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AI IN RADIOLOGY: ENHANCING IMAGE QUALITY AND REDUCING NOISE

Naimul Islam Mehedi

1. Introduction

The acquisition of high-fidelity diagnostic images stands as a cornerstone in the practice of radiology, playing an indispensable role in the accurate detection of diseases and the formulation of effective treatment strategies. The clarity and detail present in these images directly influence the confidence of diagnoses and the subsequent management of patient care. However, a fundamental challenge within this domain lies in the inherent trade-off between achieving optimal image quality and other critical factors such as the level of radiation exposure imparted to patients, the duration of image acquisition procedures, and the potential for artifacts that can compromise the interpretability of the resulting scans.¹ Traditional methods aimed at enhancing image quality often necessitate higher radiation doses or prolonged scanning times, both of which carry potential drawbacks and limitations.

In recent years, the field of Artificial Intelligence (AI) has emerged as a transformative force, offering novel and increasingly sophisticated solutions to address these long-standing challenges in medical imaging. AI encompasses a wide array of techniques that can be leveraged to significantly enhance the quality of radiological images, effectively reduce the presence of noise and artifacts that can obscure diagnostic information, and ultimately improve the overall resolution across various imaging modalities. This technological evolution promises to reshape the landscape of radiology, enabling clinicians to extract more information from medical images while mitigating some of the inherent risks and inefficiencies associated with traditional imaging protocols.

The primary focus of this research report is to meticulously investigate the application of cutting-edge AI techniques for the specific purpose of improving image quality and achieving substantial noise reduction in the three primary radiological imaging modalities: Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and X-ray imaging. These modalities represent the workhorses of modern medical diagnostics, each offering unique advantages and facing distinct challenges related to image quality. Advancements in their respective image qualities through the application of AI have the potential to yield profound benefits for healthcare, impacting everything from early disease detection to personalized treatment planning.

This report will provide a structured and comprehensive overview of the role of AI in radiological

image enhancement. Following this introduction, the fundamental AI principles and techniques that are most relevant to this field will be discussed. Subsequent sections will delve into specific AI-powered noise reduction techniques and methods for enhancing image quality and resolution. The report will then explore modality-specific applications and present illustrative case studies in CT, X-ray, and MRI. A dedicated section will address the crucial aspects of evaluation and validation of AI-enhanced images, followed by an analysis of the existing challenges, limitations, and promising future directions in this dynamic area of research. Finally, the report will conclude with a synthesis of the key findings and their implications for the future of radiology.

2. Fundamentals of AI in Radiological Image Enhancement

The application of Artificial Intelligence (AI) to enhance image quality and reduce noise in radiological imaging relies on a diverse set of computational techniques, primarily rooted in the field of machine learning. These techniques enable computers to learn from data, identify complex patterns, and make predictions or decisions without being explicitly programmed. In the context of medical imaging, AI algorithms are trained on vast datasets of radiological images to understand the characteristics of both high-quality and degraded (noisy or artifact-laden) images, as well as the underlying anatomical structures they represent.¹

Deep learning, a subfield of machine learning, has emerged as a particularly powerful approach for tackling image-related tasks. It utilizes artificial neural networks with multiple layers (hence "deep") to automatically learn hierarchical representations of data.² This capability is crucial for medical image analysis, where subtle features and complex relationships between pixels can hold significant diagnostic value. Several deep learning architectures have proven particularly effective in radiological image enhancement:

Convolutional Neural Networks (CNNs) are a cornerstone of deep learning for image analysis. Their architecture is specifically designed to process grid-like data such as images, employing convolutional layers that learn spatial hierarchies of features.³ CNNs excel at identifying patterns like edges, textures, and shapes, making them highly effective for noise reduction, artifact removal, and overall image quality improvement.¹

Generative Adversarial Networks (GANs) represent another class of deep learning models that have shown remarkable success in image generation and enhancement.⁴ A GAN consists of two competing neural networks: a generator, which tries to create realistic or enhanced images, and a discriminator, which tries to distinguish between real and generated images. Through this adversarial process, the generator learns to produce increasingly high-quality outputs, making GANs particularly useful for tasks like denoising and super-resolution in medical imaging.¹

Autoencoders are neural networks designed to learn compressed representations of input data.¹ They consist of an encoder that maps the input to a lower-dimensional latent space and a decoder that reconstructs the original input from this compressed representation. By training an

autoencoder on clean medical images, it learns to capture the essential features while discarding noise. When a noisy image is passed through a trained autoencoder, the reconstructed output is often a denoised version of the input.¹

Transformer Networks, initially developed for natural language processing, have recently demonstrated significant potential in computer vision.⁵ Their core mechanism, known as self-attention, allows them to capture long-range dependencies within an image, enabling a more holistic understanding of the context. This capability is increasingly being explored for medical image enhancement tasks, including improving resolution and reducing artifacts by considering global relationships between different image regions.⁶

Diffusion Models are a class of generative models that have gained prominence for their ability to produce high-fidelity images.¹⁴ They operate by learning to reverse a process that gradually adds noise to training data. Once trained, they can start from random noise and iteratively refine it to generate realistic and high-quality images, making them promising for tasks like image enhancement, super-resolution, and reconstruction in medical imaging.¹⁵

While deep learning represents the cutting edge of AI in this field, traditional machine learning techniques, such as support vector machines, random forests, and others, have also been applied to medical image analysis, particularly in earlier stages of research.²⁵ These methods often rely on manually extracted features from images, whereas deep learning excels at automatically learning these features.

The effectiveness of these AI techniques in enhancing radiological images stems from their ability to learn the complex characteristics of medical data. For instance, deep learning algorithms can be trained to recognize and suppress specific noise patterns that are common in certain imaging modalities or acquisition protocols.¹ They can also learn to reconstruct missing information in under-sampled or low-dose scans by leveraging patterns learned from large datasets of high-quality images.¹ Furthermore, AI can enhance diagnostically relevant features, making subtle abnormalities more visible to the human eye.

AI models for radiological image enhancement are trained using different learning paradigms, each with its own advantages and requirements. Supervised learning involves training a model on a dataset of paired noisy and clean images, allowing the model to learn a direct mapping between the two.¹⁵ Unsupervised learning, on the other hand, uses unlabeled data to learn the underlying structure of the images, which can be beneficial for tasks like denoising or anomaly detection without the need for explicit paired examples.¹⁸ Self-supervised learning represents an intermediate approach where the model learns from the input data itself, often by predicting a masked portion of the image or by solving a related task, thus reducing the reliance on large, manually labeled datasets.¹⁵

The diverse range of AI techniques being applied to radiological image enhancement reflects the

complexity of the task and the ongoing efforts to find optimal solutions for different scenarios. The choice of technique often depends on the specific imaging modality, the nature of the image degradation, and the desired outcome in terms of image quality and diagnostic utility.

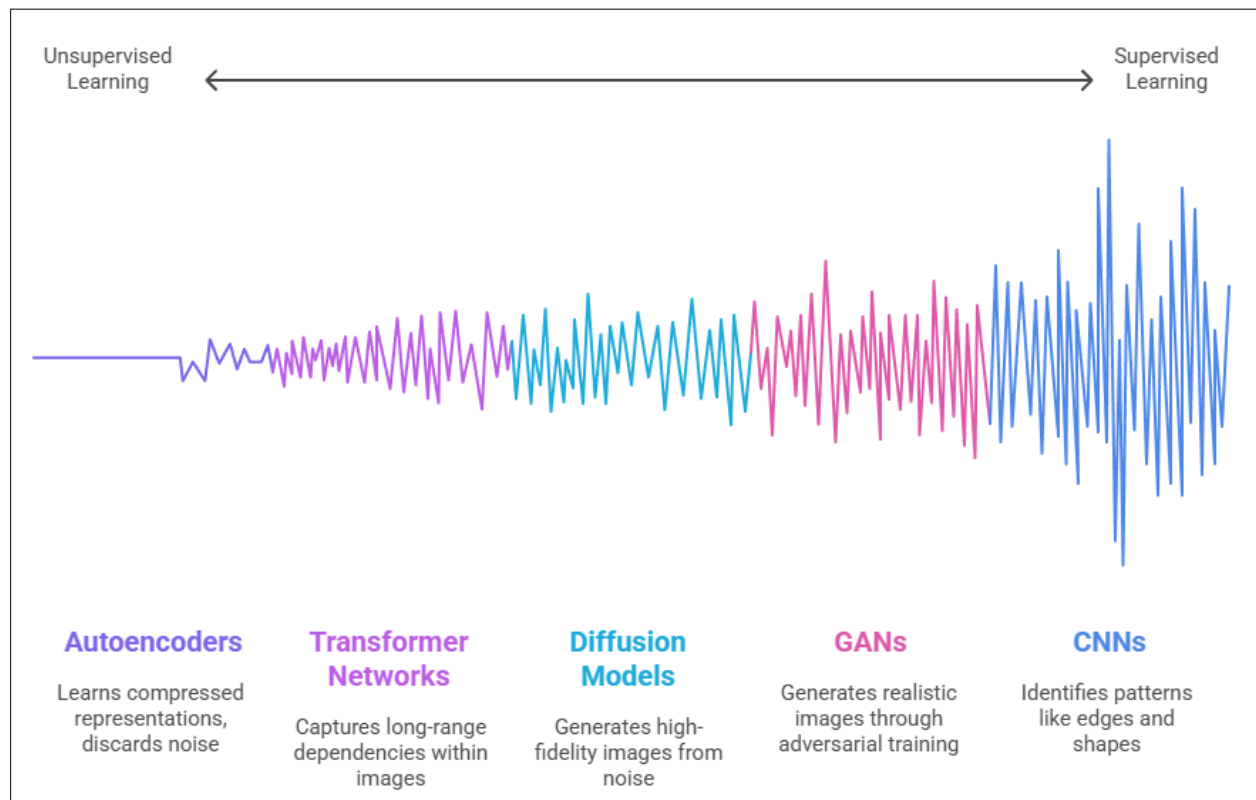


Figure 01: The spectrum categorizes AI techniques based on their reliance on labeled data for training, which impacts their applicability and performance in radiological image enhancement.

3. AI-Powered Noise Reduction Techniques

Noise is an inherent component of all radiological imaging modalities, arising from various sources such as the statistical nature of radiation, electronic components in the imaging system, and patient-related factors. Excessive noise can significantly degrade image quality, making it challenging to visualize subtle anatomical structures and pathological findings, potentially leading to diagnostic errors. Artificial Intelligence, particularly through deep learning, has offered powerful new approaches to effectively reduce noise in medical images while preserving essential clinical information.

Convolutional Neural Networks (CNNs) have emerged as a foundational technique for denoising radiological images due to their ability to learn complex spatial patterns.¹ CNN-based denoising models are typically trained on large datasets of noisy and clean image pairs. During training, the network learns to identify the characteristics of noise and to predict the underlying clean image. The convolutional layers in the CNN are adept at extracting local features, allowing the model to

effectively differentiate between noise and meaningful image structures. Once trained, a CNN can take a noisy radiological image as input and output a denoised version with improved clarity, often achieving significant reductions in noise levels.¹

Generative Adversarial Networks (GANs) have also proven highly effective in noise reduction and artifact removal, especially in challenging scenarios like low-dose imaging.¹ GANs, with their adversarial training process, can learn to generate highly realistic and clean images from noisy inputs. The generator network in a GAN tries to produce denoised images that are indistinguishable from real, high-quality images, while the discriminator network tries to tell the difference. This competition drives the generator to learn increasingly sophisticated denoising functions. GAN-based methods have shown particular promise in enhancing the quality of PET and SPECT images, which are inherently noisy due to the nature of the imaging process.²⁶

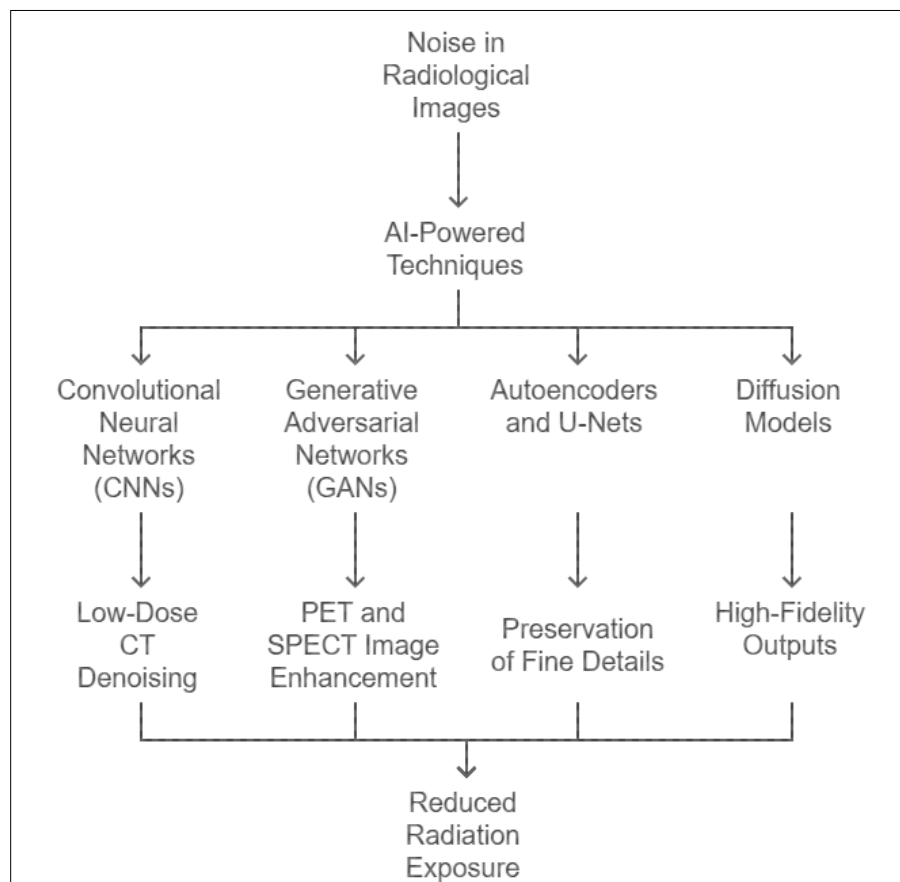


Figure 02: AI-Powered Noise Reduction Techniques in Radiology

Autoencoders and other deep learning architectures, such as U-Nets, have also been successfully employed for image denoising in radiology.¹ Autoencoders learn a compressed representation of the input image, effectively capturing the essential information while discarding noise. The decoder part of the autoencoder then reconstructs the image from this compressed representation, resulting in a denoised output. U-Nets, with their encoder-decoder structure and skip connections,

are particularly effective at preserving fine details during the denoising process, which is crucial in medical imaging where structural integrity is paramount.

More recently, diffusion models have emerged as a cutting-edge approach to medical image denoising.¹⁵ These models learn to reverse a process of gradual noise addition, allowing them to generate high-quality, despeckled images from noisy inputs. The forward diffusion process progressively adds Gaussian noise to an image over a series of steps, eventually transforming it into random noise. The reverse process, which the model learns, starts from this noise and iteratively removes it, conditioned on the noisy input, to reconstruct a clean image. Diffusion models have shown remarkable results in various image processing tasks and are increasingly being explored for their potential in medical image denoising due to their ability to capture complex noise distributions and generate high-fidelity outputs.

The effectiveness of these AI-driven denoising techniques varies across different radiological modalities. For instance, CNNs and GANs have been particularly successful in low-dose CT denoising, enabling significant reductions in radiation exposure.¹ The choice of the most appropriate AI technique depends on the specific characteristics of the noise present in the images, the desired level of noise reduction, and the need to preserve fine anatomical details for accurate diagnosis.

4. Enhancing Image Quality and Resolution with AI

Beyond just reducing noise, Artificial Intelligence is also playing a critical role in enhancing the overall quality and resolution of radiological images, pushing the boundaries of what is achievable with traditional imaging techniques. AI-based Super-Resolution (SR) techniques are at the forefront of this advancement, aiming to generate higher-resolution images from lower-resolution inputs.²⁷ These deep learning models are trained on vast amounts of data to learn the complex mappings between low-resolution and high-resolution images. By leveraging this learned knowledge, they can effectively "hallucinate" fine details and textures that are not present in the original low-resolution image, leading to significant improvements in visual clarity and diagnostic potential.²⁹

One of the most impactful applications of AI in image quality enhancement is in the realm of low-dose CT imaging.¹ AI techniques, particularly Deep Learning Reconstruction (DLR), are enabling the acquisition of CT scans with significantly reduced radiation exposure while maintaining or even improving diagnostic image quality.³² These methods utilize sophisticated algorithms to reconstruct high-quality images from the limited data acquired at lower radiation doses, effectively compensating for the increased noise that would typically result from such protocols. This is crucial for patient safety, especially in cases requiring repeated CT scans, such as in pediatric imaging or longitudinal studies.

AI is also revolutionizing sparse-view CT reconstruction.¹⁵ Traditional CT scans acquire a large

number of X-ray projections from different angles to create a detailed 3D image. Sparse-view CT aims to reconstruct comparable image quality using a significantly smaller number of projections, thereby drastically reducing radiation exposure. AI models, particularly generative models like DiffusionBlend, are demonstrating remarkable capabilities in this area, learning to infer the missing information and reconstruct high-quality 3D volumes from very limited data.¹⁵

Artifacts, which are unwanted features in medical images that do not represent actual anatomical structures, can severely degrade image quality and obscure important clinical information.¹ AI-driven artifact reduction methods are being developed for CT, MRI, and X-ray imaging to address this issue. Deep learning models, such as autoencoders and U-Nets, can be trained to identify and remove various types of artifacts, leading to clearer and more interpretable images.¹

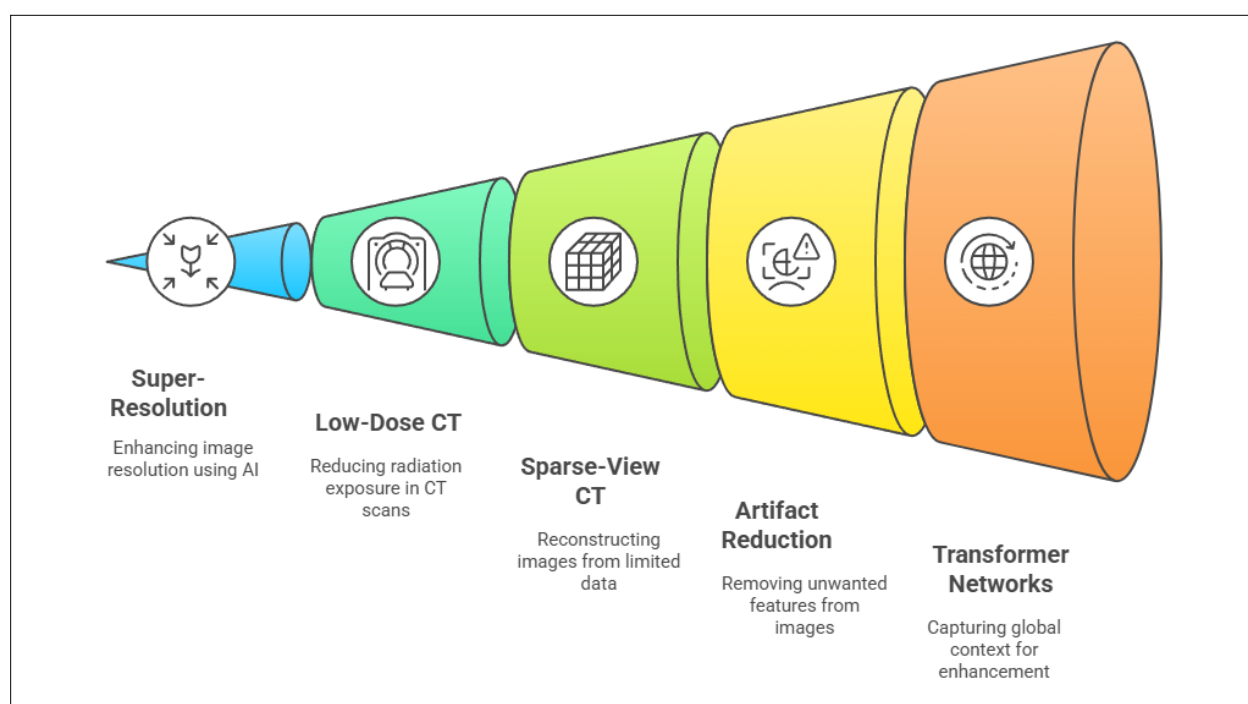


Figure 03: AI-Driven Radiological Image Enhancement

The emergence of transformer networks in medical imaging is also contributing to advancements in image quality and resolution.⁶ Their ability to capture long-range dependencies allows them to consider the global context of an image when performing enhancement tasks. This can be particularly beneficial in identifying and correcting inconsistencies or subtle degradations that might be missed by models with more localized receptive fields.

The progress in AI-driven image quality and resolution enhancement is paving the way for safer, more efficient, and more informative radiological imaging, ultimately benefiting both patients and clinicians.

5. Modality-Specific Applications and Case Studies

The application of AI for enhancing image quality and reducing noise in radiology is highly tailored to the specific characteristics and challenges of each imaging modality: Computed Tomography (CT), X-ray, and Magnetic Resonance Imaging (MRI).

5.1 Computed Tomography (CT)

Research in AI-enhanced CT imaging has significantly benefited from publicly available datasets like the LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative).³⁴ This dataset, containing thoracic CT scans with annotations from multiple radiologists, has been instrumental in developing and validating AI algorithms for tasks such as lung nodule detection and characterization.⁴¹

Case studies abound showcasing AI's impact on CT image quality. For instance, in chest CT imaging for lung disease, AI-powered denoising techniques have demonstrated the ability to improve the visualization of subtle lung abnormalities.⁵⁵ Similarly, in abdominal and neuro CT, AI algorithms are being used to reduce noise and enhance contrast, leading to improved diagnostic confidence.⁷⁵

A particularly noteworthy area is Deep Learning Reconstruction (DLR) in CT.³² DLR leverages deep neural networks to reconstruct high-quality images from lower-dose CT scans, achieving faster reconstruction times than traditional iterative methods.³² The principles behind DLR involve training networks on large datasets to learn the complex relationships between raw CT data and high-quality images.³² Technical approaches include using Convolutional Neural Networks (CNNs) in various configurations, as well as sinogram-based, image-based, and hybrid methods.³² The advantages of DLR are manifold, including improved image quality with reduced noise and artifacts, significant radiation dose reduction (up to 71% in some cases), and faster reconstruction times, enhancing workflow efficiency.³² However, limitations exist, such as the heavy reliance on the quality and quantity of training data, potential issues with generalizability across different scanners, and the inherent "black box" nature of deep learning models.³² Several vendors, including GE HealthCare with their TrueFidelity engine, are actively developing and implementing DLR solutions in clinical practice.⁷⁷

5.2 X-ray

The application of AI in enhancing X-ray image quality and reducing noise has also seen substantial progress, often driven by challenges like Kaggle's RSNA Pneumonia Detection Challenge.⁷⁸ This challenge focused on developing algorithms to detect pneumonia in chest X-rays, utilizing a large dataset with bounding box annotations for lung opacities.

Case studies demonstrate the effectiveness of AI in improving X-ray image quality for various diagnostic purposes. For instance, Carestream Health has released Smart Noise Cancellation

(SNC), an AI-based technology that significantly improves X-ray image clarity.¹¹³ This technology can enhance anatomical clarity, preserve fine details, and improve the contrast-to-noise ratio, potentially increasing diagnostic confidence and reducing physician fatigue.¹¹³ AI is also being used to improve diagnostic accuracy in chest X-rays for conditions like pneumonia.⁷⁰ Furthermore, AI has the potential to assess the quality of X-ray images, which could help in identifying images that might need to be repeated before radiologist review.⁹⁴

5.3 Magnetic Resonance Imaging (MRI)

AI is also making significant strides in enhancing the quality and efficiency of Magnetic Resonance Imaging (MRI). One key application is in accelerating MRI acquisition, which has traditionally been a time-consuming process.³¹ AI-powered reconstruction algorithms can enable high-quality images to be generated from under-sampled data, significantly reducing scan times.³¹

Case studies illustrate the use of AI for noise reduction and resolution enhancement in various MRI applications. In neuroimaging, AI is being used to improve the clarity of brain scans, aiding in the detection of subtle abnormalities.¹¹⁶ Similarly, in cardiac MRI, AI techniques are being explored to enhance image quality and improve the assessment of cardiac function.³⁰

Generative Adversarial Networks (GANs) are finding increasing use in MRI for image synthesis and translation.⁴ For example, GANs can be used to generate synthetic MRI images of specific pathologies, which can be valuable for training AI models when real data is scarce.⁴ They can also be used to translate images between different MRI sequences, potentially reducing the need for patients to undergo multiple scans.³³

The development of AI products in radiology shows a significant focus on neuroimaging and chest imaging, reflecting the high clinical demand and complexity in these areas.¹¹⁶ However, the impact of AI on image acquisition and radiographer workflows in radiography remains an area that requires further exploration.¹²¹ The success of deep learning in challenges like the RSNA Pneumonia Detection Challenge highlights the potential of AI to achieve high accuracy in specific diagnostic tasks, sometimes even surpassing the performance of radiologists.⁴⁷ However, it is important to note that in some real-world scenarios, radiologists have been found to outperform AI in detecting lung diseases, underscoring the complexities and nuances involved in medical image interpretation.¹⁰⁴

6. Evaluation and Validation

The evaluation and validation of AI-driven image enhancement techniques in radiology are critical to ensure their clinical utility and diagnostic reliability.¹ Several standard evaluation metrics are used to assess the performance of these techniques. Quantitative metrics like Peak Signal-to-Noise Ratio (PSNR)¹ and Structural Similarity Index (SSIM)¹ are commonly used to measure the quality of the enhanced images by comparing them to a ground truth or a reference image. Contrast-to-Noise Ratio (CNR)¹ is another important metric that assesses the visibility of diagnostically

relevant structures against the background noise. Other quantitative metrics such as Mean Squared Error (MSE) ¹, Intersection over Union (IoU) ⁷³, and Dice Score ⁴⁹ are used in specific tasks like segmentation and object detection. Diagnostic accuracy metrics, including sensitivity, specificity, precision, and F1-score, are crucial for evaluating the impact of AI-enhanced images on the performance of diagnostic algorithms or human readers.¹

Validating the clinical utility of AI-enhanced images involves comparing their performance with standard images in diagnostic tasks. This often includes assessing whether the AI-driven improvements in image quality lead to more accurate diagnoses or better clinical outcomes.¹ Observer studies, where radiologists review and interpret both standard and AI-enhanced images, are essential for obtaining subjective feedback and assessing the clinical acceptability and diagnostic reliability of these new techniques.¹¹³ These studies help determine if the AI-driven enhancements truly benefit clinical practice and improve the confidence of radiologists in their diagnoses.

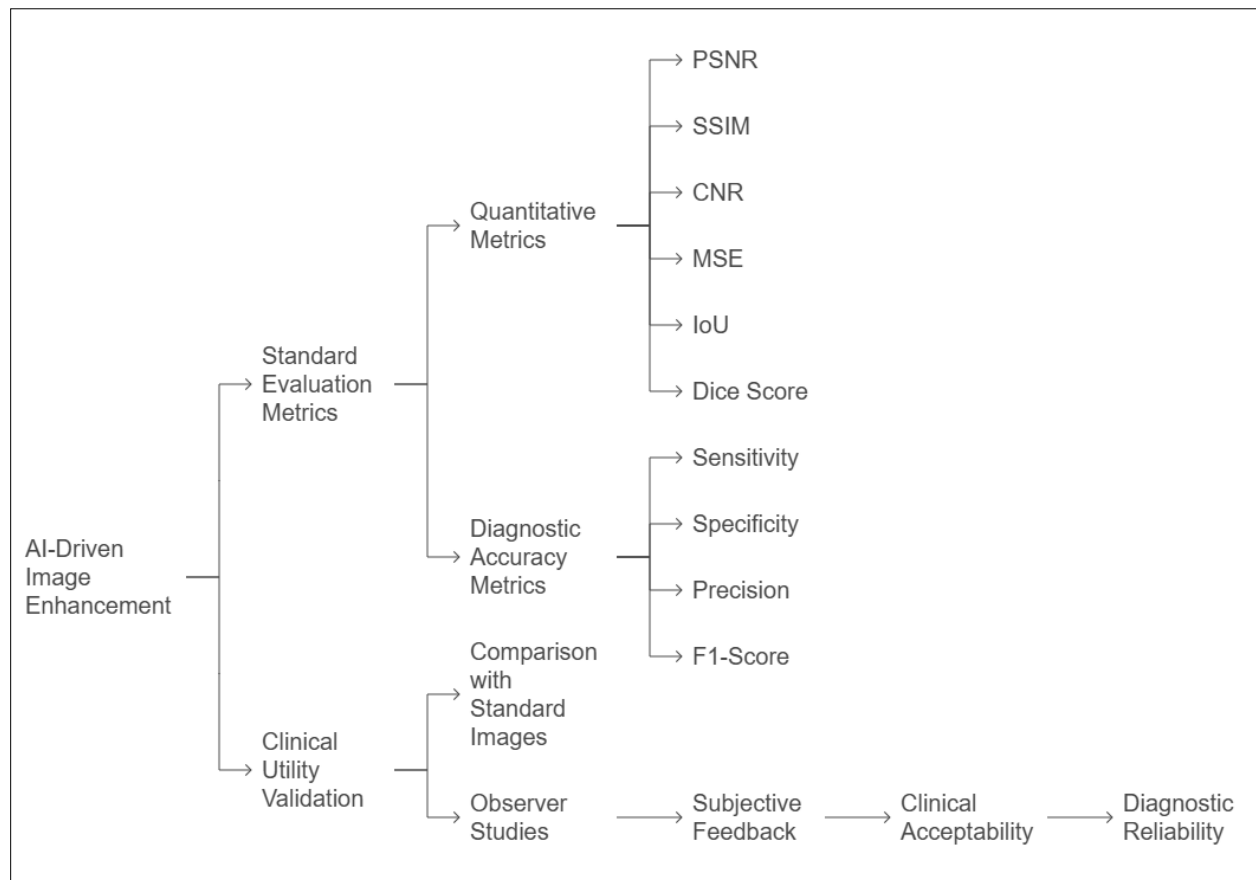


Figure 04: Evaluation and Validation of AI-Driven Image Enhancement Techniques

The use of standardized evaluation metrics is crucial for objectively assessing the effectiveness of AI-enhanced techniques.¹ These metrics provide a common ground for comparing different

algorithms and approaches. However, it is important to note that traditional image-quality metrics might not always be appropriate for evaluating the preservation of diagnostic accuracy, especially in tasks like low-contrast imaging.¹³² In such cases, task-specific evaluation methods that directly assess the impact on diagnostic performance are necessary. Furthermore, for specialized applications like the reconstruction of detailed trabecular bone, common metrics like PSNR and SSIM might have limited physiologic relevance, highlighting the need for domain-specific evaluation metrics that better reflect the clinical value of the enhanced images.²³

7. Challenges, Limitations, and Future Directions

The integration of AI into radiological image enhancement, while promising, is not without its challenges and limitations. Regulatory hurdles and ethical considerations surrounding the deployment of AI in healthcare, including data privacy, patient safety, and algorithmic bias, need careful attention.¹¹⁶ Ensuring the security and confidentiality of patient data used to train and operate AI models is paramount. Furthermore, the responsibility and accountability for AI-driven diagnostic decisions need to be clearly defined.

Data standardization across different imaging modalities, institutions, and manufacturers remains a significant challenge that can hinder the development of robust and generalizable AI models.¹²¹ The variability in image acquisition protocols, data formats, and annotation standards makes it difficult to train AI models that can perform consistently across diverse clinical settings. The need for large, high-quality, and diverse datasets for training effective AI models is also a critical limitation.¹ Obtaining such datasets, especially for rare diseases or specific clinical conditions, can be challenging due to data scarcity and privacy concerns.

The "black box" nature of many deep learning models poses another challenge in the field.²⁵ Understanding why an AI model makes a particular prediction or enhancement is crucial for building trust and facilitating clinical adoption. The development of explainable AI (XAI) techniques that can provide insights into the decision-making processes of these models is an active area of research.

The increasing use of AI in radiology will also impact the workflows of radiographers and radiologists.¹ While AI can automate certain tasks and improve efficiency, it also necessitates training and adaptation for healthcare professionals to effectively integrate these new tools into their practice. The role of humans in overseeing and validating AI-driven results will remain critical.

Looking towards the future, several promising research prospects and emerging trends are shaping the field of AI for radiological image enhancement. The integration of AI with wearable devices could enable continuous patient monitoring and real-time diagnostics.¹³⁶ Federated learning, a technique that allows AI models to be trained on decentralized data sources without sharing sensitive patient information, could help address data privacy concerns and facilitate the

development of more robust and generalizable models.¹³⁷ The exploration of novel AI architectures, such as transformer networks⁵ and diffusion models¹⁴, holds the potential for further significant advancements in image quality and noise reduction.

The field of AI in radiology has witnessed a rapid increase in product development in recent years, followed by a period of stabilization.¹¹⁶ This suggests a maturing market where the focus is shifting towards more focused and validated applications. It is crucial to address the potential biases in AI development and ensure rigorous validation and testing to guarantee the reliability and fairness of these technologies.¹³⁴ Continued investment in AI research, the establishment of ethical guidelines, and comprehensive training for healthcare professionals are essential to ensure the patient-centered development and deployment of AI in radiology.¹³³

8. Conclusion

The application of Artificial Intelligence for enhancing image quality and reducing noise in Computed Tomography, X-ray, and Magnetic Resonance Imaging represents a significant and rapidly evolving field within radiology. AI techniques, particularly deep learning models like CNNs, GANs, autoencoders, transformers, and diffusion models, have demonstrated remarkable capabilities in addressing the inherent challenges of medical imaging. These advancements are leading to tangible improvements in diagnostic accuracy, enhanced patient safety through the enablement of low-dose imaging protocols, and increased healthcare efficiency by optimizing image acquisition and reconstruction processes.

The immense potential of AI to revolutionize medical imaging is evident in the numerous successful applications and ongoing research efforts across different radiological modalities. From improving the clarity of low-dose CT scans and enabling sparse-view reconstruction to enhancing the diagnostic accuracy of chest X-rays and accelerating MRI acquisition, AI is proving to be a powerful tool for overcoming the limitations of traditional imaging techniques. The development and utilization of large, well-annotated datasets like LIDC-IDRI and the RSNA Pneumonia Detection Challenge have been crucial in driving progress in this field.

However, the integration of AI into radiology is not without its complexities. Challenges related to regulatory approval, ethical considerations, data standardization, the interpretability of AI models, and the impact on clinical workflows need to be carefully addressed. Future research should focus on developing more robust and generalizable AI models, ensuring their fairness and transparency, and seamlessly integrating them into clinical practice.

In conclusion, AI holds tremendous promise for transforming the landscape of radiological image enhancement. Continued rigorous research, fostering interdisciplinary collaboration between radiologists and AI developers, and maintaining a steadfast commitment to ethical and responsible innovation are essential to fully realize the benefits of AI in this critical area of healthcare, ultimately leading to improved patient care and outcomes.

Table 1: Comparison of AI Techniques for Radiological Image Enhancement

AI Technique	Primary Application(s)	Key Strengths	Key Limitations	Example Snippet IDs
Convolutional Neural Networks (CNNs)	Denoising, Artifact Reduction, Super-Resolution	Effective at learning spatial hierarchies of features, widely used.	Can be computationally intensive, may require large labeled datasets.	1
Generative Adversarial Networks (GANs)	Denoising, Super-Resolution, Image Synthesis	Generates realistic and detailed images, effective for low-dose imaging.	Training can be unstable, may suffer from mode collapse.	1
Autoencoders	Denoising, Artifact Correction	Learns efficient data representations, useful for filtering out noise.	Performance depends on network architecture and training data.	1
Transformer Networks	Image Enhancement, Super-Resolution	Captures long-range dependencies, models global context.	Requires significant amounts of training data, computationally demanding.	6_13
Diffusion Models	Denoising, Super-Resolution, Reconstruction	Generates high-fidelity images, robust results.	Can be computationally expensive, may require careful tuning.	15_24

Table 2: Modality-Specific AI Applications and Datasets

Modality	Specific AI Application	Example Datasets	Key Findings/Outcomes	Relevant Snippet IDs
CT	Lung Nodule Detection/Characterization	LIDC-IDRI	AI algorithms show high accuracy in detecting and classifying lung nodules.	41
CT	Low-Dose CT Denoising/Reconstruction	LIDC-IDRI, NLST	DLR techniques enable significant dose reduction while maintaining image quality.	32
X-ray	Pneumonia Detection	RSNA Pneumonia Detection Challenge	Deep learning models can effectively detect and localize pneumonia in chest X-rays.	81
X-ray	Noise Reduction in General Radiography	Proprietary datasets	AI-based noise cancellation improves image clarity and diagnostic confidence.	113
MRI	Accelerated Acquisition and Reconstruction	Various clinical MRI datasets	AI algorithms can significantly reduce scan times while preserving image quality.	31
MRI	Image Synthesis and Translation	Brain MRI datasets	GANs can generate synthetic MRI images and translate between different sequences.	33

Table 3: Evaluation Metrics for AI-Enhanced Radiological Images

Evaluation Metric	Type	Description/Interpretation	Snippet IDs
PSNR	Quantitative	Ratio between maximum signal power and noise power; higher is better.	1
SSIM	Quantitative	Measures structural similarity between two images; higher (closer to 1) is better.	1
CNR	Quantitative	Contrast between signal and noise; higher is better for visibility.	1
MSE	Quantitative	Average squared difference between pixel values; lower is better.	1
IoU	Quantitative	Intersection over Union; measures overlap between predicted and ground truth regions.	73
Dice Score	Quantitative	Measures overlap between two segmentations; higher (closer to 1) is better.	49
Accuracy	Quantitative	Proportion of correctly classified cases.	36
Sensitivity (Recall)	Quantitative	Ability to correctly	1

		identify positive cases.	
Specificity	Quantitative	Ability to correctly identify negative cases.	1
Precision	Quantitative	Proportion of positive identifications that were actually correct.	36
F1-score	Quantitative	Harmonic mean of precision and recall.	36
Observer Studies	Qualitative	Subjective assessment by radiologists on image quality and diagnostic reliability.	113

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