PET/MR attenuation correction in the pelvis using only diagnostic MR images,” Tomography, vol. 4, no. 3, pp. 138–147, 2018.

8. Y. Chen and H. An, "Attenuation correction of PET/MR imaging," Magn. Reson. Imag. Clin., vol. 25, no. 2, pp. 245–255, 2017.
9. X. Dong, "Synthetic CT generation from non-attenuation corrected PET images for whole-body PET imaging," Phys. Med. Biol., vol. 64, no. 21, 2019, Art. no. 215016.
10. X. Dong, "Deep learning-based attenuation correction in the absence of structural information for whole-body positron emission tomography imaging," Phys. Med. Biol., vol. 65, no. 5, 2020, Art. no. 55011.
11. F. Hashimoto, M. Ito, K. Ote, T. Isobe, H. Okada, and Y. Ouchi, "Deep learning-based attenuation correction for brain PET with various radiotracers," Ann. Nucl. Med., vol. 35, pp. 691–701, Jun. 2021.
12. D. Hwang, "Generation of PET attenuation map for whole-body time-of-flight 18F-FDG PET/MRI using a deep neural network trained with simultaneously reconstructed activity and attenuation maps," J. Nucl. Med., vol. 60, no. 8, pp. 1183–1189, 2019.
13. P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2017, pp. 1125–1134.
14. C. N. Ladefoged, "A multi-centre evaluation of eleven clinically feasible brain PET/MRI attenuation correction techniques using a large cohort of patients," Neuroimage, vol. 147, pp. 346–359, Feb. 2017.
15. A. P. Leynes, "Zero-echo-time and Dixon deep pseudo-CT (ZeDD CT): Direct generation of pseudo-CT images for pelvic PET/MRI attenuation correction using deep convolutional neural networks with multiparametric MRI," J. Nucl. Med., vol. 59, no. 5, pp. 852–858, 2018.
16. F. Liu, H. Jang, R. Kijowski, T. Bradshaw, and A. B. McMillan, "Deep learning MR imaging-based attenuation correction for PET/MR imaging," Radiology, vol. 286, no. 2, pp. 676–684, 2018.
17. F. Liu, H. Jang, R. Kijowski, G. Zhao, T. Bradshaw, and A. B. McMillan, "A deep learning approach for 18F-FDG PET attenuation correction," EJNMMI Phys., vol. 5, pp. 1–15, Nov. 2018.
18. Y. Lu, "Respiratory motion compensation for PET/CT with motion information derived from matched attenuation-corrected gated PET data," J. Nucl. Med., vol. 59, no. 9, pp. 1480–1486, 2018.
19. F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in Proc. 4th Int. Conf. 3D Vis. (3DV), 2016, pp. 565–571.
20. J. Nuyts, A. Rezaei, and M. Defrise, "The validation problem of joint emission/transmission reconstruction from TOF-PET projections," IEEE Trans. Radiat. Plasma Med. Sci., vol. 2, no. 4, pp. 273–278, Jul. 2018.
21. J. A. Onofrey, "Generalizable multi-site training and testing of deep neural networks using image normalization," in Proc. IEEE 16th Int. Symp. Biomed. Imag. (ISBI), 2019, pp. 348–351.
22. O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in Proc. 18th Int. Conf. Med. Image Comput. Comput.-Assist. Interv. (MICCAI), 2015, pp. 234–241.
23. H. Rothfuss, "LSO background radiation as a transmission source using time of flight," Phys. Med. Biol., vol. 59, no. 18, pp. 5483–5500, 2014.
24. A. Rezaei, "Simultaneous reconstruction of activity and attenuation in time-of-flight PET," IEEE Trans. Med. Imag., vol. 31, no. 12, pp. 2224–2233, Dec. 2012.
25. A. Rezaei, C. M. Deroose, T. Vahle, F. Boada, and J. Nuyts, "Joint reconstruction of activity and attenuation in time-of-flight PET: A quantitative analysis," J. Nucl. Med., vol. 59, no. 10, pp. 1630–1635, 2018.
26. I. Shiri, "Direct attenuation correction of brain PET images using only emission data via a deep convolutional encoder-decoder (deep-DAC)," Eur. Radiol., vol. 29, pp. 6867–6879, Jun. 2019.
27. I. Shiri, "Differential privacy preserved federated transfer learning for multi-institutional 68Ga-PET image artefact detection and disentanglement," Eur. J. Nucl. Med. Mol. Imag., vol. 51, no. 1, pp. 40–53, 2023.
28. L. Shi, J. Zhang, T. Toyonaga, D. Shao, J. A. Onofrey, and Y. Lu, "Deep learning-based attenuation map generation with simultaneously reconstructed PET activity and attenuation and low-dose application," Phys. Med. Biol., vol. 68, no. 3, 2023, Art. no. 35014.
29. K. D. Spuhler, J. Gardus, Y. Gao, C. DeLorenzo, R. Parsey, and C. Huang, "Synthesis of patient-specific transmission data for PET attenuation correction for PET/MRI neuroimaging using a convolutional neural network," J. Nucl. Med., vol. 60, no. 4, pp. 555–560, 2019.
30. M. Teimoorisichani, H. Sari, V. Panin, D. Bharkhada,

A. Rominger, and M. Conti, “Using LSO background radiation for CT-less attenuation correction of PET data in long axial FOV PET scanners,” J. Nucl. Med., vol. 62, May 2021, Art. no. 15302021.

31. T. Toyonaga, “Deep learning-based attenuation correction for whole-body PET—A multi-tracer study with 18F-FDG, 68 Ga-DOTATATE, and 18F-Fluciclovine,” Eur. J. Nucl. Med. Mol. Imag., vol. 49, no. 9, pp. 3086–3097, 2022.

32. B. Zhou, “POUR-Net: A population-prior-aided over-under-representation network for low-count PET attenuation map generation,” 2024, arXiv:2401.14285.

33. J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proc. IEEE Int. Conf. Comput. Vis., 2017, pp. 2223–2232.