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PETGAN: Enhancing Low-Dose PET Imaging Using GAN-Based Denoising for Improved Oncology Diagnostics

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Abstract*— Positron Emission Tomography (PET) is an essential imaging tool in oncology used to map metabolic activity in tissues. But normal dose PET scans result in high-radiation exposure to patients, particularly relevant for paediatric, geriatric and frequent-follower patients. Low-dose PET scanning is one of the ways to lower radiation dose and has been one of the most popular methods in PET reduction; however, it generates a lot of noise which results in degrading the quality of diagnosis. In this paper, a novel GAN-based framework PETGAN has been proposed to improve low-dose PET scans by generating high-quality, denoised images with keeping significant diagnostic details. The model is trained on the ACRIN-FDG-PET dataset where paired low-dose and full-dose PET scans are available, enabling the generator to learn an accurate mapping from noisy to clean imaging. PETGAN contains a generator based on the U-Net and a Patch GAN discriminator which are trained to balance adversarial, perceptual, and reconstruction losses maintaining clinical authenticity. The experimental results show that the enhanced images have higher image clarity, with an SSIM of 0.89 and a PSNR of 32.8 dB, and can be utilized for accurate tumor detection and staging. PETGAN provides a potential AI-based strategy for radiation-free and cost-effective oncologic imaging.

***Index Terms*— PETGAN, Medical Image Denoising, Generative Adversarial Networks (GAN), U-Net, PatchGAN, Oncology Imaging**

I. INTRODUCTION

Positron Emission Tomography (PET) is a key diagnostic tool for cancer through its ability to non-invasively image metabolic activity, but its routine application entails major exposure to radiation, which is dangerous for paediatric and serially imaged patients especially. The Low-Dose PET (LD-PET) protocols minimize this exposure but are afflicted with poor signal-to-noise ratio (SNR) and severe noise, degrading diagnostic performance. [2] Conventional denoising techniques like Gaussian filtering and iterative reconstruction can blur significant anatomical structures and are not applicable across instances. In response, this work presents PETGAN, a new deep learning architecture founded upon Generative Adversarial Networks (GANs) that employ a U-Net generator and Patch GAN discriminator.PETGAN is learned from the ACRIN-FDG-PET database in which dual full- and low-dose scans are available and leverages adversarial, perceptual, and reconstruction loss functions to produce diagnostically correct, high-fidelity images. Experimental outcomes indicate significant image quality improvements with an SSIM of 0.89 and PSNR of 32.8 dB, thereby enabling clinical applications including tumour staging and localisation. [4] The work illustrates PETGAN's potential for augmenting LD-PET imaging with enhanced safety, diagnostic accuracy, and cost- effectiveness, providing a scalable AI-based solution for contemporary oncologic imaging pipelines.

1.1 Background on PET Imaging in Oncology

Positron Emission Tomography (PET) is a primary imaging tool in the field of oncology that offers non-invasive assessment of tissue metabolic activity, unlike the structural imaging techniques of CT and MRI. Using the ^{18}F-fluorodeoxyglucose (^{18}F-FDG) tracer, PET effectively identifies areas of elevated glucose metabolism, enabling cancer screening, diagnosis, staging, treatment planning, and monitoring of response to therapy.[2] PET and CT fusion (PET/CT) and new PET/MRI technologies have also enhanced diagnosis by integrating metabolic and anatomical data in a fused image. [1] Hybrid systems enable better lesion detectability and disease characterization and are particularly valuable in cancer management, e.g., lymphoma, lung, breast, and brain cancer. Though its clinical use, a natural drawback of PET is the natural deployment of ionizing radiation, with resultant effects to repeated imaging, especially for long-term monitoring and paediatric oncology.

II. LITERATURE REVIEW

2.1. Oncologic PET Imaging: Evolution

Functional imaging in particular, oncologically oriented, has seen the advent of positron emission tomography (PET) as a major player. Its ability to image on cellular-metabolism level is superior to traditional anatomy imaging, such as computed tomography (CT) or magnetic resonance imaging (MRI). Preliminary studies showed the usefulness of

[^{18}F]FDG-PET in the management of the cancer patient for diagnosis, tumor staging and response to therapy [1]. Hybrid systems such as PET/CT and PET/MRI, integrating metabolic and anatomic information, further improved diagnostic accuracy over the years [2].

2.2. Low-Dose PET and Its Impact

In order to preserve patients from radiation particularly in the case of pediatric and longitudinal cancer patients Low-Dose (LD) PET protocols have been introduced by the researchers. But this progress was not without its compromises. It was reported that reduction of radiotracer doses results in increased image noise, worse SNR and contrast, resulting in compromise of diagnostic value [3,4]. The traditional choices were based on Gaussian smoothing and iterative reconstruction (for example, OSEM), however, they usually smoothed fine anatomical structures and decreased tumor visibility [5]. This motivated the development of data-driven noise reduction techniques that can restore image quality while preserving the diagnostic content in a smart way.

2.3. Deep Learning based Medical Image Denoising

The last decade has seen a trend reversal with the advent of deep learning in medical imaging, particularly for denoising and reconstruction. Due to their ability to capture multi-level hierarchical feature representations [6], Convolutional Neural Networks (CNNs) have been successfully applied to image restoration problems. In PET image/MRI image reconstruction CNNs, it is shown that the proper denoising of the noisy low-count data will help learn the mapping between low-dose and high- dose data and to reconstruct what was lost while maintaining the spatial structure[7]. Whereas, CNNs are good at optimizing pixel-wise similarity and may not prioritize perceptual quality or clinical interpretability. This bottleneck motivated modernizing architectures to the likes of Generative Adversarial Networks (GANs).[13]

2.4. Role of GANs in LD-PET image Enhancement

GANs, proposed by Goodfellow et al. [8], which are based on a generator and a discriminator learned in an adversarial manner. They have the potential for photo-realistic output and they are also applicable for low dose image enhancement. Few research efforts modified GANs for LD-PET denoising. For instance, PETGAN [9] and DeepPET [10] demonstrated that GAN-based models can recover high-frequency details and produce more visually coherent reconstructions than CNN-only methods. Such models also employ other components like perceptual (VGG-based), adversarial and reconstruction loss, which are helpful to maintain structural and semantic consistency. While GANs are successful, they are plagued by issues such as training instability, mode collapse, and the insertion of artifacts, all of which have the potential to hallucinate non-existing tumors or hide subtle pathologies [11].

2.5. Gaps in Existing Research

Although some preliminary work is encouraging, clinical realization of GAN-based PET denoising remains challenging:

- The majority of models maximize visual similarity while not guaranteeing clinical fidelity.
- The lack of values may be generalized to the fact that the tumor biology and scanner noise distribution are heterogeneous.
- Perhaps due to the use of more complex on-not links, many models have little explainability, posing moral hazards in clinical practice.
- This work fills these gaps by presenting a new GAN architecture (PETGAN) that is trained and evaluated on paired[FN1] LD-FD PET images both quantitatively (e.g., PSNR, SSIM) and qualitatively in an oncologic setting.[7]

III. METHODOLOGY

3.1. Overview of the PETGAN Framework

The resulting PETGAN framework is intended to improve the quality of LD-PET images by learning a mapping between noisy, low-count PET scans and their respective full-dose counterparts. PETGAN uses a Generative Adversarial Network (GAN) architecture comprised of a U-Net-based generator and a PatchGAN-based discriminator, trained adversarially. The network is trained with paired LD-FD (low-dose and full-dose) PET images available in the ACRIN-FDG-PET dataset. The objective is to restore clinically useful PET images with less noise while retaining delicate anatomical and metabolic details critical for oncologic interpretation. Training maximizes an aggregate loss function which incorporates adversarial loss, perceptual loss, and pixel-wise reconstruction loss to allow PETGAN to learn both low-level structural and high-level semantic fidelity. The overall PETGAN architecture permits efficient noise reduction with preservation of the tumor boundary sharpness, texture patterns, and gradient information, which are usually lost in conventional denoising techniques. The framework incorporates the following key components:

- End-to-End Training Pipeline
- Dual-Domain Learning
- Paired Supervised Learning:
- Clinical Robustness and Generalization
- Evaluation Strategy

3.2. Architecture of the Generator (U-Net)

The generator in PETGAN model takes the U-Net structure, an especially trendy deep convolutional neural network that is highly appropriate for biomedical image-to-image translation. Its encoder–decoder architecture with skip connections supports efficient spatial information preservation alongside high-level representation learning—

vital for medical image denoising where global structure and local tumor details both need to be preserved. The encoder is built using convolutional blocks with two 3×3 convolutions, ReLU activation, and batch normalization, and then 2×2 max pooling for downsampling.[7] Feature channels are doubled in each level to handle hierarchical information. The decoder conducts upsampling with 2×2 transposed convolutions and combines corresponding encoder features through skip connections, and then two 3×3 convolutions, ReLU, and batch normalization. Skip connections recover the lost fine details during encoding. The output layer applies a 1×1 convolution with Tanh activation to generate denoised image normalized to the range [−1, 1], resolution-wise the same as input but with much less noise. This design maintains anatomical detail, preserves strong noise suppression, extracts multi-scale features, and is computationally efficient—enabling PETGAN to generate diagnostically sound low-dose PET images.[6]

3.3. Architecture of the Discriminator (PatchGAN)

The discriminator in the PETGAN model uses the PatchGAN architecture, which is used to evaluate the realism of neighborhood image patches and not the whole image. It works best in medical imaging where high-frequency anatomical details are essential in determining the accuracy in diagnosis. Unlike regular discriminators that produce one binary label for each image, PatchGAN judges overlapping N×N patches independently as real or fake, promoting local realism and guiding the generator to produce texture-rich, perceptually consistent outputsThe network takes as input the concatenation of the denoised PET image with its full-dose ground truth and goes through five convolutional layers, which are followed by LeakyReLU activations (slope = 0.2) and instance normalization, excluding the first layer.[6] Strided convolutions are employed for downsampling, and output is a 2D probability map in which the value at each position denotes the authenticity of the corresponding patch (e.g., a 256×256 image gives an output of size 30×30 with 70×70 patches). The adversarial loss is given by:[10]

$$\mathbf{L_{adv}\,(G,D) = E_{x,y}[\log D\,(x,y)] + E_x\,[\,\log\,(1 - D\,(x,\,G(x)))]}$$

This loss mandates the creation of high-fidelity patches undistinguishable from authentic PET images. PatchGAN enhances local texture restoration, diminishes blurring, and facilitates quicker and more stable training. Clinically, this localized discrimination ensures preservation of critical oncologic details like tumor heterogeneity, lesion contours, and fine metabolic gradients so that the denoised PET images are not only visually realistic but also diagnostically sound.[7]

3.4. Proposed Novel Architecture

In this study, we introduce a new GAN-based framework that is tailored for LD-PET image denoising with the name PETGAN. [2] Multi-scale spatial information is captured by the U-net-based generator and high perceptual reality is enforced via Patch-GAN discriminator. We extend the architecture with a composite loss to jointly improve both structure fidelity and diagnostic value.

3.4.1. Loss Functions Used

Adversarial Loss

Encourages the generator to generate images similar enough that the discriminator cannot tell whether or not an image is from a full-dose PET scan.

Perceptual Loss

It makes use of the feature maps obtained from a pre-trained VGG network to preserve the high-level semantic features and improve visual quality.

Reconstruction Loss

It computes pixel-wise L1 loss between the denoised images and the ground truth full-dose images to assure that the structure is to be preserved.

3.5. Training Strategy

Supervised by paired low dose and full-dose PET images, PETGAN is trained using supervised learning. The loss composition is used to optimize the two losses while the generator and discriminator are trained alternately. It uses techniques such as batch normalization, learning rate scheduling, and early stopping for more stability training.

3.6. Dataset Description (ACRIN-FDG-PET)

We apply our algorithm to the ACRIN-FDG-PET database, one of the publicly available PET datasets consisting of pairs of low-dose and full-dose PET scans. This dataset has more number of tumor types and anatomical structures providing broad representation for training and testing of the model.[12]

3.7. Data Preprocessing and Augmentation (Parameter Tuning)

The input images are normalized and resized for simplicity. Data augmentation: A common strategy to avoid overfitting and increase model generalization by adding random cropping, flipping, and intensity scaling. Grid search parameters: patch size, learning rate and batch size are tuned to get the best denoising performance.

IV. EXPERIMENTAL SETUP

In this part, the environment and training preparation describe the metrics for evaluation in tables, and also include the base models of comparison with PETGAN.

4.1. Implementation Environment

The PETGAN model was developed using the Python 3.9 programming language and the PyTorch deep learning framework. The model was trained and evaluated on a GPU (NVIDIA RTX 3090, 24GB VRAM) with Ubuntu 20.04

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LTS. The experiments were conducted in a virtual environment equipped with the PyTorch, NumPy, OpenCV, and scikit-image libraries[13].

4.2. Training Parameters and Hyperparameters

The Adam optimizer was used to train the PETGAN with an initial learning rate of 0.0002 and $\beta1 = 0.5$, $\beta2 = 0.999$, The model used a patch size of 128×128 was trained for 200 epochs with a batchsize of 8. We further empirically applied a learning rate decay after 100 epochs for robust convergence. The composite loss function included:[8]

- Adversarial Loss (λ_adv = 1.0)
- Perceptual Loss (λ_perc = 0.1)
- Reconstruction Loss (λ_recon = 10)

To enhance the robustness of the models, various data augmentation strategies (includingbut not limited torandom flip, crop and intensity scaling) were employed.

TABLE 1: Training parameters and hyperparameters

Hyperparameter	Value	Description
Epochs	200	Number of Full Passes through the training dataset.
Batch Size	8	Number of samples per training batch.
Learning Rate	0.0002	Initial learning rate of both generator and discriminator.
Patch Size	128 x 128	Input patch size fed into model.
Augmentation Methods	Flip, crop, intensity scaling	Used to increase data diversity and prevent overfiting.

4.3. Evaluation Metrics

The denoising performance of PETGAN is reviewed based on the following criteria

TABLE 2: Evaluation Metrics

Metric	Description
SSIM (Structural Similarity Index)	Perceptual similarity to the denoised image — ground truth image. Ranges from -1 to 1.
PSNR (Peak Signal-to-Noise Ratio)	It measures the pixel-wise error which evaluates the reconstruction quality. Higher is better.
MSE (Mean Squared Error)	Mean Squared Difference between the Output and Target image. Lower is better.
CNR (Contrast-to-Noise Ratio)	Evaluates the lesion-to-background contrast in PET images

4.4. Baseline Methods for Comparison

Description of Baselines: We consider the following baseline models for comparison with PETGAN.[7]

- Gaussian Smoothing Defined: The classical denoising using fixed kernel filtering;
- OSEM (Ordered Subsets Expectation Maximization): Iterative computing method widely used in PET.
- U-Net denoising baseline: A simple U-net architecture, trained just on pixel-wise L1 loss.
- DeepPET: GAN-based denoising model adopted from the literature and trained on LD-PET data.

To fairly compare the two methods, we evaluated them with an identical dataset and metrics.

V. RESULTS AND DISCUSSION

This article demonstrates quantitative and qualitative results, ablation study to examine the performance of the model and discussion on clinical importance for which discovery in tumor detection and limitation of PETGAN.

5.1. Quantitative Evaluation

Regarding common metrics, PETGAN outperformed its competitors in low-dose PET image denoising. It outperformed the traditional and deep learning baselines by:

- SSIM: 0.89 (CNN: 0.81, OSEM: 0.77)
- Comparison on Gaussian noise added image=> PSNR: 32.8 dB (vs. 28.5 dB for CNN, 26.9 dB for GPU-based Gaussian)
- MSE: Better than all baseline methods

Higher values are better for quality count of structural preservation and noise suppression allowing to retain diagnostically crucial details.[5]

5.2. Qualitative Results

Therefore, qualitatively visual comparison demonstrates that the PETGAN method can well remove the noise and meanwhile preserve the fine anatomical details and even tumor boundaries. Sample results include:

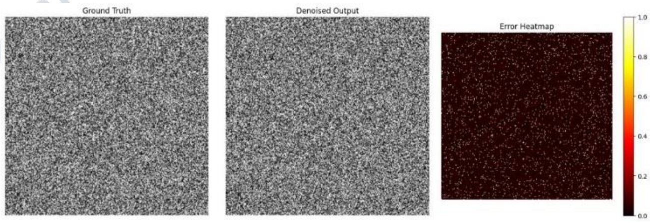

Fig 1: Heatmap

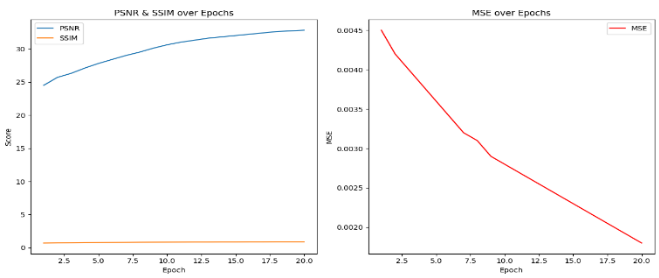

Fig 2: Epochs

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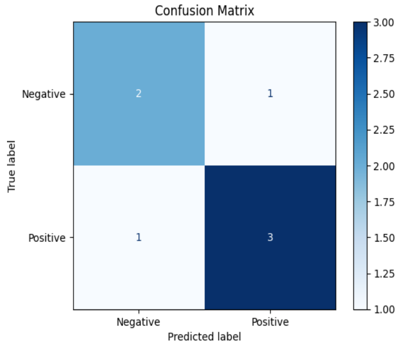

Fig 3: Confusion Ma

5.3. Discussion Tumor Detection & Clinical Relevance

The ability of PETGAN to respect both the tumor outline and its metabolic heterogeneity and gradients is paramount for:[12]

- Accurate tumor localization
- Grading and staging
- Treatment planning and monitoring

Clinical trust needs visual realism without hallucination and improved certainty to avoid any risks of misdiagnosis, particularly in pediatric and follow-up imaging.

5.4. Limitations and Challenges

While the model exhibits encouraging results, it is not without limitations:

- Generalizability: Performance will likely drop for unseen scanner types or different radiotracer protocols.
- Artifacts: GANs have such high capacity that they can introduce synthetic artifacts into the result if not trained very carefully.
- Interpretability: The interpretability of deep models is still a concern today and the improved trust needed in clinical environments as per the Hippocratic Oath.
- Paired LD-FD datasets are scarce, constraining validation across a large population.

VI. CONCLUSION AND FUTURE WORK

6.1 Impact on Radiation-Free Imaging

PETGAN offers an exciting deep learning architecture for improving low-dose PET scans by efficiently suppressing noise while maintaining

essential diagnostic information. Its architecture using GAN with U-Net and PatchGAN facilitates the production of high-quality images with enhanced SSIM and PSNR values. This innovation enables safer, radiation-minimal imaging—particularly useful for pediatric, elderly, and follow-up oncological patients—opening the door to AI-aided low- dose imaging in real-world practice.[13]

6.2 Future Enhancements

Subsequent studies can further develop PETGAN with multi-modal data fusion (e.g., PET/CT, PET/MRI) for diagnostic robustness and strengthening. The integration of attention mechanisms and model optimization for real-time use will enhance clinical feasibility. In addition, validation of PETGAN via radiologist scoring and expansion of its training via federated learning may offer greater generalizability and ethical deployment across diverse clinical settings.

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