International Journal of Radiology Research
www.radiologyjournal.in
E-ISSN: 2663-4562
Received: 26-11-2025, Accepted: 21-01-2026, Published: 05-02-2026
Volume 8, Issue 1, 2026, Page No. 7-11

Deep learning–based image reconstruction in Low-Dose CT

Diya Ul Nisa[1], Pratik Virat[2]
[1] Department of Radiological imaging techniques, Sharda School of Allied Health Sciences, Sharda University, Uttar Pradesh, India
[2] Assistant professor, Department of Radiological imaging techniques, Sharda School of Allied Health Sciences, Sharda University, Uttar Pradesh, India

Abstract

In computed tomography (CT), artificial intelligence-based image reconstruction has become a revolutionary method for enhancing image quality and lowering radiation exposure.When compared to traditional filtered back projection and conventional iterative reconstruction, AI techniques, especially deep learning, enable superior noise reduction and artifact suppression by learning intricate mappings from noisy or undersampled projection data to high-quality images. For low-contrast lesion detection and overall diagnostic confidence, these models can maintain or even improve spatial resolution and noise texture. AI reconstruction has shown previously unheard-of performance in difficult situations like low-dose, sparse-view, and limited-angle CT, enabling clinically acceptable images from drastically reduced data.

Beyond image quality, AI methods can be incorporated into current CT systems as a software update and provide quick reconstruction times that are compatible with standard workflows. In order to guarantee generalizability, interpretability, and safety across vendors and patient populations, ongoing research focuses on network architectures, training techniques, and strong validation. AI image reconstruction is anticipated to become a crucial part of next-generation CT as these issues are resolved, facilitating dose optimization, increased diagnostic precision, and better patient care.

Keywords: Artificial intelligence, CT image reconstruction, deep learning, Artifact suppression, Iterative reconstruction

Introduction

Computed Tomography (CT) is one of the most widely used diagnostic imaging modalities in modern medicine due to its ability to provide detailed cross-sectional images of the human body. It plays a crucial role in the diagnosis, treatment planning, and follow-up of a wide range of clinical conditions, including trauma, cancer, cardiovascular diseases, and neurological disorders. The quality of CT images directly influences diagnostic accuracy; however, achieving high-quality images has traditionally required higher radiation doses, raising concerns about patient safety.

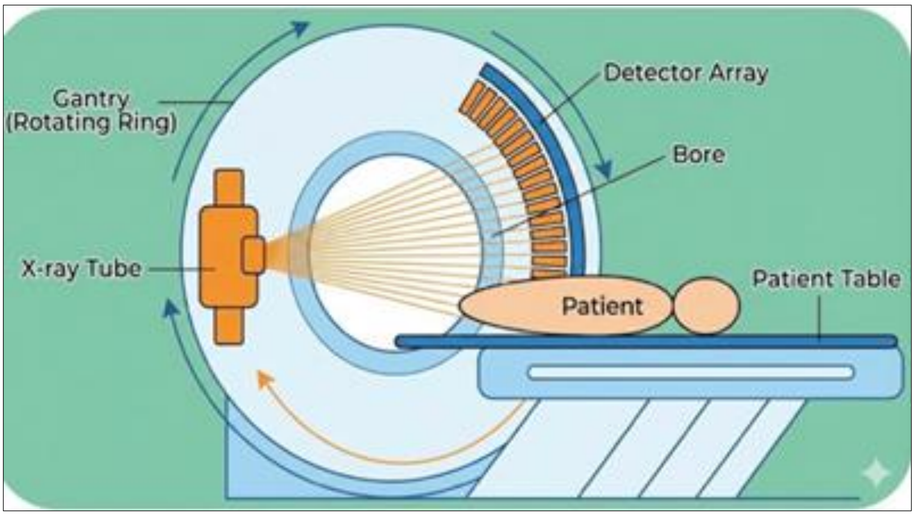

Fig 1: CT machine

Conventional CT image reconstruction techniques, such as Filtered Back Projection (FBP), are computationally fast but highly sensitive to image noise, especially in low-dose imaging. To address this limitation, iterative reconstruction (IR) methods were introduced, offering improved noise reduction and image quality at lower radiation doses. Although IR techniques represented a significant advancement, they are associated with increased computational complexity, longer reconstruction times, and in some cases, excessive image smoothing that may obscure fine anatomical details.

In recent years, Artificial Intelligence (AI), particularly deep learning, has emerged as a revolutionary approach in CT image reconstruction. AI-based reconstruction methods utilize advanced neural networks trained on large datasets of CT images to learn complex relationships between raw projection data and high-quality reconstructed images. Unlike traditional algorithms that rely on predefined mathematical models, AI systems can adaptively identify patterns, suppress noise, reduce artifacts, and preserve anatomical structures with remarkable accuracy.

One of the most significant contributions of AI in CT reconstruction is its ability to enhance image quality in low-dose and ultra-low-dose CT examinations. By effectively differentiating between noise and true signal, AI-based techniques enable substantial radiation dose reduction without compromising diagnostic confidence. This is particularly important for vulnerable patient populations such as pediatric patients and individuals requiring repeated CT scans, where radiation exposure must be minimized.

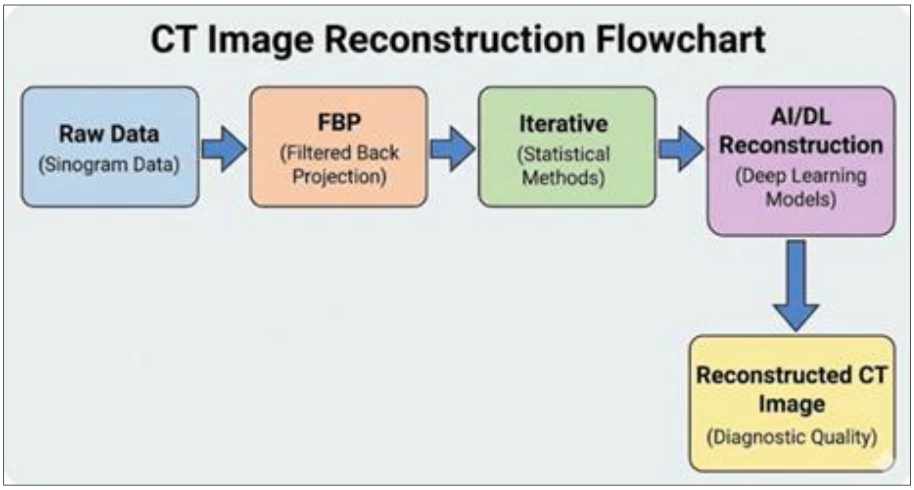

Fig 2: image reconstruction flow chart

In addition to improving image quality, AI techniques can be added to existing CT systems as a software update and offer fast reconstruction times that work with conventional workflows. Current research focuses on network architectures, training methods, and robust validation to ensure generalizability, interpretability, and safety across vendors and patient populations. As these problems are fixed, AI image reconstruction is expected to play a significant role in next-generation CT, enabling dose optimization, improved diagnostic accuracy, and better patient care.

Recent advances in artificial intelligence, particularly deep learning, offer a promising solution to this trade-off by directly learning the mapping from low-quality to high-quality CT images. AI-based reconstruction methods can simultaneously reduce noise, suppress artifacts, and preserve fine anatomical details, thereby enabling substantial dose reduction without sacrificing diagnostic performance. As these techniques mature and are integrated into commercial CT systems, they have the potential to redefine image reconstruction workflows and play a central role in next-generation, patient-centered CT imaging.

Deep learning-based image reconstruction

AI methods can be incorporated into current CT systems as a software update and provide quick reconstruction times that are compatible with traditional workflows, in addition to enhancing image quality. In order to guarantee generalizability, interpretability, and safety across vendors and patient populations, current research focuses on network architectures, training techniques, and robust validation. AI image reconstruction is anticipated to be crucial to next-generation CT as these issues are resolved, allowing for dose optimization, increased diagnostic precision, and better patient care.

Depending on the clinical task, current methods can be adjusted to prioritize either sharper, high-resolution images or smoother, low-noise images. They can function on raw projection data, on reconstructed images, or in a hybrid manner. Commercial deep learning-based tools that integrate with current scanners without requiring significant hardware modifications have already made their way into standard CT workflows as software solutions that denoise or improve images.

Reconstruction Methods

DLR uses convolutional neural networks (CNNs) to identify and remove noise patterns from sinograms or reconstructed images, trained on paired noisy-clean datasets. Post-processing DLR refines FBP/IR outputs, while end-to-end methods fully replace them for sparse-view or low-dose scenarios. Vendors like GE HealthCare and Canon deploy commercial DLR for ultra-high-resolution and PET/CT integration.

Clinical experience reports show that deep learning reconstruction generally lowers image noise, improves low-contrast lesion visibility, and supports substantial dose reduction when compared with hybrid iterative reconstruction. At the same time, researchers emphasize the importance of validating these algorithms for different patient sizes, anatomical regions, and vendors, and they call for larger outcome-oriented studies to confirm effects on diagnostic accuracy and patient management

Artificial intelligence techniques improve CT image quality and have significant potential for radiation protection, according to recent systematic reviews and meta-analyses. However, they also show that study designs and algorithms vary widely. In order to safely apply AI-based reconstruction to widespread clinical practice, future research is anticipated to concentrate on standardization, explainability, and strong multicenter validation.

By creating synthetic thin-slice CT images from thick-slice data, deep learning has improved spatial resolution in multicentre evaluations. This has improved diagnostic accuracy for conditions like community-acquired pneumonia and lung nodules, with area under the curve values approaching those of actual thin-slice scans. High-quality 3D reconstruction from sparse-view data is now possible thanks to generative AI models like Diffusion Blend, which cut computation times from 24 hours to an hour and open up applications in dynamic imaging like gastrointestinal or cardiac motion studies. However, training data, patient size, and reconstruction strength all affect performance; excessively smooth settings may cause artifacts or blurring.

AI Reconstruction Techniques

Deep learning algorithms, particularly convolutional neural networks (CNNs), process raw CT projection data to suppress noise and sharpen anatomical details. These models learn from high-quality datasets to map noisy inputs to clearer outputs, outperforming traditional filtered back-projection (FBP) and iterative reconstruction (IR) methods. Adaptive adjustments based on tissue characteristics further improve contrast and reduce in low-dose CT scans

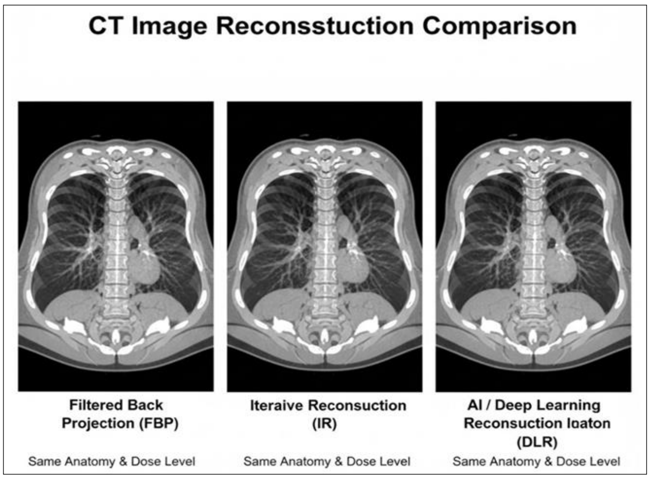

Fig 3: comparison of different reconstructions

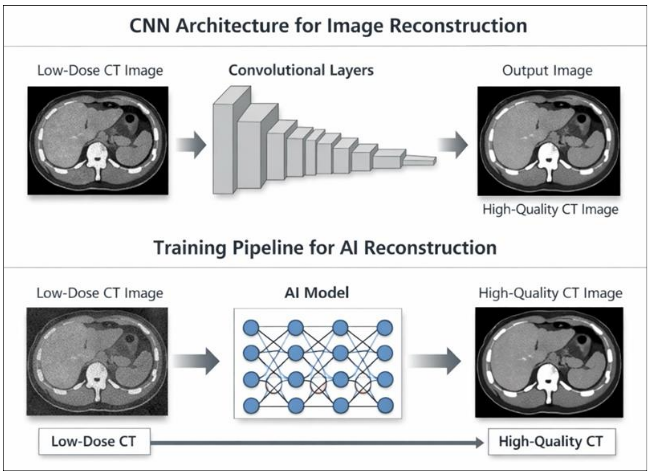

Fig 4: architectures for image reconstruction via AI model

Advanced DLR Architectures

Unrolled networks combine physics-based models with deep learning, iteratively optimizing data fidelity and regularization terms for sparse data reconstruction. Attention mechanisms and generative adversarial networks (GANs) further refine textures in ultra-low-dose scans, mimicking normal-dose quality. Hybrid approaches integrate transformer models for global context awareness in multi-phase CT.

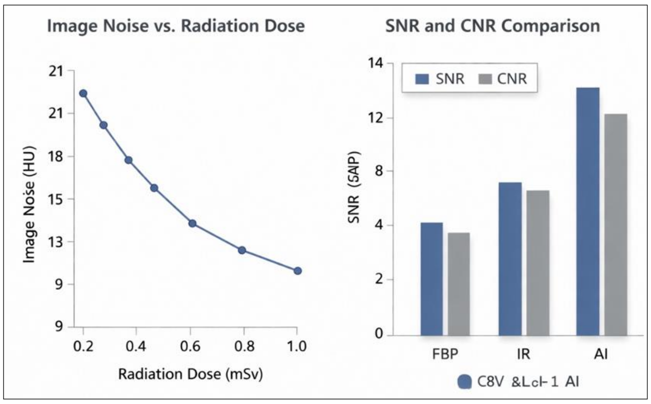

Fig 5: Dose–noise relationship and SNR/CNR performance of reconstruction methods

There were no significant differences in CT values reconstructed by FBP, hybrid IR, and DLR in abdominal organs. This shows that these reconstruction techniques are consistent in reconstructing CT values. DLR images showed a significantly higher SNR and CNR, compared to FBP and hybrid IR

CT values of abdominal CT images are similar between deep learning reconstruction (DLR), filtered back-projection (FBP), and hybrid iterative reconstruction (IR). DLR results in improved image quality in terms of SNR and CNR compared to FBP and hybrid IR images. DLR can thus be safely implemented in the clinical setting resulting in improved image quality without affecting CT values.

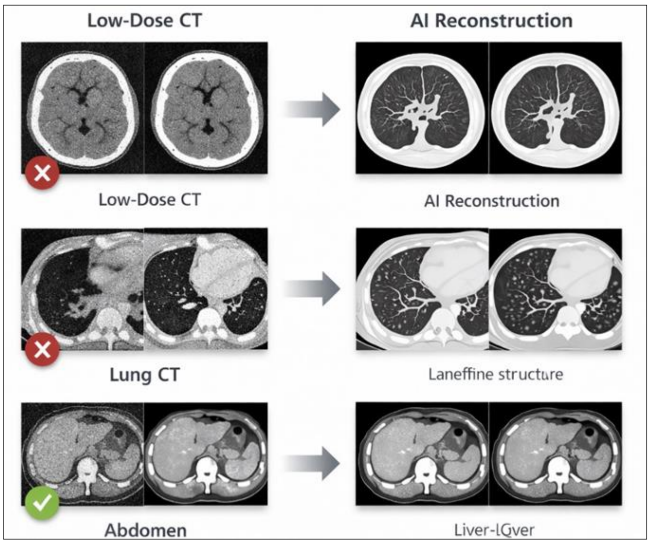

Fig 6: comparison of low dose CT images before and after AI based reconstruction

Emerging Applications

Photon-counting CT paired with AI enables virtual monoenergetic imaging and K-edge decomposition for contrast optimization. Portable CT systems leverage edge AI for trauma bays, cutting reconstruction from minutes to seconds. Multi-modal fusion with MRI/PET uses cross-attention for joint reconstruction, enhancing oncology workflows.

Validation Protocols

Multi-scanner phantoms test generalizability, revealing 10-20% SSIM drops across vendors without domain adaptation. Reader studies employ Likert scales and ROC curves, confirming noninferiority for polyp detection (AUC > 0.90). Uncertainty quantification via ensembles or Bayesian NNs flags unreliable regions, critical for regulatory clearance.

Recent Advances in AI-Based CT Image Reconstruction

Recent advances in generative artificial intelligence (AI) have significantly transformed computed tomography (CT) image reconstruction, particularly in challenging acquisition scenarios such as sparse-view CT and limited-angle CT imaging. These scenarios, which traditionally suffer from streak artifacts and loss of spatial resolution, are now effectively addressed by deep learning–based reconstruction techniques. Generative models, including convolutional neural networks (CNNs) and diffusion-based architectures, learn complex image priors from large datasets and can accurately recover missing projection data while preserving anatomical details.

Deep Learning Reconstruction (DLR) has demonstrated clear advantages over conventional Model-Based Iterative Reconstruction (MBIR) methods. While MBIR relies on predefined mathematical models and iterative optimization processes, DLR leverages data-driven learning to achieve superior noise suppression, contrast preservation, and edge sharpness with significantly reduced reconstruction times. This improvement enables faster clinical workflows, particularly in high-throughput emergency and trauma settings.

Ongoing clinical research has shown noninferiority and, in some cases, superiority of DLR compared to standard reconstruction methods for critical diagnostic tasks. Studies focusing on liver lesion detection and intracranial pathology assessment report maintained or improved diagnostic accuracy even at reduced radiation dose levels. These findings support the integration of AI-based reconstruction into routine clinical imaging protocols.

Ethical Considerations in AI-Driven CT imaging

Despite these advancements, ethical considerations remain central to the responsible deployment of AI in radiology. One major concern is algorithmic bias, which can arise when training datasets underrepresent certain demographic groups, body types, or pathological conditions. Such biases may lead to uneven diagnostic performance and potential health disparities. To mitigate this risk, researchers emphasize the use of diverse, multi-institutional datasets and conduct fairness audits to evaluate model performance across different patient populations. Another critical ethical aspect is explainability and transparency. AI systems are often criticized as “black boxes,” making it difficult for clinicians to understand how specific diagnostic outputs are generated. The adoption of Explainable AI (XAI) techniques, such as saliency maps and feature attribution methods, helps visualize which image regions influence AI decisions. This transparency enhances clinician confidence and supports regulatory approval.

In response to these concerns, multiple FDA-approved deep learning reconstruction products have incorporated validation frameworks emphasizing safety, performance consistency, and clinical reliability. Furthermore, long-term outcome studies are being conducted to monitor false positive and false negative rates over extended follow-up periods, ensuring that AI deployment does not inadvertently compromise patient care.

Several challenges must be addressed before AI-based CT reconstruction achieves universal clinical adoption. A key issue is algorithm generalizability across different CT vendors, scanner models, imaging protocols, and anatomical regions. Models trained on data from a limited set of scanners may not perform consistently when applied to heterogeneous clinical environments. Additionally, interpretability and clinician trust remain ongoing challenges. Radiologists must be confident that AI-enhanced images accurately reflect true anatomical structures rather than algorithm-generated artifacts. Standardized validation metrics and reporting frameworks are therefore essential.

Clinical trial meta-analyses consistently demonstrate improvements in image quality, workflow efficiency, and dose reduction, but they also highlight the need for standardized imaging procedures and long-term outcome data. Such data are crucial for accurately assessing the impact of AI-based reconstruction on radiation safety, diagnostic confidence, and patient management decisions. With the emergence of new FDA-approved AI reconstruction solutions, there is strong potential for the broader adoption of routine low-dose CT protocols, particularly in emergency imaging, cardiology, and oncology. As technology matures, these advancements may redefine CT imaging standards by achieving optimal image quality at substantially lower radiation doses.

Conclusion

In conclusion, artificial intelligence–driven image reconstruction has emerged as a transformative advancement in computed tomography (CT), marking a clear paradigm shift from traditional reconstruction techniques such as filtered back projection (FBP) and iterative reconstruction (IR). By leveraging deep learning architectures trained on large, high-quality datasets, AI-based reconstruction methods achieve superior noise reduction, enhanced artifact suppression, and improved preservation of spatial and contrast resolution. These improvements result in clearer visualization of anatomical structures and pathological findings, even under challenging low-dose or limited-data acquisition conditions.

One of the most significant clinical benefits of AI-driven reconstruction is its ability to facilitate substantial radiation dose reduction, with reported reductions of up to 71% in selected imaging protocols, without compromising diagnostic confidence. This is particularly valuable in high-risk populations, including pediatric patients and individuals requiring repeated imaging for oncology follow-up, cardiac assessment, and emergency trauma evaluation. Maintaining diagnostic accuracy at lower dose levels directly supports radiation protection principles such as ALARA (As Low as Reasonably Achievable).

Furthermore, AI-based reconstruction enhances workflow efficiency by reducing reconstruction times compared to computationally intensive model-based iterative techniques. Faster image availability supports timely clinical decision-making, especially in acute care settings. Clinical studies increasingly demonstrate noninferiority or superiority of AI-reconstructed images in lesion detection, tissue characterization, and diagnostic consistency across a wide range of clinical applications.

Despite these advantages, the continued success of AI-driven CT reconstruction depends on addressing challenges related to generalizability, transparency, and long-term clinical outcomes. Ongoing validation across diverse scanner platforms, patient populations, and anatomical regions, along with the integration of explainable AI tools, is essential for sustained clinician trust and regulatory compliance.

Overall, AI-driven image reconstruction is redefining CT imaging standards by enabling high-quality, low-dose imaging, improving patient safety, and supporting precision diagnostics. As regulatory-approved solutions continue to evolve and clinical evidence expands, AI-based reconstruction is expected to become an integral component of routine CT practice, shaping the future of diagnostic radiology.

References

1. Zhang M, Gu S, Shi Y. The use of deep learning methods in low-dose computed tomography image reconstruction: A systematic review. Complex Intelligent Systems, 2022.
2. Zeng M, Zhou H, Chen Y, *et al*. Image quality improvement in low-dose chest CT with deep learning image reconstruction. Journal of Applied Clinical Medical Physics, 2022.
3. Suzuki K, Abe H, Aoki T, *et al*. Deep learning–based reconstruction improves the image quality of low-dose CT colonography. Academic Radiology, 2024.
4. Yoo HS, Park JE, Lee JH. Application of deep learning image reconstruction in low-dose chest CT scan. British Journal of Radiology, 2022.
5. Kim JH, Park MS, Lee HJ. Deep learning reconstruction improves pulmonary nodule detection in ultra-low-dose chest CT. BMC Medical Imaging, 2025.
6. Liu F, Jang H, Kim S. Deep learning reconstruction of low-dose chest CT for improved lung parenchyma assessment. Radiology, 2025.
7. Matsumoto K, Ito H, Watanabe Y. Can deep learning improve image quality of low-dose CT? A prospective study in interstitial lung disease imaging. European Radiology, 2025.
8. Ma J, Wang Q, Chen H. Low-dose CT denoising using deep residual learning with wavelet transform. IEEE Transactions on Medical Imaging, 2023.
9. Liang K, Feng X, Gao Y. Model-based deep learning for X-ray CT reconstruction. arXiv preprint, 2019.
10. Gunduzalp D, Yurt M, Özkaya S. 3D U-NetR: Low dose CT reconstruction via deep learning and 3D convolutions. arXiv preprint, 2021.
11. Kang E, Min J, Ye JC. A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction. arXiv preprint, 2016.
12. Zhu B, Liu JZ, Cauley SF, *et al*. Image reconstruction by domain-transform manifold learning. Nature, 2018.
13. Knoll F, Clason C, Bredies K. Deep learning techniques for MRI and CT reconstruction — a review of algorithms and clinical prospects. IEEE Signal Processing Magazine, 2020.
14. Han Y, Ye JC. Framing U-Net via deep convolutional framelets: Application to low-dose CT. IEEE Transactions on Medical Imaging, 2019.
15. Huang L, Shan J, Vaidya V. Low-dose CT denoising with generative adversarial networks. Medical Physics, 2020.