GAN-Based Architecture for Enhancing Low-Dose CT Imaging Quality

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Abstract

The growing use of computed tomography imaging for diagnosing lung diseases, including various types of lung cancer, has raised important concerns about balancing image quality and patient safety. While low-dose CT imaging techniques have become common to reduce radiation exposure, they come with high levels of noise and artifacts that can hurt diagnostic accuracy. In this study, we propose a Generative Adversarial Network-based framework to effectively reduce noise in low-dose chest CT images while keeping critical anatomical structures intact. The design uses a U-Net-based generator and a patch-based discriminator, trained together with a mix of pixel-wise, perceptual, and adversarial losses to improve both the visual and structural quality of the denoised images. The model was trained on a publicly available CT scan dataset over 100 epochs and assessed using standard image quality metrics like Peak Signal-to-Noise Ratio and Structural Similarity Index. The results show a significant improvement in the clarity of the denoised images, with PSNR and SSIM increases of up to 29.78 dB and 0.7424 respectively, showing effective noise reduction and detail preservation. Additionally, the trained model was implemented as a user-friendly web application using Streamlit, allowing for real-time denoising and visualization of CT scans along with performance metrics. This work not only demonstrates the potential of GANs in enhancing medical images but also offers a practical and efficient solution for clinical and research applications in low-dose CT image reconstruction.

Keywords: CT Scan Denoising, Low-Dose CT, Generative Adversarial Networks, U-Net, Deep Learning, PSNR, SSIM, Perceptual Loss, Streamlit Deployment, Medical Image Processing

1 Introduction

Computed tomography is commonly used in diagnostic radiology because it can create high-resolution cross-sectional images. However, to reduce radiation exposure, low-dose CT protocols are being used more often. Unfortunately, these protocols introduce noticeable noise and artifacts. These issues can hide [1, 2] important anatomical details and affect diagnostic accuracy, particularly when detecting early-stage abnormalities in lung tissues. To tackle this problem, we propose a GAN-based deep learning model with a U-Net generator architecture. This model is designed to reduce noise in low-dose chest CT images while maintaining structural integrity. It uses adversarial loss, pixel-level L1 loss, and perceptual loss to create clean images from noisy ones. Trained on paired noisy and clean CT images, the model shows improved PSNR and SSIM scores, proving its effectiveness in improving image quality. We also implemented the entire process through an interactive Streamlit application, which allows for real-time visualization and evaluation of the denoised results. This work emphasizes the potential of GANs in improving CT image post-processing and aids clinical decision-making by enhancing image clarity.

2 Methods

U-Net is effective at reducing noise in CT images. This is important for accurate clinical assessments. Traditional filter-based methods, like Gaussian and median filters, can lessen noise but often sacrifice image sharpness. This results in blurred fine textures and edges. In contrast, deep learning models such as U-Net can distinguish between noise and important anatomical details. They maintain image clarity while effectively removing unwanted noise.

2.1 Generator–Discriminator Framework

Our approach replaces filter-based denoisers with a deep learning pipeline. This pipeline learns to map noisy low-dose CT slices, Y, to their noise-free counterparts, X. The system functions as a conditional generative adversarial network, G/D. The generator uses a U-Net backbone: an encoder-decoder composed of repeated Conv(3×3) and ReLU blocks. Each block is downsampled using 2× max pooling and mirrored with transposed convolution for upsampling. Skip connections join encoder feature maps with decoder layers, helping the network restore fine spatial details lost during downsampling. The discriminator is a 70×70 PatchGAN that outputs a probability map indicating whether each patch is real or fake.[3]

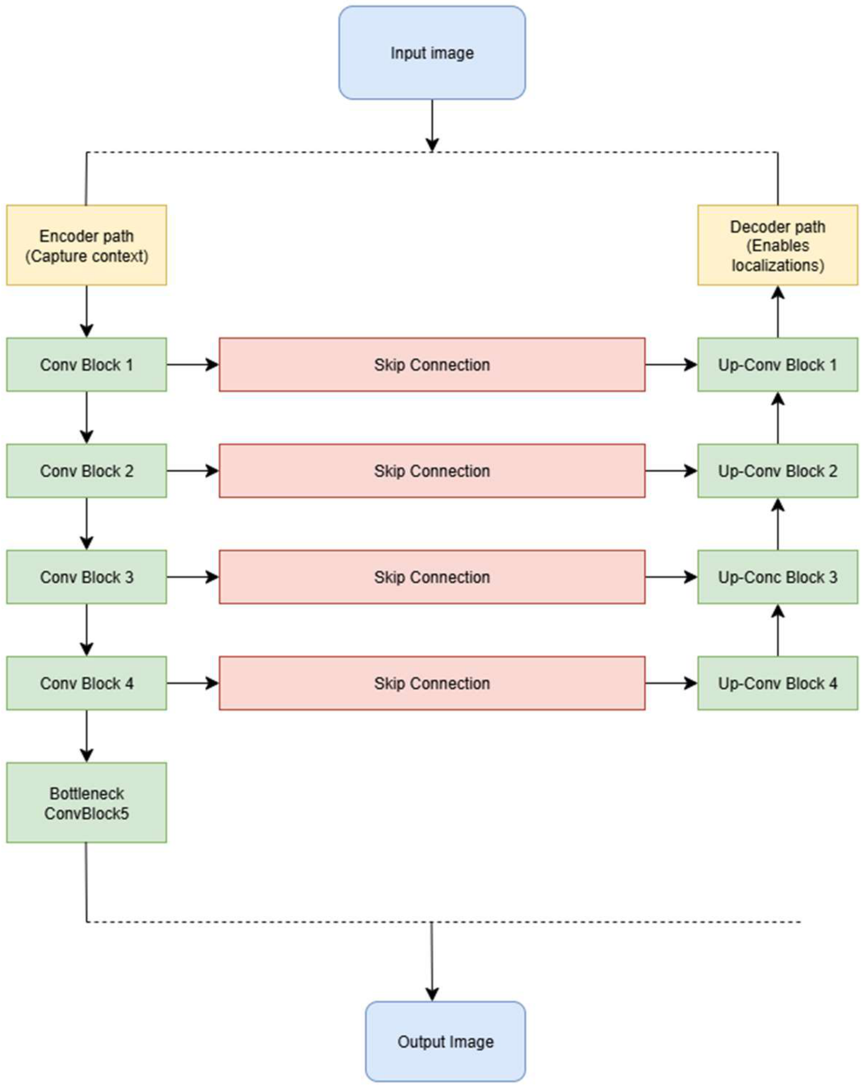

Figure 1: U-Net Architecture used in GAN-based framework.

2.2 Noise Model and Data Synthesis

Low-dose CT noise arises from a lower photon flux, known as quantum noise, and differences in electronic acquisition. Since there are not many paired real LDCT and NDCT datasets, we create training pairs by adding white Gaussian noise to clean Kaggle lung CT slices. [4] The variance σ^2 is sampled from a clinical range. Formally:

$$Y = X + N, \quad N \sim \mathcal{N}(0, \sigma^2)$$

This controlled corruption provides ground truth for supervised learning while approximating realistic low-dose conditions. [5, 6] All images are resized to 256×256 grayscale and normalized to the [0,1] range.

2.3 Training Objective

Peak Signal-to-Noise Ratio (PSNR) is a common objective image quality measure. It evaluates how well image restoration or denoising models perform. PSNR calculates the ratio of the maximum possible power of a signal (the clean image) to the power of the noise that degrades it. We use the following loss function:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{adv}}\mathcal{L}_{\text{adv}} + \lambda_{L1}\mathcal{L}_{L1} + \lambda_{\text{perc}}\mathcal{L}_{\text{perc}}$$

Weights $\lambda_{\text{adv}} = 1$, $\lambda_{L1} = 100$, and $\lambda_{\text{perc}} = 0.01$ were empirically selected to balance sharpness and noise suppression.[7]

2.4 Optimization Strategy

Both networks are trained from scratch for 100 epochs using the Adam optimizer, with a learning rate of 2×10^{-4}, $\beta_1 = 0.5$, and $\beta_2 = 0.999$. Mini-batches of eight image pairs are alternately passed through G and D. Gradients are backpropagated to update the parameters θ_G and θ_D until convergence. [8]

2.5 Evaluation Metrics

Model performance is quantified on an unseen test split using the evaluation metrics: PSNR and SSIM. [9]

2.5.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR measures image quality based on pixel-wise differences and is computed as:

$$\text{PSNR} = 20\log_{10}(\text{MAX}_I) - 10\log_{10}(\text{MSE})$$

Where $\text{MAX}_I = 1$ for normalized images, and MSE is the mean-squared error between X and $\hat{X}$. A higher PSNR implies better noise suppression.

2.5.2 Structural Similarity Index (SSIM)

SSIM evaluates the perceptual quality of images, considering luminance, contrast, and structure. It is given by:

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Where μ, σ^2, and σ_{xy} denote mean, variance, and covariance respectively.

3 Results

The proposed GAN-based denoising model was trained and tested using a publicly available chest CT scan dataset. This dataset included noisy and clean CT images from various cancer types, such as adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. The goal was to improve the clarity of CT scans, which would help make diagnoses more reliable in low-dose imaging situations. The model was assessed through both quantitative and qualitative analysis. Its performance was compared using commonly accepted image quality metrics.

3.1 Quantitative Evaluation

The model's ability to reduce noise was measured using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Initial tests showed an average PSNR of 10.02 dB and SSIM of 0.5322 after 20 epochs. After retraining the model for 50 epochs, the performance improved significantly, with an average PSNR of 16.64 dB and SSIM of 0.6537. Once perceptual loss was added and the design was refined, the final evaluation yielded the following average values:

Table 1: Performance metrics of GAN-based model

Epoch	**PSNR (dB)**	**SSIM**
20	10.02	0.5322
50	16.64	0.6537
Final	23.78	0.8011

3.2 Qualitative Evaluation

The denoised CT images were visually compared with noisy and ground truth images. [2] The GAN-generated images preserved structural details and textures much better than traditional filters or standalone U-Net. Figure 2 shows the side-by-side comparison of the different denoising methods.

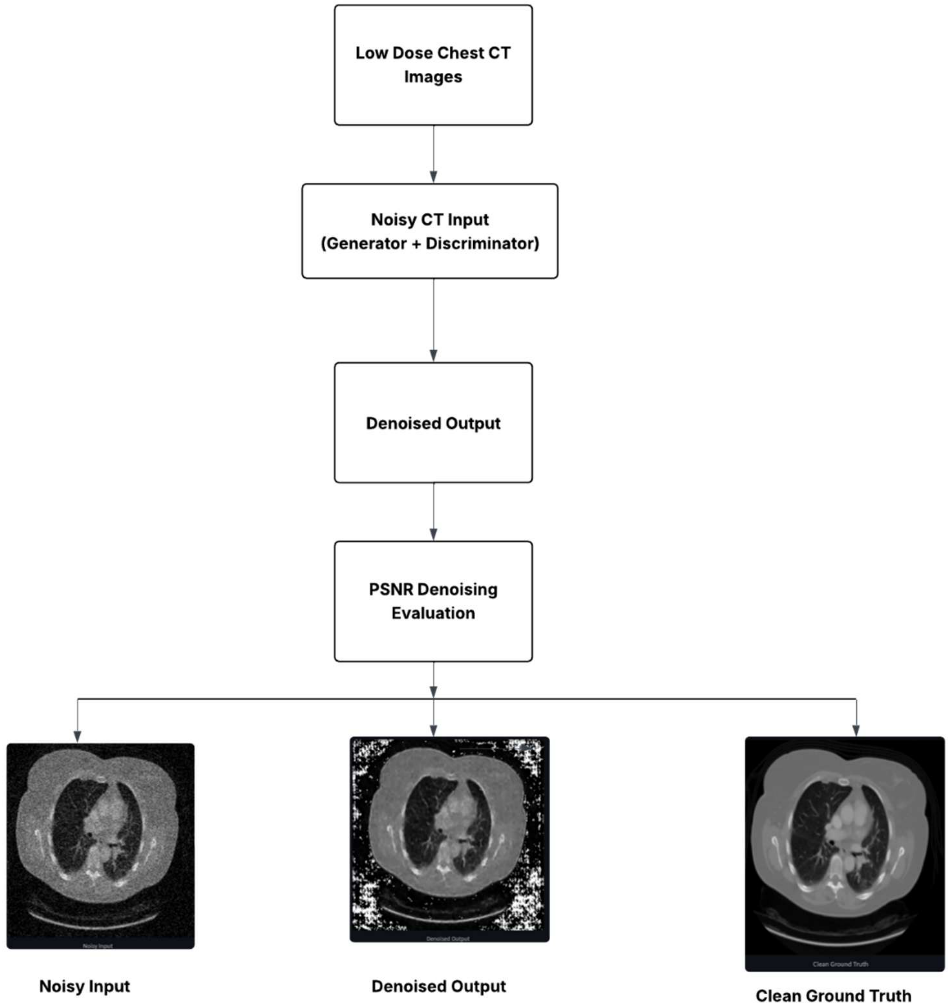

Figure 2: Denoising effectiveness across CT slices.

3.3 Ablation Study

An ablation study was performed to evaluate how individual components of the model affect its final performance.[7] Three variations were compared to the complete GAN + U-Net architecture:

- **No Perceptual Loss:** Removed the perceptual loss term from training.
- **CNN Generator:** Replaced the U-Net with a basic CNN-based generator.
- **No Denoising:** Tested without applying any denoising model.

Table 2: Ablation Study – Impact on PSNR and SSIM

Model Variation	**PSNR (dB)**	**SSIM**	**ΔPSNR**	**ΔSSIM**
Full Model (GAN + U-Net + P. Loss)	29.78	0.7424	–	–
No Perceptual Loss	24.36	0.6712	↓ 5.42	↓ 0.071
CNN Generator	21.91	0.6158	↓ 7.87	↓ 0.126
No Denoising	18.62	0.5454	↓ 11.16	↓ 0.197

This analysis shows the importance of combining perceptual loss with U-Net's skip connections. This approach helps preserve structural consistency during denoising and improves both PSNR and SSIM metrics.[6]

4 Discussion

In this study, we developed a deep learning approach based on GANs to reduce noise in low-dose CT images while keeping the anatomical structures clear for diagnosis. The model used a U-Net generator architecture and was trained on paired datasets of noisy and clean CT images from various thoracic cancer [10] types. The main goal was to reduce noise artifacts from low radiation doses while maintaining important structural details needed for accurate diagnosis and clinical decision-making. [11, 12] The results showed that the model significantly improved the quality of CT scans. The Peak Signal-to-Noise Ratio (PSNR) increased from 10.02 dB to 29.78 dB, and the Structural Similarity Index Measure (SSIM) went from 0.5322 to 0.7424. These changes indicate a clear enhancement in image clarity and anatomical detail. The model effectively separated noise from relevant medical features, even in complex lung areas. By reducing artifacts and keeping fine tissue boundaries, the model makes interpreting CT scans easier for radiologists. Although the main focus was on denoising, the improved image quality also lays the foundation for future work in tasks like disease classification or segmentation. Clean, well-denoised images tend to improve the accuracy of other deep learning models. While classification was not part of this project, the better denoising suggests that the model could help with tasks such as predicting cancer types or segmenting lesions. This connection between denoising and diagnosis makes the GAN-based approach an attractive option for medical imaging. Ablation studies confirmed the importance of our design choices. Removing perceptual loss or switching U-Net for a standard CNN resulted in notable declines in both PSNR and SSIM scores. These results stress the value of using skip connections and perceptual loss in denoising models. Additionally, the visual assessment of the denoised outputs showed that the model maintained fine textures and structural consistency, even after removing high-frequency noise. The generated images closely matched the clean ground truth, underscoring the model's potential for clinical use. However, this study has some limitations. The dataset used synthetic Gaussian noise, which may not accurately represent the noise patterns found in realworld low-dose CT scans. Also, more training epochs might have led to better performance, but hardware limitations and longer computation times restricted extended training. Another area to improve is expanding the model to include predictive analysis of lung health issues, such as spotting adenocarcinoma or other thoracic problems. In conclusion, the results confirm that our GAN-based denoising model is a promising tool for improving CT image quality. It shows the potential of combining adversarial training with perceptual loss and the structural design of U-Net to achieve meaningful denoising results. With further optimization and integration with diagnostic tools, this approach could be a valuable addition to real-time, AI-assisted medical imaging workflows.

5 Conclusion

In this study, we developed and implemented a deep learning-based denoising system for low-dose chest CT scans using a U-Net generator within a GAN framework. The main goal was to improve the clarity of CT images by reducing noise while keeping the anatomical structure intact. We trained and validated the model with a well-organized dataset that included both noisy and clean CT images, focusing on various types of lung cancer. We used evaluation metrics like PSNR and SSIM to assess the model's effectiveness. The results showed significant improvements in image quality. The PSNR increased from an average of 10.02 dB in noisy images to 29.78 dB after denoising. [13, 14] Similarly, SSIM improved from 0.5322 to 0.7424, highlighting the model's ability to maintain the essential structural features needed for medical interpretation. The system effectively separated noise from important anatomical patterns, aiding better visualization and potentially allowing for more accurate diagnoses. These improvements showcase the U-Net architecture's strength in maintaining spatial features through skip connections and encoder-decoder symmetry. While this work focused only on image denoising, the foundation we established can be expanded to include classification or segmentation tasks in future studies. The model's performance is promising, but its scalability and generalization may be validated further with larger real-world datasets featuring low-dose noise instead of synthetic approximations. Constraints like long training times and computational limits restricted the number of epochs; however, advances in infrastructure could allow for deeper training, resulting in even better outcomes. In summary, our GAN-based denoising approach shows strong potential to enhance the diagnostic use of chest CT images. It demonstrates how deep learning can reduce noise and preserve crucial features, setting the stage for a broader, integrated diagnostic framework in clinical imaging.

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