

AI-Based Image Reconstruction in MRI and CT: Principles and Advances

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Abstract

Artificial Intelligence (AI) has rapidly transformed the landscape of medical imaging, particularly in the domains of Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). Traditional image reconstruction techniques, such as filtered back projection (FBP) in CT and compressed sensing (CS) in MRI, have long been the backbone of clinical imaging workflows. However, these methods often struggle with limitations including noise, artifacts, long acquisition times, and suboptimal image quality, especially in low-dose or accelerated imaging scenarios. AI-based image reconstruction, leveraging deep learning architectures such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformer models, offers a data-driven alternative capable of learning complex mappings from raw or undersampled data to high-fidelity images. This article provides a comprehensive review of the principles and recent advances in AI-based image reconstruction for MRI and CT. We begin by outlining the foundational concepts, including data acquisition, preprocessing, network architectures, and training methodologies. We then explore key applications and breakthroughs in both MRI and CT, such as fast imaging, artifact correction, low-dose reconstruction, and multi-modal fusion. The article also addresses critical challenges including generalization, interpretability, and regulatory approval, and discusses future directions such as federated learning and hybrid physics-informed models. By synthesizing current research and clinical trends, this review aims to inform radiologists, researchers, and technologists about the transformative potential of AI in medical imaging. Ultimately, AI-based reconstruction holds promise for improving diagnostic accuracy, enhancing patient safety, and streamlining clinical workflows.

Keywords: Artificial Intelligence; MRI Reconstruction; CT Imaging; Deep Learning; Medical Image Processing

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I. Introduction

Medical imaging plays a pivotal role in modern healthcare, enabling non-invasive visualization of internal anatomical structures and physiological processes (Panayides et al., 2020; Kalita et al., 2024). Among the most widely used modalities are Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), each offering unique advantages and facing distinct challenges (Khalifa & Albadawy, 2024). MRI is renowned for its superior soft tissue contrast and versatility in imaging various body regions, including the brain, spine, joints, and abdomen (Bustin et al., 2020; Küstner et al., 2024). It operates using strong magnetic fields and radiofrequency pulses to generate detailed images without ionizing radiation (Yang et al., 2024). However, MRI scans are often time-consuming, susceptible to motion artifacts, and limited by patient compliance and comfort (Chen et al., 2022; Iuga et al., 2023).

CT, on the other hand, provides rapid imaging with high spatial resolution, making it ideal for trauma assessment, lung imaging, and vascular studies (Lell & Kachelrieß, 2023; Qureshi et al., 2026). CT uses X-rays to acquire cross-sectional images, which are reconstructed using algorithms such as filtered back projection (FBP) or iterative reconstruction (IR) (La Riviere & Crawford, 2021). Despite its speed and accessibility, CT exposes patients to ionizing radiation, raising concerns about cumulative dose and associated risks (Kambadakone, 2020; David-Olawade et al., 2025). Traditional image reconstruction techniques have served the field well but are increasingly challenged by the demand for faster, safer, and higher-quality imaging (Gothwal et al., 2022). In MRI, compressed sensing (CS) and parallel imaging techniques have been developed to

accelerate acquisition, but they often compromise image quality or require complex calibration (Bustin et al., 2020; Chen et al., 2022). In CT, iterative reconstruction methods improve noise suppression but are computationally intensive and may introduce artifacts (Koetzier et al., 2023; Yan et al., 2023).

Artificial Intelligence (AI), particularly deep learning, offers a paradigm shift in image reconstruction (Wang et al., 2020). By learning from large datasets, AI models can infer missing information, suppress noise, and enhance image quality beyond the capabilities of conventional algorithms (Chen et al., 2022; Koetzier et al., 2023). This data-driven approach enables reconstruction from undersampled or low-dose data, potentially reducing scan times and radiation exposure while maintaining diagnostic integrity (Kambadakone, 2020; Melazzini et al., 2025). The integration of AI into image reconstruction is not merely a technical upgrade—it represents a fundamental rethinking of how images are generated, interpreted, and utilized in clinical practice (Panayides et al., 2020; Lekadir et al., 2021). As AI continues to evolve, its applications in MRI and CT reconstruction are expanding rapidly, with promising results in both research and real-world settings (Paudyal et al., 2023; Ozawa et al., 2025).

This article aims to provide a structured and detailed overview of AI-based image reconstruction in MRI and CT. We begin by examining the principles underlying these techniques, including data acquisition, preprocessing, neural network architectures, and training strategies (Umraiz et al., 2025; Alnaggar et al., 2024). We then delve into specific advances in MRI and CT reconstruction, highlighting key innovations and clinical applications (Chen et al., 2022; Koetzier et al., 2023). Finally, we address the challenges and future directions that will shape the next generation of AI-driven imaging solutions (Lekadir et al., 2021; Kumar et al., 2023).

II. Principles of AI-Based Image Reconstruction

2.1 Data Acquisition and Preprocessing

AI-based image reconstruction begins with the acquisition of raw imaging data (Wang et al., 2020; Gothwal et al., 2022). In MRI, this involves sampling the k-space, a frequency-domain representation of the image (Bustin et al., 2020; Yang et al., 2024). Undersampling k-space allows for faster scans but introduces aliasing artifacts (Chen et al., 2022; Küstner et al., 2024). In CT, projection data is collected from multiple angles around the patient, and low-dose protocols reduce radiation exposure but increase noise (Kambadakone, 2020; Koetzier et al., 2023).

Preprocessing is a critical step that prepares the data for AI model training (Alnaggar et al., 2024; Umraiz et al., 2025). This includes normalization, denoising, augmentation, and alignment of input–output pairs (Cui et al., 2023; Denisova et al., 2025). For supervised learning, high-quality reference images are paired with undersampled or noisy inputs (Chen et al., 2022; Koetzier et al., 2023). Data augmentation techniques such as rotation, scaling, and flipping help improve model generalization and robustness (Rudnicka et al., 2024; Kalita et al., 2024).

2.2 Neural Network Architectures

Several deep learning architectures have been employed for image reconstruction:

- Convolutional Neural Networks (CNNs): CNNs are widely used due to their ability to capture spatial hierarchies and local features (Wang et al., 2020; Alnaggar et al., 2024). U-Net, a popular CNN variant, has shown excellent performance in medical image denoising and reconstruction (Rudnicka et al., 2024; Denisova et al., 2025).
- Generative Adversarial Networks (GANs): GANs consist of a generator and discriminator network that compete during training (Karmakar et al., 2025). GANs produce realistic images and are effective in reducing artifacts and enhancing texture details in medical image reconstruction (Marcos et al., 2024; Denisova et al., 2025).
- Recurrent Neural Networks (RNNs) and Transformers: These models capture temporal and contextual dependencies, making them particularly useful in dynamic imaging or multi-frame reconstruction (Kalita et al., 2024; Yang et al., 2025).
- Physics-Informed Neural Networks (PINNs): These hybrid models incorporate physical constraints and imaging equations into the learning process, improving interpretability and reliability of reconstruction outcomes (Wang et al., 2020; Gothwal et al., 2022).

2.3 Training and Loss Functions

Training AI models for image reconstruction involves minimizing a loss function that quantifies the difference between the predicted and reference images (Wang et al., 2020; Alnaggar et al., 2024). Common loss functions include:

- Mean Squared Error (MSE): Measures pixel-wise differences; simple but may not capture perceptual image quality (Gothwal et al., 2022; Yan et al., 2023).

- Structural Similarity Index (SSIM): Evaluates image similarity based on luminance, contrast, and structural information, making it more aligned with human visual perception (Chen et al., 2022; Denisova et al., 2025).
- Perceptual Loss: Uses features extracted from pre-trained networks (e.g., VGG) to assess image quality beyond pixel-level similarity (Marcos et al., 2024; Karmakar et al., 2025).
- Adversarial Loss: In GAN-based frameworks, the discriminator guides the generator to produce more realistic and high-fidelity outputs (Karmakar et al., 2025; Marcos et al., 2024).

Training requires large, diverse datasets and careful tuning of hyperparameters to ensure generalizability and stability (Panayides et al., 2020; Umraiz et al., 2025). Transfer learning and fine-tuning are often employed to adapt models to specific imaging protocols, scanner configurations, or patient populations (Paudyal et al., 2023; Khalifa & Albadawy, 2024).

III. Advances in AI-Based Reconstruction

3.1 MRI Applications

AI has significantly advanced MRI reconstruction in several areas (Chen et al., 2022; Küstner et al., 2024):

- **Fast MRI:** AI enables reconstruction from highly undersampled k-space data, substantially reducing scan time—often reported on the order of up to 70–80% in controlled settings—without compromising diagnostic image quality (Chen et al., 2022; Bustin et al., 2020). This capability is particularly beneficial for pediatric, uncooperative, and emergency imaging scenarios where motion and time constraints are critical (Iuga et al., 2023).
- **Artifact Correction:** Deep learning models have demonstrated strong performance in correcting motion artifacts, Gibbs ringing, and aliasing effects, leading to improved image fidelity and diagnostic reliability compared with conventional reconstruction pipelines (Chen et al., 2022; Yang et al., 2024).
- **Multi-contrast Fusion:** AI-based reconstruction frameworks can integrate information from multiple MRI sequences such as T1-weighted, T2-weighted, and FLAIR images to enhance tissue characterization and lesion conspicuity, supporting more robust clinical interpretation (Chaddad et al., 2023; Paudyal et al., 2023).
- **Quantitative Imaging:** AI facilitates rapid and robust estimation of quantitative MRI parameters, including T1 and T2 relaxation maps, enabling advanced diagnostic assessment, longitudinal monitoring, and treatment planning within clinically feasible acquisition times (Küstner et al., 2024; Yang et al., 2024).

Table 1: Advances in MRI Reconstruction Enabled by Artificial Intelligence

Area of Advancement	AI Contribution in MRI Reconstruction	Clinical Significance	Reference
Fast MRI	Enables accurate reconstruction from highly undersampled k-space data, substantially reducing scan time without compromising diagnostic image quality	Improves patient comfort; highly beneficial for pediatric, uncooperative, and emergency patients	Bustin et al., 2020; Iuga et al., 2023; Küstner et al., 2024
Artifact Correction	Deep learning models correct motion artifacts, Gibbs ringing, and aliasing effects beyond the capabilities of conventional reconstruction methods	Enhances diagnostic reliability and reduces the need for repeat scans	Denisova et al., 2025; Cui et al., 2023
Multi-contrast Fusion	Integrates multiple MRI sequences (e.g., T1, T2, FLAIR) into a unified representation to exploit complementary tissue information	Improves tissue characterization and lesion detection accuracy	Chaddad et al., 2023; Paudyal et al., 2023
Quantitative Imaging	Accelerates the estimation of quantitative parameter maps such as T1 and T2 relaxation times using AI-driven reconstruction pipelines	Supports advanced diagnostics, longitudinal disease monitoring, and treatment planning	Küstner et al., 2024; Yang et al., 2024

As shown in Table 1 above, artificial intelligence has substantially enhanced MRI reconstruction by enabling faster image acquisition, improved artifact correction, and superior image quality (Chen et al., 2022; Küstner et al., 2024). These advancements support more reliable diagnosis, particularly in time-critical and motion-sensitive clinical scenarios such as pediatric, emergency, and uncooperative patient imaging (Bustin et al., 2020; Iuga et al., 2023). Overall, AI-driven MRI reconstruction contributes to improved workflow efficiency, diagnostic accuracy, and clinical decision-making in routine and advanced MRI applications (Panayides et al., 2020; Paudyal et al., 2023).

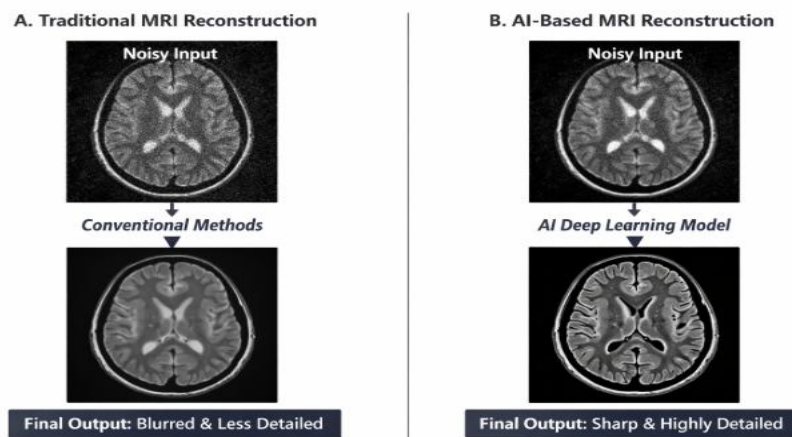


Figure 1: Comparison of Traditional vs AI-Based Reconstruction

According to Figure 1, the comparison between traditional and AI-based MRI reconstruction highlights a clear qualitative performance gap in favor of AI-driven approaches (Chen et al., 2022; Küstner et al., 2024). The traditional reconstruction pipeline, while effective in producing diagnostically usable images, exhibits noticeable blurring and residual noise, which can obscure fine anatomical details and potentially limit sensitivity to subtle pathologies (Bustin et al., 2020; Gothwal et al., 2022). In contrast, the AI-based reconstruction demonstrates superior noise suppression and edge preservation, resulting in sharper tissue boundaries and enhanced structural clarity (Chen et al., 2022; Iuga et al., 2023). This visual improvement suggests that deep learning models are better able to exploit underlying data patterns and prior information than conventional algorithms (Wang et al., 2020; Koetzier et al., 2023). However, the figure also implicitly raises critical concerns regarding generalizability, interpretability, and the potential hallucination of features by AI models, which are not evident from visual inspection alone (Panayides et al., 2020; Lekadir et al., 2021). Therefore, while Figure 1 convincingly illustrates the promise of AI-based MRI reconstruction in improving image quality, it also underscores the need for rigorous validation, quantitative evaluation, and sustained clinical oversight before widespread adoption (Chen et al., 2022; Kumar et al., 2023).

3.2 CT Applications

In CT imaging, AI has enabled several breakthroughs (Kambadakone, 2020; Koetzier et al., 2023):

- **Low-Dose CT:** AI-based reconstruction enables high-quality image generation from reduced radiation dose acquisitions, directly addressing patient safety concerns in routine, follow-up, and screening examinations (Kambadakone, 2020; David-Olawade et al., 2025).
- **Noise Suppression:** Deep learning-based denoising approaches consistently outperform traditional filtering and iterative reconstruction methods by effectively reducing image noise while preserving fine anatomical structures and diagnostic detail (Koetzier et al., 2023; Yan et al., 2023).
- **Dual-Energy CT:** AI enhances material decomposition accuracy and contrast resolution in dual-energy and spectral CT, enabling improved differentiation of tissues, lesions, and contrast materials compared with physics-only models (Ilyas et al., 2025; Pisuchpen et al., 2025).
- **Sparse View Reconstruction:** AI facilitates accurate reconstruction from a limited number of projection angles, which is particularly advantageous for portable, interventional, and intraoperative CT systems where full angular coverage may be impractical (Yan et al., 2023; La Riviere & Crawford, 2021).
- **Metal Artifact Reduction:** AI-driven reconstruction and post-processing models effectively mitigate streaking and beam-hardening artifacts caused by metallic implants or dental restorations, thereby improving overall image interpretability and diagnostic confidence (Koetzier et al., 2023; Lell & Kachelrieß, 2023).

Table 2: Artificial Intelligence Applications in Computed Tomography (CT) Imaging

CT Application Area	AI-Based Contribution	Clinical Impact	Reference
Low-Dose CT	Reconstructs diagnostically reliable images from reduced radiation dose acquisitions using AI-driven reconstruction models	Enhances patient safety in routine, follow-up, and screening examinations	David-Olawade et al., 2025; Kambadakone, 2020
Noise Suppression	Deep learning-based denoising preserves anatomical structures while effectively reducing	Improves diagnostic confidence and lesion	Yan et al., 2023; Denisova et al., 2025

	image graininess and noise	detectability	
Dual-Energy CT	Enhances material decomposition accuracy and contrast resolution through AI-driven spectral modeling	Enables improved tissue characterization and pathology differentiation	Ilyas et al., 2025; Pisuchpen et al., 2025
Sparse View Reconstruction	Accurately reconstructs images from a limited number of projection angles using learning-based algorithms	Supports portable, rapid, and intraoperative CT imaging systems	La Riviere & Crawford, 2021; Yan et al., 2023
Metal Artifact Reduction	Mitigates streaking and beam-hardening artifacts caused by metallic implants or dental restorations	Improves image interpretability in post-operative and orthopedic imaging	Lell & Kachelrieß, 2023; Koetzier et al., 2023

As shown in Table 2 above, artificial intelligence has significantly advanced CT imaging by enabling low-dose acquisition, effective noise suppression, and improved tissue differentiation (Kambadakone, 2020; Koetzier et al., 2023). AI-driven techniques also facilitate sparse view reconstruction and robust metal artifact reduction, thereby enhancing image quality in challenging clinical and interventional scenarios (Yan et al., 2023; Lell & Kachelrieß, 2023). Overall, these innovations contribute to improved diagnostic accuracy, enhanced patient safety through radiation dose reduction, and greater clinical workflow efficiency in CT imaging (David-Olawade et al., 2025; Khalifa & Albadawy, 2024).

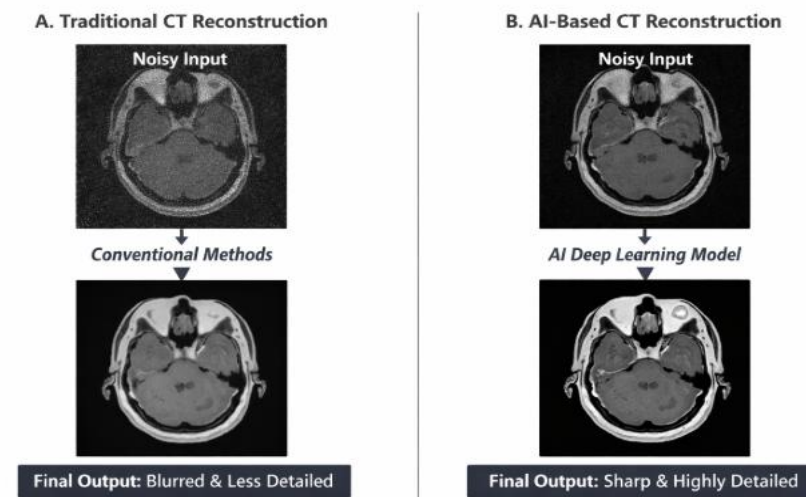


Figure 2: Comparison of Traditional vs AI-Based Reconstruction

According to Figure 2, the visual comparison between traditional and AI-based CT image reconstruction demonstrates the substantial impact of artificial intelligence on image quality enhancement (Yan et al., 2023; Lell & Kachelrieß, 2023). The traditionally reconstructed CT image exhibits increased noise levels and reduced contrast, which can obscure low-contrast anatomical structures and fine details critical for accurate diagnosis (La Riviere & Crawford, 2021; Gothwal et al., 2022). In contrast, the AI-based reconstruction produces a cleaner and sharper image with improved edge definition and contrast uniformity, indicating more effective noise suppression and structural preservation (Koetzier et al., 2023; Khalifa & Albadawy, 2024). This enhancement is particularly relevant for low-dose CT applications, where noise is a major limiting factor (David-Olawade et al., 2025; Kambadakone, 2020). Overall, Figure 2 summarizes the growing role of AI in CT reconstruction by illustrating its potential to improve diagnostic confidence and image interpretability, while also implying the necessity for careful validation to ensure that clinically relevant features are faithfully preserved (Melazzini et al., 2025; Lekadir et al., 2021).

The comparison of traditional versus AI-based reconstruction in both MRI (Figure 1) and CT (Figure 2) clearly demonstrates the transformative impact of artificial intelligence on medical imaging (Panayides et al., 2020; Kalita et al., 2024). In MRI, AI significantly improves image sharpness, reduces noise, and preserves fine anatomical details compared with conventional methods, addressing long-standing challenges such as motion artifacts and extended scan times (Chen et al., 2022; Yang et al., 2024). Similarly, in CT, AI enhances low-dose imaging, noise suppression, and metal artifact reduction, while also enabling advanced capabilities such as dual-energy decomposition and sparse view reconstruction (Pisuchpen et al., 2025; Ilyas et al., 2025; Yan et al., 2023). The visual evidence from the figures complements the tabulated summaries, showing that AI is not

merely improving image aesthetics but fundamentally enhancing diagnostic reliability and interpretability across modalities (Li et al., 2024; Oyeniyi & Oluwaseyi, 2024).

Tables 1 and 2 further quantify these advancements by outlining specific clinical and technical contributions of AI in MRI and CT imaging (Alnaggar et al., 2024; Umraiz et al., 2025). In MRI, AI facilitates fast scans, multi-contrast fusion, artifact correction, and quantitative imaging, directly supporting more efficient workflows and precise tissue characterization (Küstner et al., 2024; Chaddad et al., 2023). In CT, AI enables safe low-dose protocols, preserves anatomical fidelity, improves tissue differentiation, and mitigates artifacts caused by implants (Ohene-Botwe et al., 2026; Lell & Kachelrieß, 2023). Critically, while these improvements are visually and quantitatively compelling, they also raise important considerations regarding model generalizability, potential feature hallucination, and the need for rigorous clinical validation and trustworthy deployment (Lekadir et al., 2021; Kumar et al., 2023; Chepelev & Nicolaou, 2023). Overall, the combined evidence from figures and tables underscores AI's potential to redefine medical imaging practice, while emphasizing the necessity for careful implementation, regulatory oversight, and continuous clinical evaluation (Qureshi et al., 2026; Khalifa & Albadawy, 2024).

IV. Challenges and Future Directions

4.1 Key Challenges

Despite its promise, AI-based image reconstruction faces several challenges that must be addressed before widespread and reliable clinical adoption.

- **Generalization:** Models trained on specific datasets may not perform consistently across different scanners, imaging protocols, or patient populations, leading to variability in reconstruction quality and diagnostic reliability (Panayides et al., 2020; Kumar et al., 2023). Techniques such as domain adaptation, multi-center training, and federated learning have been proposed to improve robustness while minimizing data-sharing constraints (Lekadir et al., 2021; Umraiz et al., 2025).
- **Interpretability:** Deep learning-based reconstruction models are often regarded as “black boxes,” raising concerns related to clinical trust, accountability, and error analysis (Panayides et al., 2020; Chepelev & Nicolaou, 2023). Explainable AI (XAI) methods, including attention mapping and feature attribution, aim to provide transparency into model behavior and support clinician confidence in AI-assisted reconstructions (Lekadir et al., 2021; Alnaggar et al., 2024).
- **Regulatory Approval:** AI-based reconstruction tools must undergo rigorous technical and clinical validation to meet regulatory requirements from bodies such as the FDA and CE before deployment in routine practice (Melazzini et al., 2025; Ohene-Botwe et al., 2026). This process requires standardized evaluation protocols, comprehensive documentation, and continuous post-market surveillance to ensure long-term safety and effectiveness (Khalifa & Albadawy, 2024).
- **Integration into Clinical Workflows:** Successful adoption depends on seamless integration of AI tools into existing clinical infrastructures, including PACS, RIS, and scanner software (Chepelev & Nicolaou, 2023; Qureshi et al., 2026). User-friendly interfaces, interoperability, and minimal disruption to established workflows are critical to ensure acceptance by radiologists and technologists (Geroski & Filipović, 2024).
- **Data Privacy and Security:** Training and validating AI models require access to large-scale imaging datasets, raising concerns related to patient privacy, data ownership, and cybersecurity (Lekadir et al., 2021; Alnaggar et al., 2024). Secure data-sharing frameworks, anonymization strategies, and privacy-preserving learning approaches are essential to comply with data protection regulations while enabling continued AI innovation (Umraiz et al., 2025; Oyeniyi & Oluwaseyi, 2024).

4.2 Future Directions

Several emerging trends are shaping the future of AI-based reconstruction:

- **Federated Learning:** Federated learning enables collaborative training of AI reconstruction models across multiple institutions without centralized sharing of raw imaging data, thereby preserving patient privacy while improving model robustness and generalizability across scanners and populations (Lekadir et al., 2021; Umraiz et al., 2025).
- **Hybrid Models:** Hybrid and physics-informed reconstruction models combine data-driven learning with explicit physical constraints and imaging priors, improving reconstruction reliability, interpretability, and consistency with known acquisition physics compared with purely data-driven approaches (Wang et al., 2020; Gothwal et al., 2022).
- **Real-Time Reconstruction:** Advances in computational hardware, parallel processing, and algorithmic optimization are enabling near-real-time AI-based image reconstruction, supporting

dynamic imaging, interventional procedures, and point-of-care applications in MRI and CT (Lell & Kachelrieß, 2023; Qureshi et al., 2026).

V. Conclusion

Artificial intelligence has ushered in a new era of medical imaging, particularly in the reconstruction of MRI and CT data. By leveraging deep learning architectures such as convolutional neural networks, generative adversarial networks, and transformer-based models, AI has demonstrated the ability to overcome longstanding limitations of traditional reconstruction methods. These include noise suppression, artifact reduction, accelerated imaging, and the reconstruction of diagnostic-quality images from low-dose CT scans. The principles underlying AI-based reconstruction data acquisition, preprocessing, network design, and training form the foundation of this transformative approach. Advances in MRI reconstruction have enabled faster scans, improved artifact correction, and enhanced multi-contrast fusion, while CT applications have benefited from low-dose imaging, sparse-view reconstruction, and metal artifact reduction. Together, these innovations promise to improve diagnostic accuracy, patient safety, and clinical efficiency. Despite these successes, challenges remain. Generalization across diverse patient populations and imaging protocols is not yet fully achieved, raising concerns about robustness and reproducibility. Interpretability is another critical issue, as clinicians must trust and understand the outputs of AI systems. Regulatory approval processes demand rigorous validation, and integration into clinical workflows requires seamless interoperability with existing imaging infrastructure. Furthermore, ethical considerations regarding data privacy and security must be addressed to ensure responsible deployment.

Looking ahead, several promising directions are emerging. Federated learning offers a pathway to train models collaboratively across institutions without compromising patient privacy. Hybrid approaches that combine physics-based models with data-driven learning may enhance reliability and interpretability. Real-time reconstruction could revolutionize dynamic imaging, enabling immediate diagnostic insights during patient examinations. Explainable AI techniques will be essential to bridge the gap between algorithmic decision-making and clinical trust. In conclusion, AI-based image reconstruction in MRI and CT represents a paradigm shift in medical imaging. It holds the potential to deliver faster, safer, and more accurate diagnostic tools, ultimately improving patient outcomes and healthcare efficiency. Continued interdisciplinary collaboration among computer scientists, radiologists, engineers, and regulatory bodies will be vital to fully realize this promise. As research progresses and clinical adoption expands, AI-driven reconstruction is poised to become a cornerstone of next-generation medical imaging.

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