

Deep learning approaches for CT image reconstruction: Advancements and clinical implications

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ABSTRACT

Background: CT is a trusted imaging modality for diagnosing disease. The quality of the CT image plays the most important role in disease prediction. Images will be degraded by noise, blur, and other artifacts. Therefore, the enhancement and reconstruction of CT images are required before processing for prediction. Enhancements are only cosmetic changes in images, but reconstruction provides well-defined models for reconstruction. In this paper, we have compared the performance of these four CT brain reconstruction and enhancement techniques: Filtered back projection (FBP), Iterative reconstruction, Generative Adversarial Network (GAN), and CNN autoencoder, by adding Speckle and Poisson noise.

Objectives: The possible objective statements of this study will cover a broad spectrum of developments in medical imaging technology. These are aimed at enhancing diagnostic test quality, patient safety, and overall care outcomes through innovative imaging methods and data analysis. The suggested objectives involve integrating an artificial intelligence algorithm to enhance them, thereby improving patient care and diagnostic accuracy across numerous medical fields. In this experiment, the CT brain stroke dataset was obtained from the Kaggle database and evaluated using performance metrics (PSNR, SSIM, and MSE) across the normal, ischemia, bleeding, and external test folders, with Poisson and Speckle noise added using the GAN, CNN autoencoder, iterative, and FBP techniques.

Materials and methods: The CT brain stroke dataset contains CT images organized in four folders: normal, ischemia, bleeding, and external test. These folders can be used to evaluate performance metrics. The methods applied include: Convolutional Neural Network (CNN) autoencoder, Generative Adversarial Network (GAN), iterative reconstruction, and FBP, each implemented with hyper-tuned parameters. Experimental results calculate PSNR, SSIM, and MSE after adding Poisson and Speckle noise to test the above deep learning algorithms.

Results: The lowest image quality was achieved for FBP for all datasets and both noise types. When the noise was Poisson, the performance of iterative reconstruction was the best, with PSNR exceeding 37 dB, SSIM exceeding 0.972, and MSE as low as 0.0002. On adding Poisson noise, the GAN achieved higher PSNR values and SSIM values up to 32.54 dB and 0.938, respectively, and with low errors in reconstruction, except for the external test folder. The CNN autoencoder (CNN-AE) also yielded significant improvements over FBP, achieving competitive PSNR and SSIM scores across all datasets.

Conclusion: The results indicate that the quality of CT images can be significantly improved using advanced deep learning and Iterative reconstruction methods compared with conventional FBP. It is observed that iterative reconstruction yields the best results for images corrupted by Poisson noise, whereas GANs perform best for images corrupted by Speckle noise. Therefore, reconstruction performance depends on the nature of the noise present in the CT images.

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Introduction

The use of computed tomography (CT) imaging has transformed medical diagnostics by providing detailed 3-D images of organs. It is a complex imaging process that begins with X-ray emission, tissue attenuation, and data acquisition. The final and most significant process for converting raw data into meaningful information is image reconstruction. Visual information of a clinician-interpretable kind. Traditional restorative methods use mathematical algorithms to facilitate this transformation, generating invaluable data for healthcare professionals to support proper diagnosis and treatment planning.¹

The development of CT imaging technology has greatly improved image quality, acquisition speed, and radiation dose. Modern CT scanners use multidetector arrays and sophisticated software algorithms to generate high-resolution images with fine detail. Such developments have expanded the uses of CT imaging in certain medical subspecialties, including oncology, cardiology, and neurology.² Also, the combination of artificial intelligence and machine learning in image reconstruction has opened new possibilities for enhancing diagnostic accuracy and efficiency. With further development of CT technology, it will become an even more important part of personalized medicine, enabling more specific, targeted interventions using detailed anatomical and functional data about patients. Deep learning has more than a basic image-improvement effect on CT image reconstruction.

More complex neural network models, such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have played a key role in expanding the possibilities in medical imaging.³ Such advanced algorithms can identify complex patterns and features in large datasets of CT images, enabling them to produce high-quality images from incomplete or noisy data.³ This capacity has led to significant improvements in sparse-view and limited-angle CT reconstruction, where conventional algorithms often fail to produce diagnostic images.

With the implementation of deep learning in CT imaging, new opportunities to make imaging protocols more adaptive and personalized have emerged.⁴ These algorithms can optimize reconstruction methods in real-time by performing patient-specific analyses and adjusting imaging parameters to tailor the imaging process to each individual patient. This will not only improve image quality but also reduce radiation exposure and enhance patient safety. In addition, deep learning-based CT reconstruction has demonstrated potential in multimodal imaging, synthesizing data from multiple modalities to provide a more detailed perspective on anatomy and physiology.

As research in this field advances, the potential for deep learning to transform the medical imaging profession and improve patient treatment becomes increasingly evident. One of the most significant changes in medical imaging technology is the integration of

deep learning models and the classical reconstruction in CT imaging. This synergy is based on the merits of both approaches, combining deep learning with the robustness of the tested reconstruction algorithms and the flexibility of deep learning. This implies that the quality of the images obtained will improve, radiation exposure will be reduced, and more accurate diagnoses are likely to be achieved by the researcher and clinician. The outcome of such improvements can be more sensitive imaging protocols that detect subtle abnormalities not easily detected with traditional imaging.⁵ Moreover, the current development of this combined strategy is set to transform personalized medicine. Using patient-specific data and leveraging the potential of artificial intelligence, the CT imaging tools may be able to provide customized diagnostic and treatment prescriptions. This individualized treatment could lead to more accurate interventions, the maximization of a treatment plan, and, consequently, improved patient outcomes. Also, the more efficient and precise nature of these new imaging methods may simplify work processes in healthcare organizations, potentially reducing costs and providing more people with access to high-quality medical imaging than previously studied.⁶

Filtered Back Projection (FBP) and iterative reconstruction methods. There is a significant difference between the principles and performance properties of these two methods for reconstructing the CT Image.⁷ The complexity and speed of FBP arise from the straightforward nature of the mathematical model, which consists of applying a filter to the projection data and then back-projecting it to create the image. This approach is a set of conditions under which ideal imaging is considered, making its real-world application problematic due to imperfect geometry and the lack of noiseless data.¹ The performance of FBP can also be damaged in the low-dose CT scans that have a more dominant noise, leading to streaks and poor image quality. Despite these disadvantages, FBP remains highly applicable in clinical environments due to its computational power and ability to provide immediate results, particularly in emergencies and high-throughput settings.⁸

Iterative reconstruction methods, on the other hand, provide a more advanced method of image reconstruction. These procedures are achieved through successive improvements of a pre-estimation of the original image, comparison with actual data, and comparison of results to implement corrections. In this manner, complex physical models can be incorporated to account for various aspects of the imaging system, such as detector response, beam hardening, and scattering. Also, statistical noise models can be incorporated into iterative methods, allowing noise to be more effectively suppressed and potentially enabling dose reduction without degrading image quality. The adaptability of iterative methods also allows the incorporation of prior knowledge about the object being

imaged, which further improves image quality. Better image quality, however, is obtained at the expense of greater computational complexity and leads to longer think time. This trade-off between image quality and reconstruction speed is a major consideration in the current development and optimization of iterative reconstruction algorithms for clinical use.⁹

The two approaches to CT image reconstruction, FBP and iterative techniques, each present considerable challenges that affect image quality and diagnostic accuracy. Increased sensitivity to noise might cause artifacts and poor image quality, whereas a possible loss of spatial resolution might obscure fine-detail tips, which are important for making an accurate diagnosis. The reconstruction process is also complicated by incomplete or inconsistent data, which is frequently encountered in clinical settings. These constraints have motivated scientists to investigate hybrid schemes and develop superior algorithms that methodically average both FBP and iterative schemes while addressing their drawbacks.¹⁰

The dynamic nature of the field and the significance of CT image reconstruction to medical imaging are evident in current developments in this area. Scientists and practitioners are working around the clock to achieve the best image quality while addressing key issues, including reducing radiation doses and improving reconstruction efficiency. Those attempts have resulted in new reconstruction algorithms that use machine learning and artificial intelligence methods, and adaptive ones that modify reconstruction parameters according to a particular imaging situation. These new techniques are set to increase diagnostic accuracy, improve the quality of patient care, and even expand the use of CT imaging in other medical areas as they continue to improve. Further advances in the field underscore the importance of image reconstruction in maximizing the benefits of CT technology and its impact on healthcare outcomes in deep medical image processing.¹¹

In medical imaging, neural network architectures have been significantly improved, and each type offers distinct advantages for clinical use. Due to their ability to automatically extract hierarchical features from raw pixel data, CNNs have become a staple of image analysis. This feature enables CNNs to be especially effective in lesion detection, organ segmentation, and disease classification across different imaging modalities, including X-rays, CT scans, and MRIs. They are very useful in the analysis of 2D and 3D medical images, as their convolutional layers and pooling operations enable them to capture both local and global features, which is characteristic of CNNs.¹²

Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs) have expanded the potential of medical imaging beyond single-image analysis. RNNs, due to their ability to process sequential data, have been used to analyze dynamic medical

images (e.g., cardiac MRI sequences) and longitudinal patient data. This dynamic nature enables one to understand the disease course and treatment response over time. On the other hand, GANs have succumbed to one of the most critical issues in medical imaging, namely, the lack of labeled data. This is because GANs can produce synthetic but realistic medical images, which, in turn, allow data augmentation strategies to enhance the resilience and generalization of other neural network models. Also, GANs have demonstrated utility in image enhancement and noise removal and can make future disease predictions using current imaging data.¹³

Medical imaging with deep learning has transformed the field, delivering levels of accuracy and efficiency never achieved before. These superior algorithms have demonstrated extraordinary capabilities in radiography, CT, MRI, ultrasound, and pathology, enabling more informed decisions and better patient outcomes. Lesion detection, organ segmentation, disease classification, and image reconstruction are other areas where deep learning has been particularly effective. As an illustration, deep learning systems have demonstrated quite impressive performance in identifying diabetic retinopathy in retinal fundus images and malignant lung nodules in chest computed tomography, and, in many cases, outperform human experts.¹⁴

Although the implementation of deep learning in medical image analysis has made these improvements, there are major challenges associated with the process. The most important issue is patient data privacy, since medical images are sensitive data that ought to be secured. Also, creating powerful deep learning models requires large, annotated datasets, which can be time-consuming and costly. The problem of model interpretability remains a critical concern because healthcare professionals need to understand the rationale behind AI-generated decisions to trust them and comply with regulations. Moreover, it is necessary to ensure that deep learning models can generalize across patient groups and imaging modalities to be used widely. The success of introducing deep learning technologies into clinical care largely depends on overcoming these obstacles, which can ultimately lead to higher diagnostic accuracy, more efficient workflows, and better patient care.¹⁵

CT reconstruction based on deep learning has transformed the field of medical imaging by enabling vast improvements in imaging and the potential to reduce radiation dose. They operate on complex neural network designs used to derive relationships between low- and high-quality CT images. CNNs have been especially successful in noise and artifact removal, leveraging their hierarchical feature extraction capabilities to exploit the data they process in images. Skip connections and encoder-decoder architecture U-Net variants are highly competitive in fine anatomy

and structural information, which is why they are highly applicable to tasks that need fine segmentation and localization.¹⁶

The use of GANs has become one of the most promising tools for CT reconstruction, demonstrating strong results in producing high-quality images from low-dose acquisitions. Using a generator-discriminator architecture, GANs can generate realistic, high-fidelity CT images that closely resemble standard-dose scans. Such a method not only enhances image quality but can also significantly minimize radiation exposure in patients. Recently, there have also been studies examining hybrid architectures that integrate the benefits of different types of networks, e.g., CNN-GAN or U-Net-GAN models, to further improve reconstruction quality and address specific issues in CT imaging.¹⁷

CT reconstruction quality is assessed using a holistic method that is both objective-based and subjective. Quantitative measures give numerical data that can be used to make standard comparisons between the various reconstruction methods. The PSNR compares the maximum possible signal power to the noise power, providing information about the overall quality of the image. The SSIM measures the structural similarity between the reconstructed and reference images, reflecting perceptual differences. The MSE measures the mean squared reconstruction error. These measures are important but not necessarily directly correlated with clinical utility, which is why a qualitative assessment must be added.¹⁸

Expert radiologists with expertise in qualitative assessment are important in the clinical assessment of CT reconstruction quality.^{5,19} These tests are aimed at factors that directly influence diagnostic accuracy, including the clarity of anatomical structures, the appearance and severity of artifacts, and overall image quality with respect to a given diagnostic task. Task-based measurements represent the transition between quantitative and qualitative measurements, in which the performance of the reconstructed image is assessed in a clinical scenario. As an example, lesion detectability assesses whether an abnormality and its characterization can be detected, and segmentation accuracy measures the accuracy of delineating anatomical or pathological regions.²⁰ These decisions on which evaluation metrics to use are dependent on the reconstruction algorithm and the planned clinical

use, and the unique issues relating to that anatomical region or pathology.

This research aims to assess and compare the performance of conventional and deep learning-based CT image reconstruction and enhancement techniques for improving the quality of brain-degraded CT images with Poisson and Speckle noise. The study focuses on the FBP, IR, GANs, and CNN-AE on the public dataset of CT brain stroke images.

The objective of the research is to compare quantitative image quality metrics across reconstruction methods under various noise settings and to identify the best method to improve diagnostic accuracy and support reliable clinical decision-making in medical imaging.

Materials and methods

Dataset used

Brain-stroke-CT dataset downloaded from Kaggle. It contains four folders named Normal (4428 PNG images), Ischemia (1131 PNG images), Bleeding (1094 PNG images), and external test (200 PNG images). We execute such folders using Python code with Google Colab in online mode.²¹

Methods

Firstly, there is dataset preparation for processing. The dataset contains 6,853 clean CT brain images in the folders normal, ischemia, bleeding, and external test, sourced from the Kaggle database. The images were resized and normalized to achieve uniform resolution, which is crucial for input. Then, to obtain a noisy image that simulates realistic low-quality CT images, we inject synthesis noise: Poisson and Speckle (Variance=0.04). These noisy images act as the inputs to reconstruction models (Figure 1). To train deep learning models, GAN and CNN-AE, the dataset was split into training, validation, and testing sets in a 70-15-15 ratio for each dataset folder. Then we applied image reconstruction techniques: GAN, CNN-AE, iterative, and FBP successively at this point. The fifteen captured images were used as the output, and the performance evaluation metrics were PSNR, SSIM, and MSE, calculated to assess the image quality of these models. The performance evaluation metrics of these fifteen images were averaged to achieve the average performance evaluation metrics.

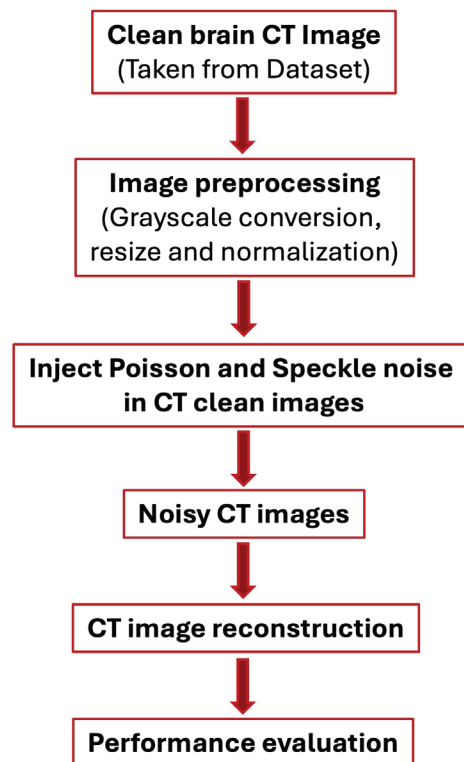


Figure 1. Workflow of the model.

Proposed deep learning methodology

Convolutional Neural Network Autoencoder (CNN autoencoder)

An unsupervised machine learning method is an autoencoder, which learns an approximation of the identity function, with the output being like the input data. A CAE uses a simple autoencoder architecture and replaces the hidden layers with convolutional layers, combining the features of an autoencoder and a CNN. The objective of end-to-end training is to teach CNNs to learn feature representations for classification, whereas CAEs are trained only to learn feature representations of the data that can be used to reconstruct the input. A CNN-AE is a deep learning model that learns compact feature representations and reconstructs images by minimizing reconstruction error. In this work, we use a CNN-AE to remove noise and reconstruct high-quality brain CT images from noisy input images. The CNN-AE has two components.²²

1. Encoder

The encoder converts the input image into a highly compressed representation using convolutional and max-pooling layers. Feature maps of the convolutional layers in the encoder block were expressed as

$$F_{\text{encoder}}^{(i,j)} = \sigma(W_{\text{encoder}}^{(j)} F_{\text{encoder}}^{(i-1, \forall j)} + b_{\text{encoder}}^{(j)}) \quad (1)$$

Where ; $F_{\text{encoder}}^{(i,j)}$ output feature map, σ represents rectified linear unit (ReLU); $b_{\text{encoder}}^{(j)}$ the bias for the j^{th} feature map of the i^{th} layer, and $W_{\text{encoder}}^{(j)}$ the j^{th} filter or kernel of the i^{th} layer.

2. Decoder

The decoder is used to recreate the original image using deconvolution and up-sampling of the outputs in low-dimensional feature maps of decoder block. Feature maps of the convolutional layer in the decoder block were expressed as

$$F_{\text{decoder}}^{(i,j)} = \sigma(W_{\text{decoder}}^{(j)} F_{\text{decoder}}^{(i-1, \forall j)} + b_{\text{decoder}}^{(j)}) \quad (2)$$

Where, $b_{\text{decoder}}^{(j)}$ represents bias for the j^{th} feature map of the i^{th} layer; and $W_{\text{decoder}}^{(j)}$ is the j^{th} filter or kernel of the i^{th} layer.

Generative Adversarial Network (GAN)

GANs produce fake data that, in theory, cannot be distinguished from real data. They use two parallel networks: the generator (G) and the discriminator (D), pitted against each other in a minimax game. G produces new data, which dreads reads, and dread must decide whether the data it has received is synthetic (generated by G) or real. GAN discriminator (D) is trained by using a set of real images, whereas generator(G), which did not consider the training dataset, is forced to create images that resemble real ones mostly, based on the feedback that it gets from discriminator (D), which knows what real images look like. Simultaneously, as G produces images, D would be continually trained to distinguish between real and generated (fake) images. This is done repeatedly; thus, the two networks keep improving their performance, and the aim is to produce images that are not recognizable as the originals. By doing so, the generator will be trained to generate

increasingly realistic images. GANs are widely used in medical imaging through either their generative or

discriminative roles. Figure 2 shows the functioning of a GANs.²³

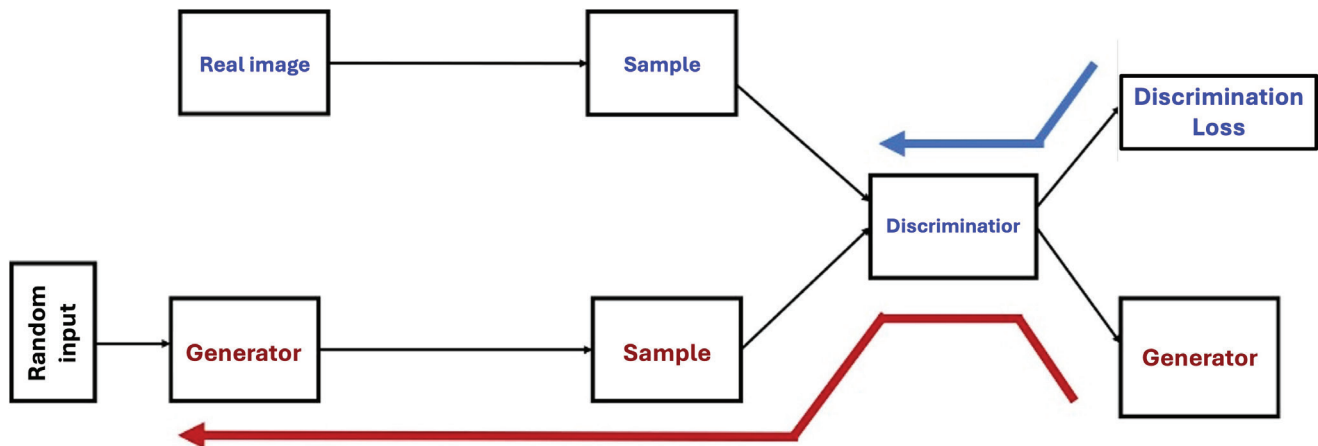


Figure 2. Functioning of GANs. The blue arrow shows the discriminators' loss backpropagation, and the red arrow shows the generator's loss backpropagation. The generator creates synthetic images from random noise, while the discriminator must distinguish between real and synthetic images.

Training process

One of the most important parts of training a machine learning model is choosing the loss function and optimization algorithm. The loss function measures the gap between the actual and predicted values and guides the model's learning. Regular loss functions are mean squared error for regression and cross-entropy for classification. A loss-minimizing algorithm, based on an optimization method (e.g., stochastic gradient descent [SGD] or Adam), determines how to update the model parameters. The choice of an appropriate combination of loss function and optimizer is also crucial for efficient, effective model training. Hyperparameter tuning and model selection involve selecting the most suitable combination of the model architecture and training parameters.

Methods that commonly involve this process and operate on different combinations of hyperparameters, such as learning rate, batch size, and network depth, include grid search, random search, and Bayesian optimization. In model selection, various architectures or algorithms are compared to identify the best-performing model for a given task. The training plan includes methods such as transfer learning, in which pre-trained models are fine-tuned to perform new tasks, and fine-tuning, in which a pre-trained model is further trained on task-related data. The strategies may greatly enhance model performance, especially when using small datasets or complicated tasks. The hyperparameters are a learning rate of 0.001 for the CNN autoencoder and 0.0001 for the GAN model. The batch size is 16 (Figure 1).

Evaluation metrics

Quantitative measures of reconstruction quality are objective indicators of the accuracy and fidelity of the reconstructed data or images. Common metrics

include the mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM). These measures compare the reconstructed output with the input, measure disparities in pixel values, provide a general comparison, and assess the conservation of structural information. Besides that, task-related metrics, e.g., segmentation error or object detection rate, may be used to estimate the usefulness of the reconstructed information in practice.

Qualitative assessment procedures involve subjective evaluation by human observers. Such a methodology considers aspects that are not easily measured numerically, including visual appeal, perceptual quality, and the availability of artifacts in the picture. The qualitative evaluations are usually based on ratings, preference studies, or expert assessments to determine the overall quality and usability of the reconstructed data. Comparison with baseline methods is important for contextualizing the performance of new reconstruction techniques. This involves applying and testing the pre-existing algorithms and the suggested method on the same data, using the same assessment criteria. These comparisons help demonstrate improvements in reconstruction quality, computational efficiency, and the new method's applicability to specific domains, providing a comprehensive view of its advantages and constraints.

Results

The experimental results show that a CNN with an autoencoder provides better reconstruction capability. Statistical analysis is conducted to interpret and assess the significance of the data. This was done by using statistical tests to establish the reliability and validity of the results. The methods researchers can use to evaluate the statistical significance of

their findings include hypothesis testing, confidence intervals, and analysis of variance (ANOVA). Besides, they can investigate relationships among variables, identify trends, and assess measurement uncertainty. It is important to compare state-of-the-art methods to situate research within the current body of knowledge.

This is done by comparing the proposed approach with known methods and highlighting advancements or new contributions. Comparative analysis is presented with performance indicators side by side, underscoring where the approach is superior or provides special benefits, as shown in Figure 3 and Figure 4.

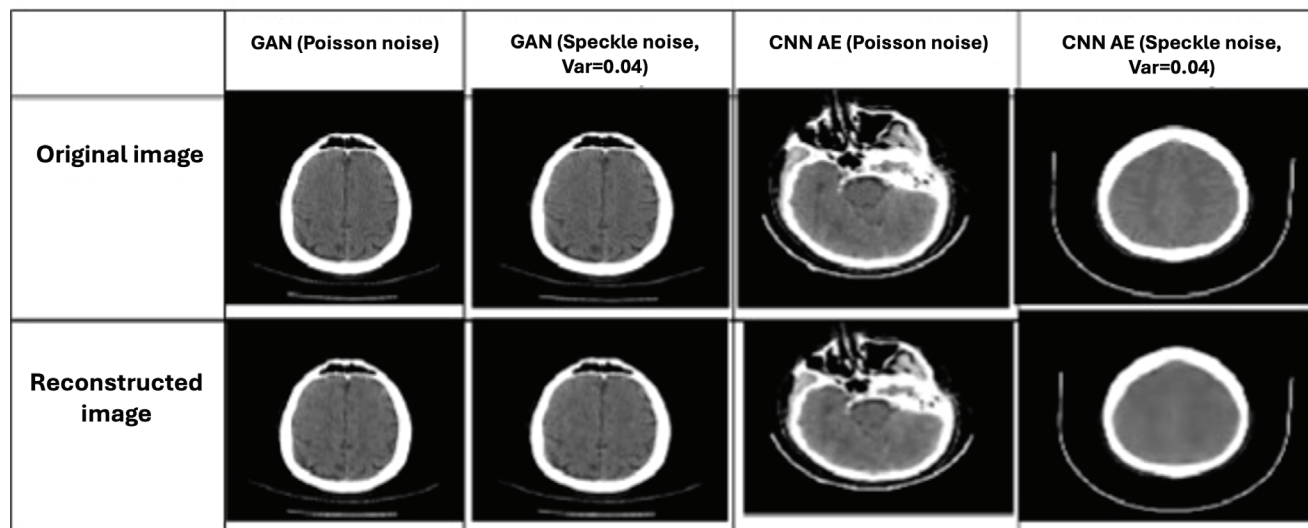


Figure 3. Comparative figure of GAN and CNN autoencoder method, original image vs reconstructed image.

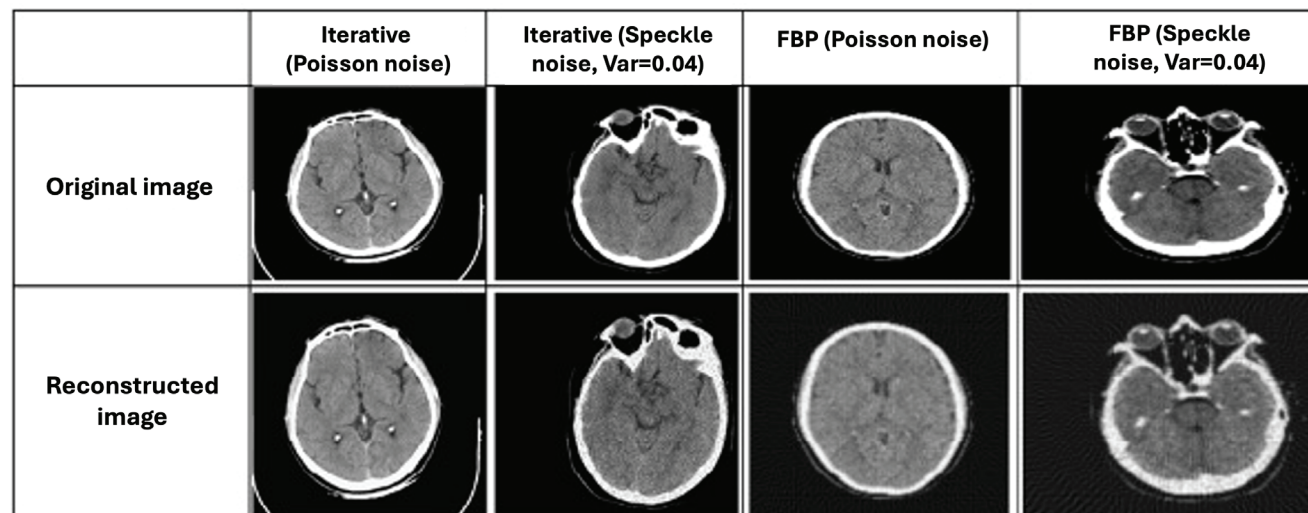


Figure 4. Comparative figure of FBP and the iterative method, original image vs reconstructed image.

The parametric evaluation of the results is presented in the presence of GAN and CNN-AE; FBP and iterative methods with Poisson and Speckle noise are reported in Table 1 and Table 2.

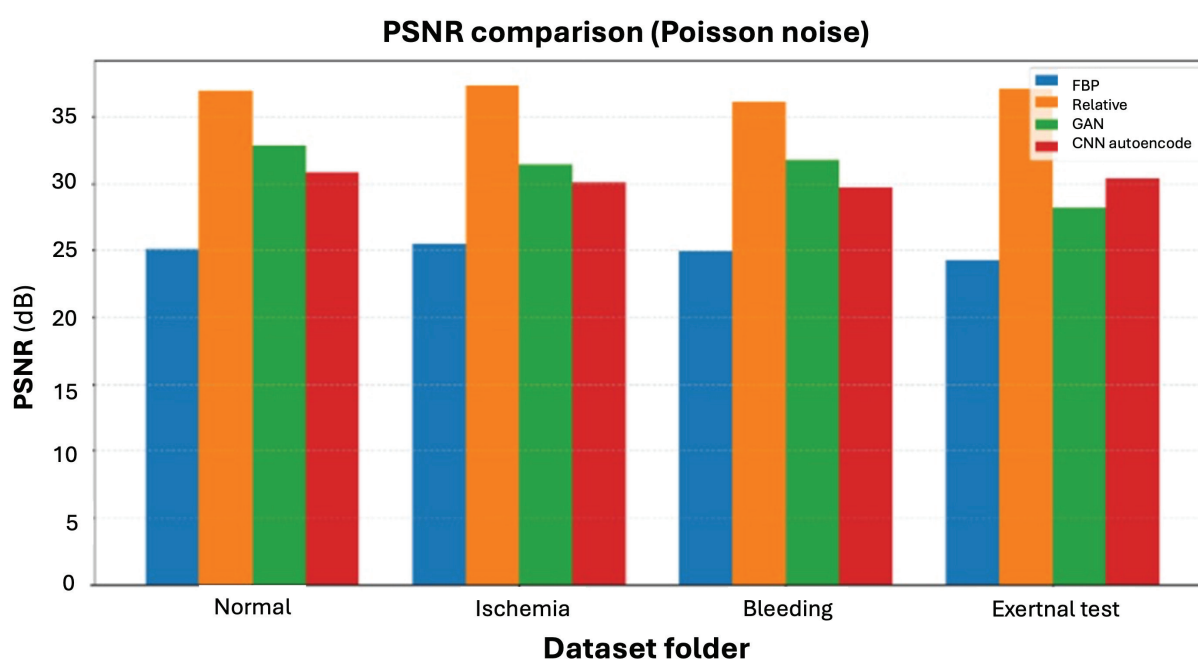
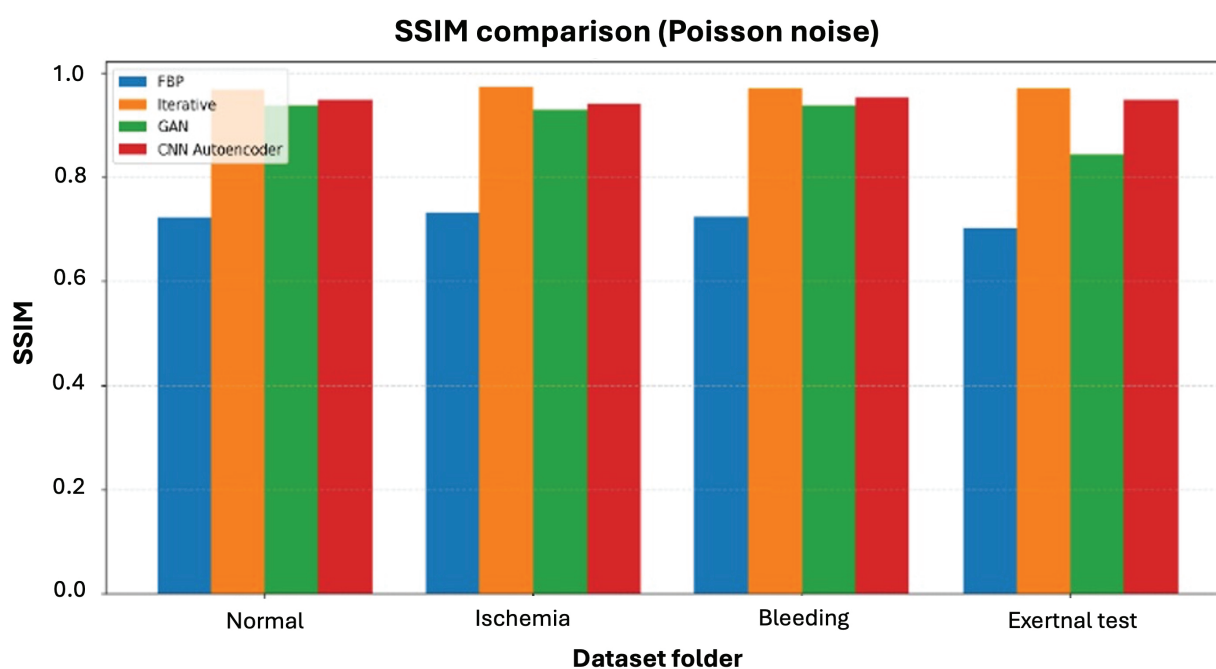
Figure 5-Figure10 present the values of MSE PSNR of different methods in presence of Poisson noise and Speckle noise.

Table 1. Average PSNR, SSIM, and MSE value of 15 CT images using GAN and CNN autoencoder, FBP, and iterative methods with Poisson and Speckle noise.

Noise type	Dataset folder	Method	PSNR (dB)↑	SSIM↑	MSE↓
Speckle (Var=0.04)	Normal	FBP	23.25	0.634	0.0049
		Iterative	27.77	0.890	0.0017
		GAN	32.54	0.938	0.0006
		CNN-AE	29.02	0.926	0.0016
	Ischemia	FBP	23.71	0.651	0.0045
		Iterative	28.88	0.917	0.0013
		GAN	32.17	0.937	0.0006
		CNN-AE	26.46	0.897	0.0028
	Bleeding	FBP	23.19	0.644	0.0050
		Iterative	27.45	0.899	0.0019
		GAN	31.25	0.938	0.0008
		CNN-AE	26.87	0.913	0.0024
	External test	FBP	22.66	0.625	0.0057
		Iterative	28.11	0.897	0.0016
		GAN	27.66	0.870	0.0018
		CNN-AE	24.54	0.864	0.0042
Poisson	Normal	FBP	25.10	0.722	0.0033
		Iterative	37.00	0.967	0.0002
		GAN	32.88	0.937	0.0006
		CNN-AE	30.84	0.947	0.0011
	Ischemia	FBP	25.54	0.730	0.0031
		Iterative	37.34	0.972	0.0002
		GAN	31.43	0.929	0.0008
		CNN-AE	30.06	0.941	0.0012
	Bleeding	FBP	24.90	0.723	0.0035
		Iterative	36.12	0.970	0.0003
		GAN	31.76	0.937	0.0007
		CNN-AE	29.71	0.952	0.0012
	External test	FBP	24.29	0.701	0.0041
		Iterative	37.10	0.970	0.0002
		GAN	28.16	0.843	0.0016
		CNN-AE	30.37	0.947	0.0011

Table 2. Comparison of the proposed model with existing models.

Author	Method	PSNR (dB)	SSIM	MSE
Runkel C, <i>et al.</i> ²⁵	FBP	16.81	0.0602	-
Xiaobao Liu ⁹	GAN	28.34	0.945	-
Qing Li, <i>et al.</i> ²⁴	CNN-AE	29.91	0.909	-
Proposed	FBP	25.10	0.722	0.0033
	Iterative	37.34	0.972	0.0002
	CNN-AE	30.37	0.947	0.0011
	GAN	32.54	0.938	0.0006

**Figure 5.** Comparison of PSNR of GAN and CNN-AE (with Poisson noise).**Figure 6.** Comparison of SSIM of FBP, iterative, GAN, and CNN-AE (with Poisson noise).

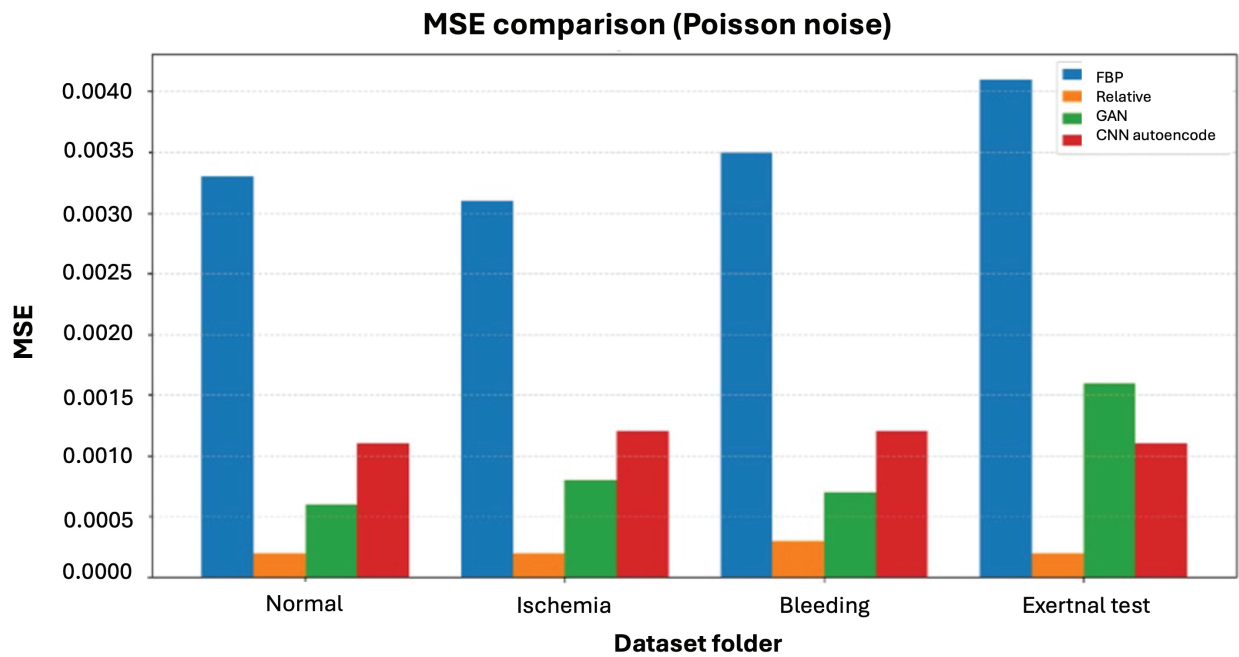


Figure 7. Comparison of MSE of FBP, Iterative, GAN, and CNN-AE (with Poisson noise).

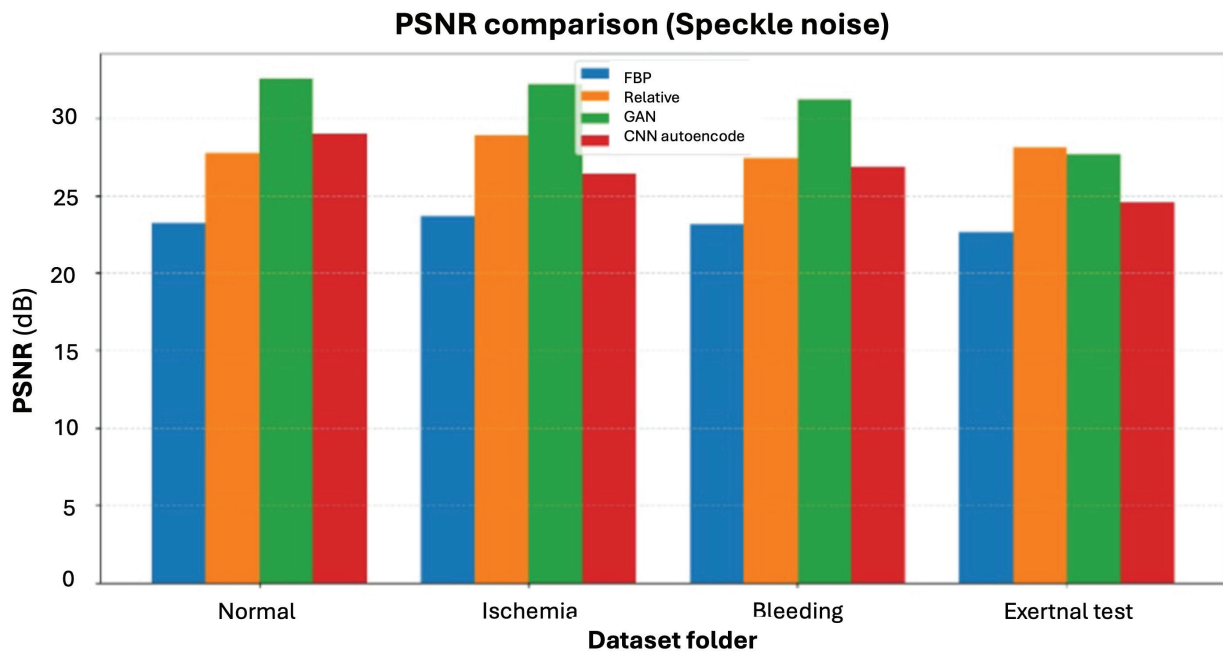


Figure 8. Comparison of PSNR of FBP, Iterative, GAN, and CNN-AE (with Speckle noise).

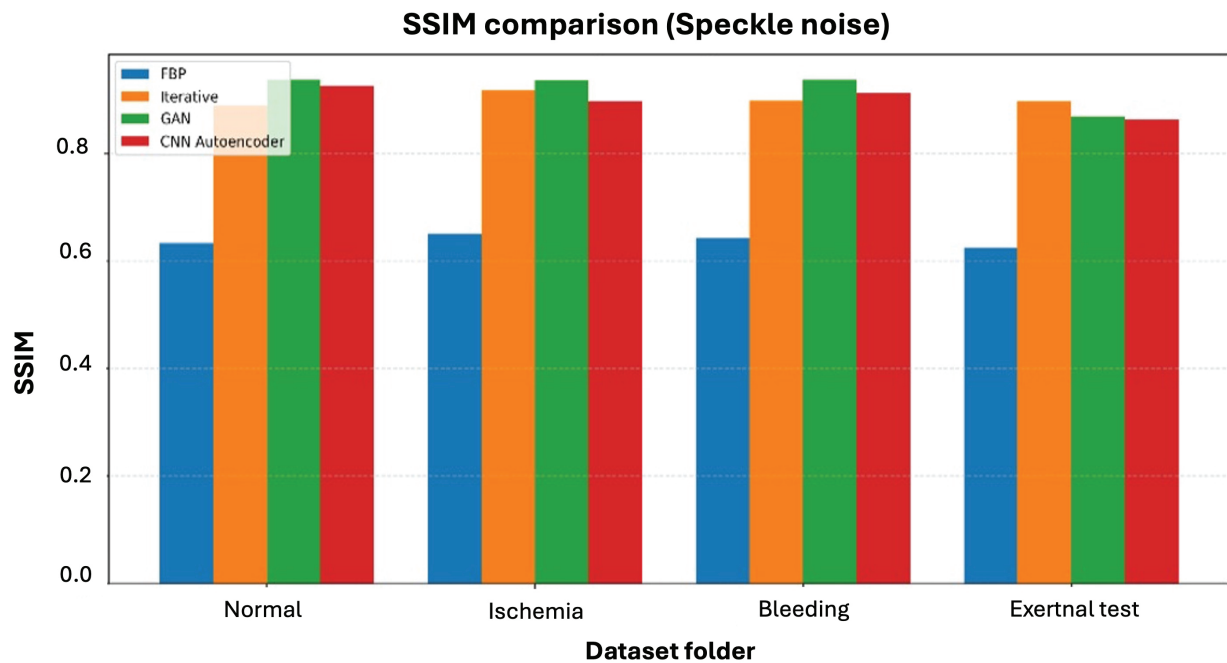


Figure 9. Comparison of SSIM of FBP, Iterative, GAN, and CNN-AE (with Speckle noise).

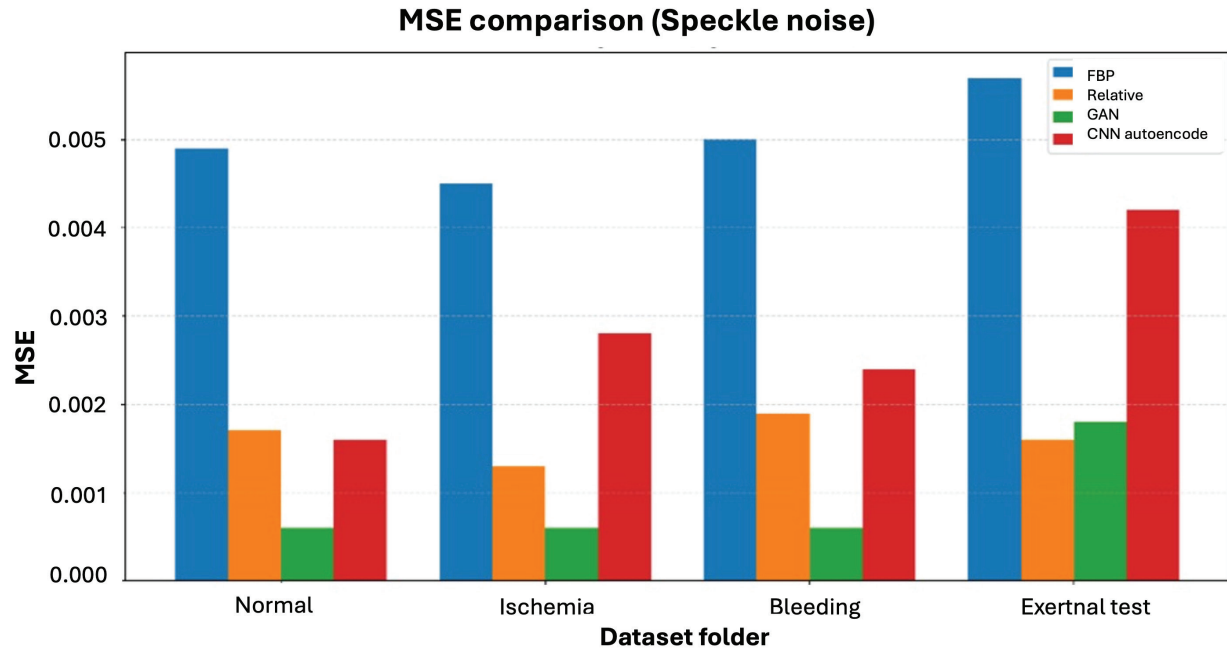


Figure 10. Comparison of MSE of FBP, Iterative, GAN, and CNN-AE (with Speckle noise).

The experimental evaluation is indicated in Table 1. We have compared the results of FBP, iterative, GAN, and CNN-AE-based reconstruction on two noise models, i.e., Poisson and Speckle. The assessment metrics used are peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and mean squared error (MSE) across four dataset folders, i.e., normal, ischemia, external-test, and bleeding.

Analysis of the results

Table 1 shows the results of four CT image reconstruction methods: FBP, IR, GAN, and CNN-AE, with the addition of two types of noise, Speckle and Poisson, in four dataset folders named normal, ischemia, bleeding, and external test folder. The performance parameters evaluated are PSNR, SSIM, and MSE.

1. Performance on Speckle noise

When applying Speckle noise to the four CT image datasets, the GAN approach yields the highest-quality images across all datasets. In the case of the Normal dataset folder, the GAN achieves the highest PSNR of 32.54 dB and SSIM of 0.938, while also having the lowest MSE of 0.0006, indicating that its reconstruction is most like other techniques. However, FBP, a conventional reconstruction approach, performed the worst, achieving a PSNR of 23.71 dB and an SSIM of 0.650. This is also true in the Ischemia dataset folder, where the GAN method achieved a PSNR of 32.17 dB, an SSIM of 0.937, and an MSE of 0.0006, which are better than those of the Iterative and CNN Autoencoder methods. The CNN autoencoder is more successful than the iterative method yet still lower than the GAN approach.

In the bleeding dataset folder, the method achieves the best reconstruction with a PSNR of 31.25 dB and an SSIM of 0.938, whereas the FBP method yields the worst PSNR and the highest MSE. For the external test dataset folder, GAN performance was reduced, yielding PSNR 27.66 dB and SSIM 0.870, indicating reduced generalization to unseen data.

2. Performance on Poisson noise

When Poisson noise is applied to the dataset folder, the iterative method yields the best PSNR of 37.00 dB and SSIM of 0.967.

The CNN-AE and GAN algorithms yielded higher image quality than FBP, but the iterative method performed best in the presence of Poisson noise. CNN-AE produced higher SSIM values compared to GAN on the external dataset, for CNN-AE (0.947) and GAN (0.843), indicating better preservation of structural information on unseen data. FBP again yields the poor performance, with PSNR values 25.54.

Based on the above results, we suggest that reconstruction performance depends on the type of noise.

Discussion

There are differences in the number of CT images across the folders (normal, ischemia, bleeding, and external test). With 4,428 images, more than the ischemia folder (1,131 images), the bleeding folder (1,094 images), and the external test folder (200 CT images). This imbalance may bias model training, which could affect the generalization capacity of reconstruction models. To overcome this, training, validation, and testing were conducted independently for each data folder. Image quality was then assessed using the performance metrics of PSNR, SSIM, and MSE.

Limitation

The brain-stroke-CT dataset was taken from Kaggle. It's not real clinical data, and it does not have the same number of images. Therefore, the experimental results obtained using the above methods may differ. There was synthetic noise (Speckle and Poisson noises), but real-world CT images can have complex noise and artifacts. There was no emphasis on clinical diagnosis or radiologist assessment; only image quality metrics were assessed. These limitations should be addressed in future research.

Conclusion

This paper shows that GAN, iterative, and CNN-AE approaches substantially outperform the conventional approach, FBP, in all datasets and noise addition. When adding Speckle noise, the GAN yields the highest performance matrices (PSNR=32.54, SSIM=0.938, MSE=0.0006). For the external dataset with Speckle noise, IR gives the best performance, but slightly higher than GAN. Under Poisson noise, the IR technique yields the best performance on all dataset folders. GAN and CNN-AE yield improved image quality compared with the traditional method, FBP, but their performance is below that of the Iterative method, even with the addition of Poisson noise.

Finally, conclude that IR is most effective for Poisson-noise-corrupted CT images. Whereas the GAN reconstruction method provides the best performance for Speckle noise addition. Thus, it demonstrates the potential of deep learning and Iterative methods for enhancing image quality and removing noise while preserving anatomical structures.

Ethical approval

This research did not involve any human participants, human data, human tissue, or animal experiments. Therefore, ethical approval was not required.

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Conflict of interest

The authors declare no conflicts of interest regarding this manuscript. No commercial or financial relationships were present in the study that could be considered a possible conflict of interest. The authors also state that there is no conflict of interest in this work. There are no personal, professional, or financial associations that affected the behavior or the results of this study.

CRediT authorship contribution statement

Rita Yadav: conceptualization, investigation, data curation, software, formal analysis, validation, visualization, writing: original draft; **Rajesh Kumar:** research idea, formulated the problem, conceptualization, methodology, supervision, project administration, writing: critically review and edit; **Kavita Singh:** visualization, data curation, writing: manuscript draft, review and edit.

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