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Case Report

Comparative Effectiveness of Deep Learning and Adaptive Iterative Reconstruction in Oncology CT: A Mixed-Methods Systematic Review of Radiation Dose and Image Quality

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Abstract

Introduction: Computed tomography (CT) is integral to oncology imaging, yet repeated scans increase cumulative radiation risks. This systematic review evaluates the comparative effectiveness of deep learning-based image reconstruction (DLR) versus adaptive iterative reconstruction (AIR) in reducing radiation dose and enhancing diagnostic image quality in oncology patients undergoing frequent CT imaging.

Methods: A systematic search of PubMed, EMBASE, Cochrane CENTRAL, Elsevier, and Google Scholar was conducted for studies published between January 2020 and April 2025. Eligible studies included oncology patients undergoing CT using DLR or AIR techniques. Study designs included experimental, observational, phantom, and systematic reviews. Data was extracted on radiation dose metrics, image quality scores, contrast-to-noise ratio (CNR), and lesion detectability. Methodological quality was assessed using appropriate risk-of-bias tools.

Results: Hundred studies met inclusion criteria. DLR consistently outperformed AIR in noise suppression, image clarity, and lesion detectability while achieving radiation dose reductions up to 75%. High-strength DLR algorithms (e.g., DLR-H, AiCE) showed superior performance in enhancing CNR and SNR. DLR maintained diagnostic accuracy across various anatomical regions and dose levels. Comparative studies confirmed DLR's clinical utility, especially in oncology imaging requiring frequent follow-ups.

Conclusions: DLR significantly improves CT image quality and enables greater radiation dose reduction compared to AIR techniques. Its integration into oncologic imaging protocols supports safer, more effective imaging with high diagnostic precision. Standardization, long-term outcome evaluation, and integration with multimodal imaging are recommended to optimize DLR's clinical adoption.

Keywords: Oncology patients; Radiation Dose Optimization; CT; Diagnostic Image Quality; Deep Learning Reconstruction; Adaptive Iterative Reconstruction AiR; Reconstruction Methods

Introduction

Computed tomography (CT) is a cornerstone imaging modality in oncology, utilized for diagnosis, treatment planning, therapy monitoring, and follow-up evaluations [1][2]. Oncology patients often require repeated CT scans to track tumor progression, evaluate therapeutic response, and detect recurrence [3]. However, the frequent use of CT scans poses challenges, particularly

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regarding cumulative radiation exposure and associated risks, such as radiation-induced secondary malignancies and other long-term health effects, especially in younger patients and those with longer life expectancies post-treatment [4]. Hence, reducing radiation dose without compromising diagnostic accuracy is critical for ensuring patient safety and optimizing long-term outcomes. Reconstruction algorithms in CT, have focused on minimizing radiation exposure while maintaining or improving image quality to support accurate clinical decision-making [5][6]. Adaptive Iterative Reconstruction (AIR) algorithms iteratively refine CT image data by reducing noise and improving image quality compared to conventional filtered back projection methods [7][8][9][10]. While AIR has significantly lowered radiation dose requirements, its effectiveness is limited by diminishing returns at very low dose levels, and it may produce artifacts in certain imaging scenarios [7]. Deep Learning-Based Reconstruction (DLR) represented in **Figure 1.1** [7] represents a newer approach that employs neural networks trained on large datasets to reconstruct high-quality CT images with enhanced noise reduction and detail preservation [11]. Unlike AIR, DLR leverages artificial intelligence to achieve superior image quality even at ultra-low radiation doses, potentially overcoming the limitations of traditional iterative methods. Preliminary studies suggest DLR can maintain or improve diagnostic accuracy while further reducing radiation dose, offering significant potential for oncology imaging [4]. The transition from AIR to DLR is a paradigm shift in CT imaging, promising substantial benefits for oncology patients requiring frequent scans. It is crucial to determine their comparative advantages over AIR in terms of balancing radiation dose reduction and image quality enhancement. Frequent imaging needs in oncology create an urgent need for evidence-based guidance on adopting advanced reconstruction technologies to enhance patient outcomes as it has direct implications for patient safety, particularly in minimizing secondary cancer risks [4]. Improved image quality with reduced noise can enhance diagnostic confidence, leading to better treatment planning and monitoring. This review aims to compare DLR and AIR in terms of radiation dose reduction and diagnostic image quality in oncology patients undergoing frequent CT.

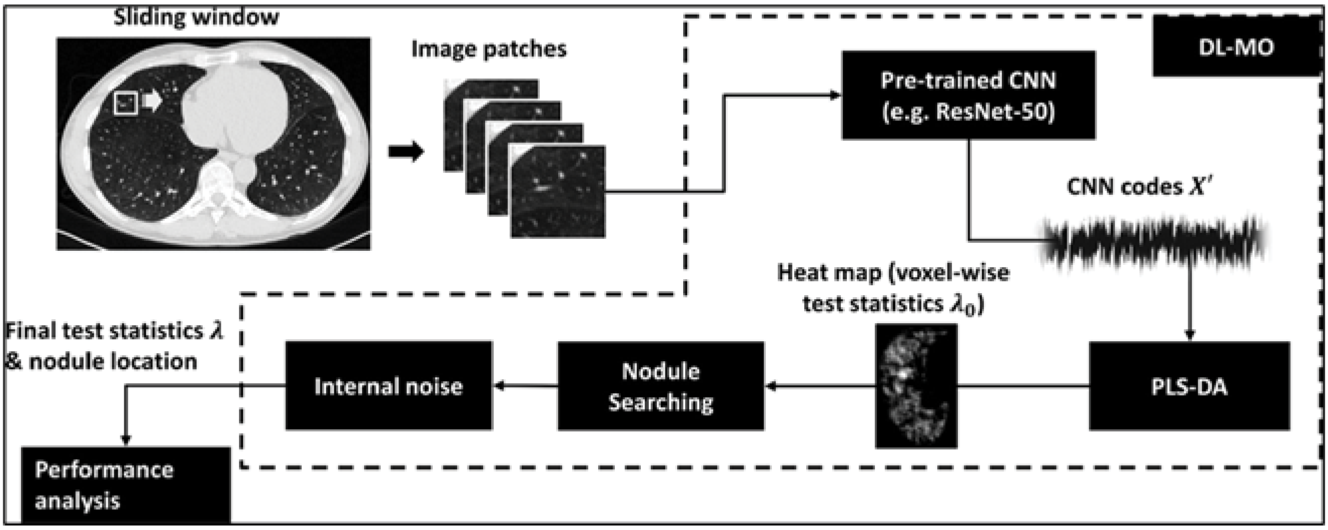

Figure 1: Framework for a deep learning–based model observer (DL-MO), which includes a pretrained deep CNN, a partial least squares regression discriminant analysis (PLS-DA), and a nodule-searching process, as well as an internal noise component [7].

Methods

Search Strategy

A systematic search was conducted to identify relevant studies published between January 2020 and April 2025 that compared deep learning-based image reconstruction (DLR) with adaptive iterative reconstruction (AIR) in oncology patients undergoing frequent computed tomography (CT) imaging. The following electronic databases were searched: PubMed, EMBASE, Cochrane CENTRAL, Elsevier, and Google Scholar. The search strategy incorporated both MeSH terms and free-text keywords related to deep learning, iterative reconstruction, computed tomography, radiation dose, and diagnostic image quality. Boolean operators and filters were applied to ensure sensitivity and specificity of retrieved results.

Eligibility Criteria

Studies were included if they met the following criteria: the population consisted of oncology patients undergoing frequent CT examinations; the intervention involved deep learning-based reconstruction methods such as DLR or Advanced intelligent clear -IQ Engine (AiCE) ; the comparator

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included adaptive iterative reconstruction methods such as adaptive statistical iterative reconstruction (ASIR) or Model-Based Iterative Reconstruction (MBIR); and the outcomes reported quantitative or qualitative evaluations of radiation dose reduction and/or diagnostic image quality. Eligible study designs encompassed experimental, observational, comparative, retrospective, prospective, phantom studies, systematic reviews, and meta-analyses. Phantom studies were included as they provide controlled evaluation of image quality, radiation dose optimization, and technical performance of deep learning reconstruction algorithm which are directly relevant to clinical applications in oncology imaging. Studies were excluded if they focused solely on clinical outcomes without assessing image quality or radiation dose, if they were case reports, editorials, letters, or conference abstracts without full text, or if they were published in a non-English language.

Study Selection

Titles and abstracts were independently screened by two reviewers to identify eligible studies. Full-text articles were then assessed against the inclusion criteria. Discrepancies between reviewers were resolved through discussion or consultation with a third reviewer.

Data Extraction

A standardized data extraction form was developed to systematically collect the following information from each included study: author name, year of publication, study design, sample size, CT protocol, reconstruction method, key outcomes (radiation dose metrics, image quality scores, signal-to-noise and contrast-to-noise ratios) and reported strengths and limitations. Two reviewers independently extracted data, and inconsistencies were resolved by consensus.

Quality Assessment

The methodological quality of included studies was assessed using appropriate tools depending on the study design. For randomized controlled trials, the Cochrane Risk of Bias tool was employed; for observational studies, the ROBINS-I tool was used. The risk of bias, consistency of findings, applicability, and precision of outcomes were considered in grading the strength of evidence. Disagreements in assessment were reviewed and resolved by a third independent assessor.

Results

Study Selection

A rigorous research strategy was employed, with numerous papers screened and assessed ultimately including 100 studies to establish a robust foundation to this review.

Study Characteristics

Table 3.2.1 provides an overview of the included studies by design, sample size range, imaging protocols, and reconstruction methods. The studies encompassed a diverse range of methodologies, including phantom, prospective, retrospective, and comparative designs, as well as systematic reviews and meta-analyses.

Deep Learning-Based Image Reconstruction (DLIR)

Deep Learning-Based Image Reconstruction (DLIR) has proven superior to Adaptive Iterative Reconstruction (AIR) in enhancing CT image quality and reducing radiation exposure. DLIR significantly improves image clarity, noise reduction, and lesion detectability [12][13][14]. It also enhances 3D reconstruction accuracy by correcting patient mispositioning through multi-view networks and fusion strategies, refining landmark detection and spatial alignment. Further optimization is achieved via weight-bearing adjustments and anatomical plane estimations, reducing rotation and misalignment errors [15][16].

Table 1: The table summarizes the study designs, sample sizes, and CT protocols of included studies, and respective techniques used to gather the information.

Study Design	Number of Studies	Sample Size Range	Reconstruction Methods
Phantom Studies	20	Variations are found among the sample sizes	DLR vs AIR
Prospective Studies	17	Variations are found among the sample sizes	DLR vs various reconstruction methods
Retrospective Studies	24	Variations are found among the sample sizes	DLR vs various reconstruction methods
Systematic Reviews/ Meta-Analyses	23	Variations are found among the sample sizes	DLR vs FBP and AIR
Mixed Methods study	5	Variations are found among the sample sizes	DLR vs various reconstruction methods
Comparative Studies	5	Variations are found among the sample sizes	DLR vs various reconstruction methods
Cross sectional study	1	112 Study	DLR vs FBP
Survey	1	127 participants	DLR
PRISMA-guided search	1	33 patients	DLR vs FBP
Experimental	3	NA	DLR vs ASIR software testing

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Enhanced Image Quality

In [17], DLIR demonstrated superior image quality scores compared to ASIR-V. Among the different DLIR strengths, DLIR-H achieved the highest scores in noise reduction, contrast, small structure visibility, and sharpness, followed by DLIR-M and DLIR-L, while ASIR-V had the lowest scores. Despite these differences, artifact ratings remained similar across all methods.

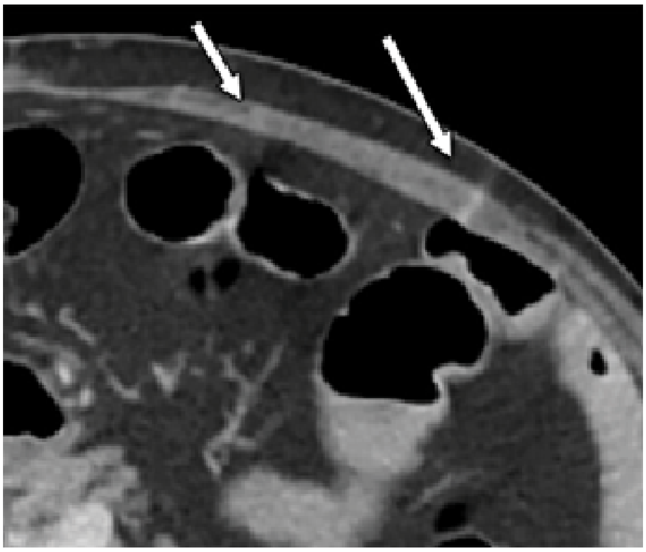

Figure 2:

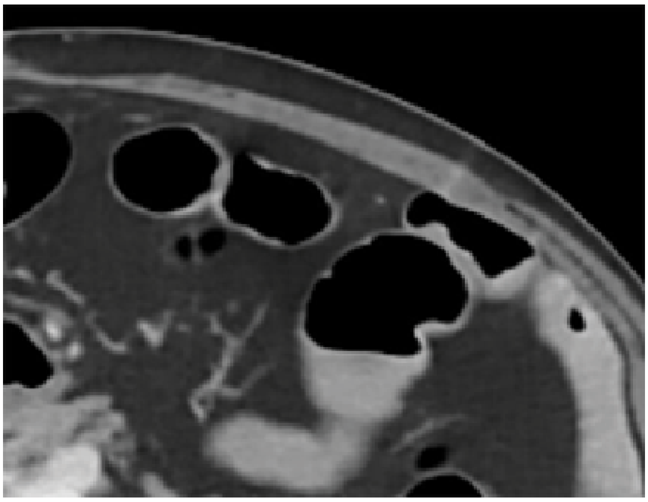

Figure 2B:

Figure 3.3.1. A — Two example cases scored as improved overall image quality with deep learning image reconstruction (DLIR) also showing decreased artifacts. A 66-year-old man with prostate cancer. Axial contrast-enhanced CT image reconstructed with 30% adaptive statistical iterative reconstruction V (30% ASIR-V) (A) shows greater artifactual streak local to air interfaces in bowel (arrows, A) than does image reconstructed with high-strength DLIR **(B)** [18].

In [19], Additionally, DLR outperformed not only ASIR but also other reconstruction techniques, including Filtered Back Projection (FBP), Statistical-Based Iterative Reconstruction (SBIR), and Model-Based Iterative Reconstruction (MBIR), as illustrated in **Figure 3.3.1.2** [20]. A comparative study [21] further confirmed that DLR significantly improved both quantitative and qualitative image quality metrics on High-Dose CT (HDCT) across various radiation dose levels and section thicknesses.

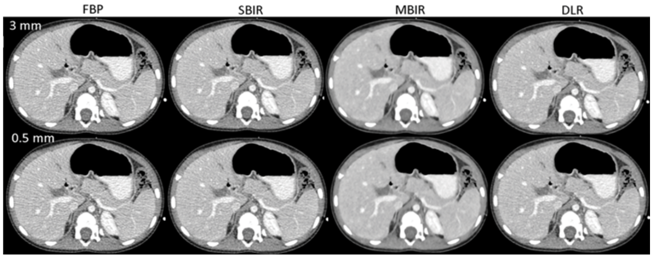

Figure 3: Axial contrast-enhanced CT images from (a) a 13-year-old, 58.3-kg male patient and (b) a 4-year-old, 13-kg male patient were reconstructed at 3-mm and 0.5-mm image thicknesses with filtered back projection (FBP), statistical-based iterative reconstruction (SBIR), model-based iterative reconstruction (MBIR), and deep learning reconstruction (DLR) [20].

Signal to Noise Ratio (SNR) and Contrast to Noise Ratio (CNR)

The retrospective study [18] found that DLIR outperformed ASIR-V 30% in contrast-to-noise ratio (CNR), particularly at high strength, achieving a 47% noise reduction and a 92–94% increase in contrast. Moreover, DLIR received higher scores in image quality, noise reduction, and texture, providing greater diagnostic confidence and lesion visibility compared to ASIR-V. Furthermore, study [21][22][23] highlighted that DLIR reduced image noise significantly more than hybrid-IR, with a median noise reduction of 8.3 Hounsfield Units (HU), thereby enhancing the signal-to-noise ratio (SNR).

The CT numbers stayed the same across different reconstruction methods noise levels were similar between ASiR-V 30% and DLIR-L, but ASiR-V 70%, DLIR-M, and DLIR-H had much lower noise. However, DLIR – H had the least noise, best CNR and SNR level and highest satisfaction outperforming the rest [24]. Furthermore, research [25] [26] demonstrated that DLR provided superior image quality in low-dose CT colonography (CTC) compared to IR, achieving lower noise, higher Signal-to-Noise Ratio (SNR) and Contrast-to-Noise Ratio (CNR), and maintaining high diagnostic performance even at substantially reduced radiation doses.

Subjective image quality assessments consistently rate DLIR higher than ASIR-V confirming its superiority in noise reduction contrast and lesion conceptuality. Specifically in stone detectability studies, DLR demonstrated excellent performance in detecting stones larger than three M with both observers rating it as highly effective [27].

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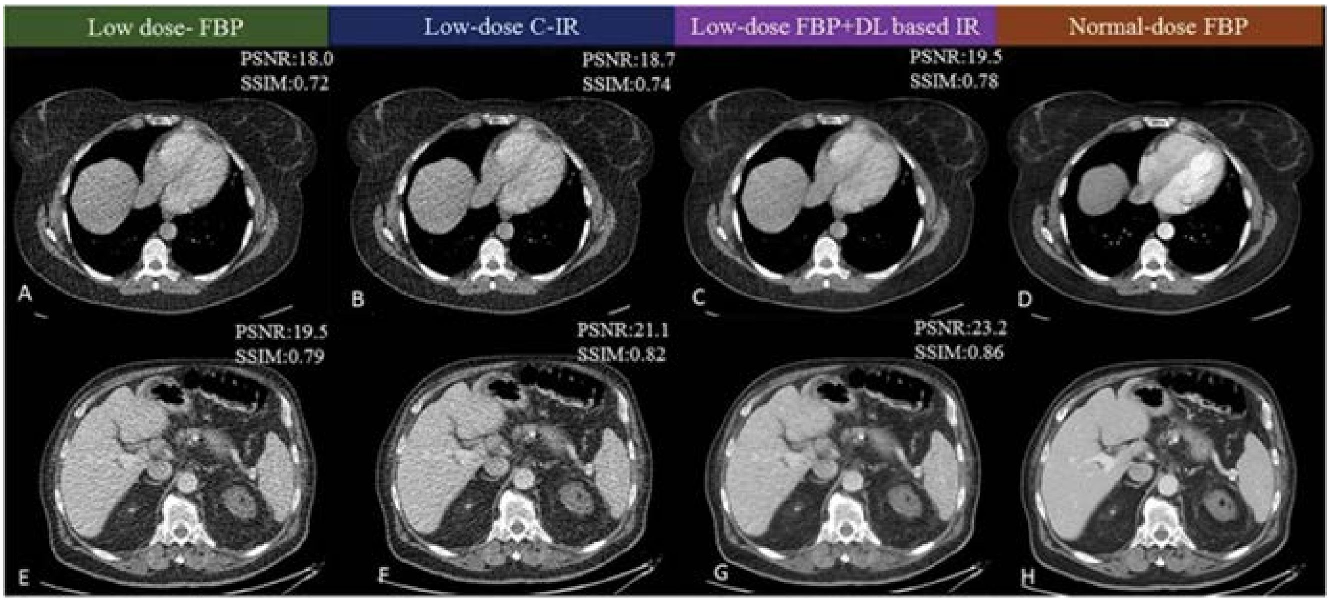

Figure 4: Low dose FBP-DL chest (C) and abdomen (G) CT images show better denoising and artifact reduction compared to low-dose FBP (A, E) and low-dose C-IR (commercial/clinical iterative reconstruction) images (B, F). Chest (low dose: CTDIvol 1.1 mGy; normal dose: 9 mGy) and abdomen (low dose: CTDIvol 1.2 mGy; normal dose: 10 mGy) were performed with 120 kV, 0.9:1 pitch, gantry rotation time of 0.5 s, and automatic exposure control technique [28].

Deep-learning (DL)-based data-driven reconstruction methods have demonstrated remarkable performance, often surpassing iterative reconstruction (IR) techniques in noise suppression and artifact reduction [29][30][31][32][33][34].

Additionally, deep-learning methods consistently outperform traditional iterative techniques, achieving higher Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), leading to smoother reconstructions. The new DL-based AiCE algorithm is particularly notable for producing low-noise images while preserving fine structural details, unlike Model-Based Iterative Reconstruction (FIRST), which tends to produce overly smooth images. As a result, AiCE delivers enhanced detectability and spatial resolution, significantly improving the clarity of reconstructed images [35]. Among the latest advancements, SR-DLR (Super-Resolution Deep Learning Reconstruction) has emerged as one of the most effective deep-learning reconstruction techniques, excelling in spatial resolution, noise reduction, and small-structure visualization in medical imaging [36]. In quantitative evaluations, DLIR-M and DLIR-H significantly reduced noise compared to ASiR-V 30% ($p < 0.001$). Furthermore, DLIR demonstrated superior Signal-to-Noise Ratio (SNR) and Contrast-to-Noise Ratio (CNR) in all analyzed regions, achieving statistically significant improvements in CNR and SNR over ASiR-V 30% ($p < 0.001$ [37]. **Figure 3.3.2.2** illustrates these findings, showcasing DLIR's enhanced noise suppression and image clarity [37].

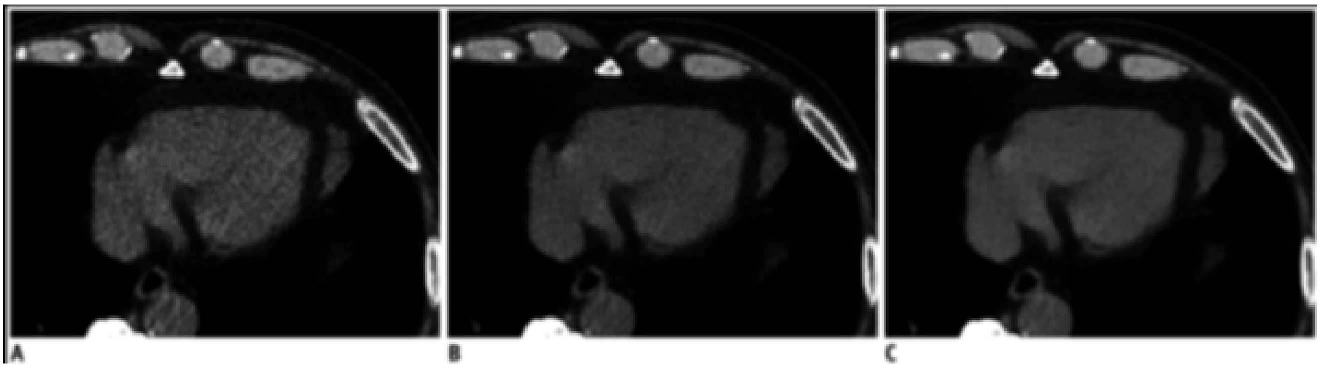

Figure 5: compares low-dose chest CT scan images of the mediastinum in a 73-year-old man, reconstructed with ASiR-V 30%, DLIR-M, and DLIR-H. While signal levels remained similar across the reconstructions, DLIR images exhibited significantly lower noise compared to ASiR-V 30% ($p < 0.001$) [37].

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Radiation Dose Optimization

A study using a test model (phantom) showed that the deep learning deconstruction made CT images clearer help in detecting the lesion better and improve the computer aided measurement older methods DLR provided sharper images and more accurate results, even with lower radiation [38]. This means that the DLR can help doctors diagnosis diseases more accurately while reducing the radiation risks especially for cancer patients who need frequent scans [38][39][40][41]. Moreover, DLIR reduces radiation by 43% to 0.8 mSv while keeping image quality and diagnostic accuracy stable. CCTA scans showed no change in signal intensity, DLR-H had lower noise than ASiR-V70%, providing deep learning is better for clearer images with less radiation.

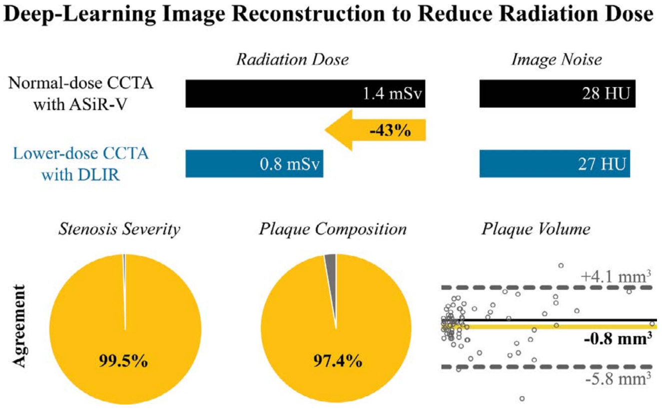

Figure 6: summarizes the key findings of the study conducted prospectively [14].

In [42] [43], both qualitative and quantitative analyses confirmed that low-dose CT reconstructed with DLIR significantly reduced noise and artifacts, maintaining image quality despite a radiation dose reduction of approximately 70% and similarly 67% dose reduction was observed while using LDCT. DLR help in particle therapy by making radiation circulation more accurately this improved treatment planning and reduces radiation exposure for the patients [9][44]. Also, AiCE (Advanced intelligent clear -IQ Engine) following DLR algorithm enables substantial radiation dose reductions while maintaining high image quality, positioning it as a valuable innovation in clinical imaging applications [35]. **Figure 3.3.3.2** illustrates these advancements, showcasing AiCE's superior performance compared to other reconstruction methods [35].

A similar study [45] reinforced these findings, demonstrating that deep-learning reconstruction effectively reduces radiation dose while maintaining image quality, particularly in Interstitial Lung Disease (ILD) patients, compared to High-Resolution CT (HRCT) using hybrid IR [46][47]. The study conducted on the phantom demonstrated that deep learning reconstruction (DLR) significantly enhanced image quality, lesion detection, and computer-aided volumetry (CAD-v) measurements compared to traditional methods such as FBP, hybrid-type IR, and MBIR. DLR provided improved lesion visibility and more precise measurements, even with reduced radiation doses. These findings emphasize DLR's potential to improve diagnostic accuracy and reduce radiation exposure, particularly for oncological patients undergoing frequent CT scans [38][39].

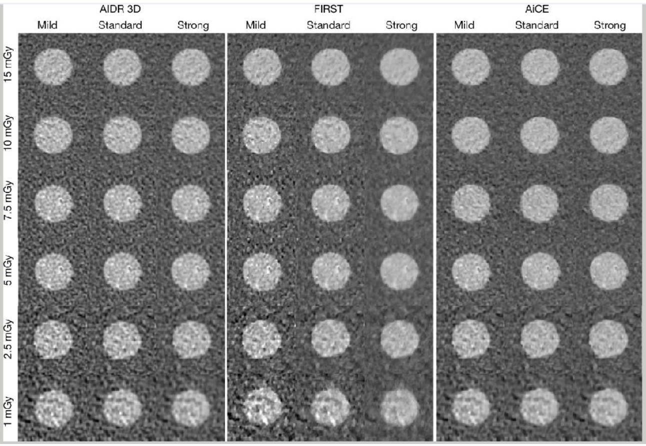

Figure 7: A 5×5 cm² region of interest on the acrylic insert compares AIDR 3D, FIRST, and AiCE at different dose levels, AiCE algorithm showing an out performance when compared to the rest. Images are shown with a soft tissue window (width 350, level 50 HU) [35].

Enhanced Image Clarity and Lesion Detection with DLIR Over ASIR-V and other reconstruction methods

DLIR improve metastasis detection by enhancing image quality in DECT and SECT with similar detection rates at equal radiation dose, higher DLIR strength reduces noise, especially in brain scans improving contrast. In liver imaging DLR performs like ASIR-V 40% but provides a better lesion clarity at high strengths, this makes DLIR useful for clearer and more accurate medical imaging reconstruction method in lesion detection [48][50]. **Figure 3.3.4.1** illustrates the lesion detection trough different strength of DLIR.

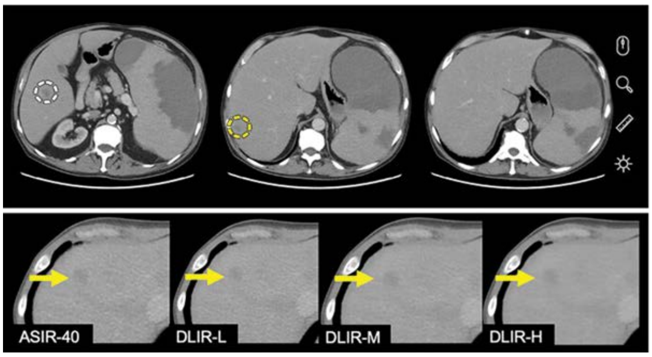

Figure 8: indicates that medium- and high-strength DLIR achieved significantly higher lesion-to-background contrast-to-noise ratios than ASIR-V 40% (OR 1.96, OR 5.36, P < .001), suggesting improved image clarity [50].

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Although no significant difference was noted in perceived resolution, DLIR proved more effective in detecting lesions, with a total of 193 lesions identified. **Figure 3.3.4.2** presents some illustrative examples from the study.

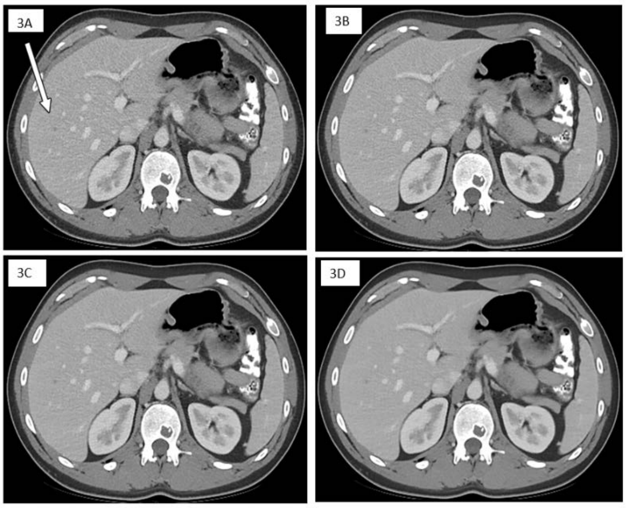

Figure 9: 3A, Axial contrast-enhanced CT images of same anatomic location show image quality comparison between standard 30% adaptive statistical iterative reconstruction V (30% ASIR-V) (A) and low-strength (B), medium-strength (C), and high-strength (D) deep learning image reconstruction (DLIR). Hepatic metastasis (arrow, A) measuring 0.5 cm is present in right liver. Readers rated overall image quality, lesion diagnostic confidence, and lesion conspicuity higher with progressively stronger levels of DLIR compared with 30% ASIR-V. Readers reported that the benefit of image noise reduction generally outweighed concerns about small lesion or vessel blurring but that use of lower denoising strengths (low- or medium-strength DLIR) mitigated this concern [18].

Different CT reconstruction methods had a varying success rate in detecting features DLIRH detected 76.5% of cases, while lesser percentage was in DLIR-M, ASIR-V and FBP. However, ASIR-V 50% had more false positives (mistaken detections). DLIR-H was the best at identifying details structures, making it more useful for medical diagnosis [50][51]. Additionally, a review of 99 studies analyzed how deep learning algorithms identify lesions in PCT-CT scans. These algorithms effectively detected lesions, segmented tumors, and classified diseases, extracting key features from PET/CT images to improve diagnostic accuracy and efficiency [51][52][53][54].

Moreover, when a scan of a 67-year-old female with small hepatic cysts was reviewed, DLIR-H in the delayed phase significantly reduced image noise and enhanced the clarity of cyst boundaries, thereby improving diagnostic confidence compared to ASIR-V50%, as shown in **Figure 3.3.4.3** [55].

A study involving 48 patients assessed nodule detection across different reconstruction methods. The results indicated that while there was no significant difference in the detection rates of nodules among Standard-Dose CT (SDCT), Low-Dose CT (LDCT), DLIR-M, and DLIR-H, variations were observed in the appearance and visualization of the nodules [57]. **Table 3.3.4.1** illustrates these differences, highlighting how DLIR reconstructions enhance morphological clarity compared to other methods.

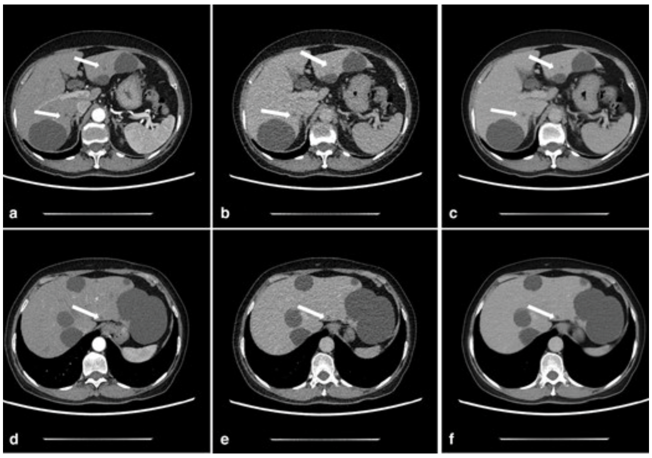

Figure 10: A 67-year-old female with small hepatic cysts in the arterial-phase (AP) and delayed-phase (DP). CTDIvol value was 6.8 mGy and 1.7 mGy in AP and DP, respectively. A and D: Axial AP images reconstructed with ASIR-V50% shows small hepatic cysts (arrows) with high diagnostic confidence. B and E: Axial DP images reconstructed with ASIR-V50% shows small hepatic cysts (arrows) with low diagnostic confidence due to unclear cyst boundary and high image noise. C and F: Axial DLIR-H DP images for confidence diagnosis of cysts, image noise was significantly reduced, and cyst boundary was clear [55].

Deep learning image reconstruction (DLIR) surpasses adaptive statistical iterative reconstruction (ASIR) in metastasis detection by effectively reducing noise while preserving noise texture, thereby enhancing the detectability of hypervascular lesions [56][58]. DLIR reduced image noise by 60%, improved overall image quality, and increased lung nodule detection rates compared to ASIR-V [59]. Furthermore, a study [60] concluded that high-strength DLIR significantly enhanced liver metastasis detection and conspicuity compared to ASIR-V, as summarized in **Figure 3.3.4.5**.

Overall Comparison

A comparative evaluation of Deep Learning Reconstruction (DLR) and Adaptive Iterative Reconstruction (AIR) reveals that DLR offers greater reductions in radiation dose, improved image quality, and superior lesion detectability. DLR reduces image noise and enhances contrast-to-noise ratio (CNR) while maintaining diagnostic accuracy, achieving dose reductions up to 71% without compromising image integrity [59][60][61]. DLR-H, in particular, outperforms AIR methods like ASIR-V in noise reduction (up to 61.6%) and lesion conspicuity [51][24], and demonstrates robust performance across various conditions,

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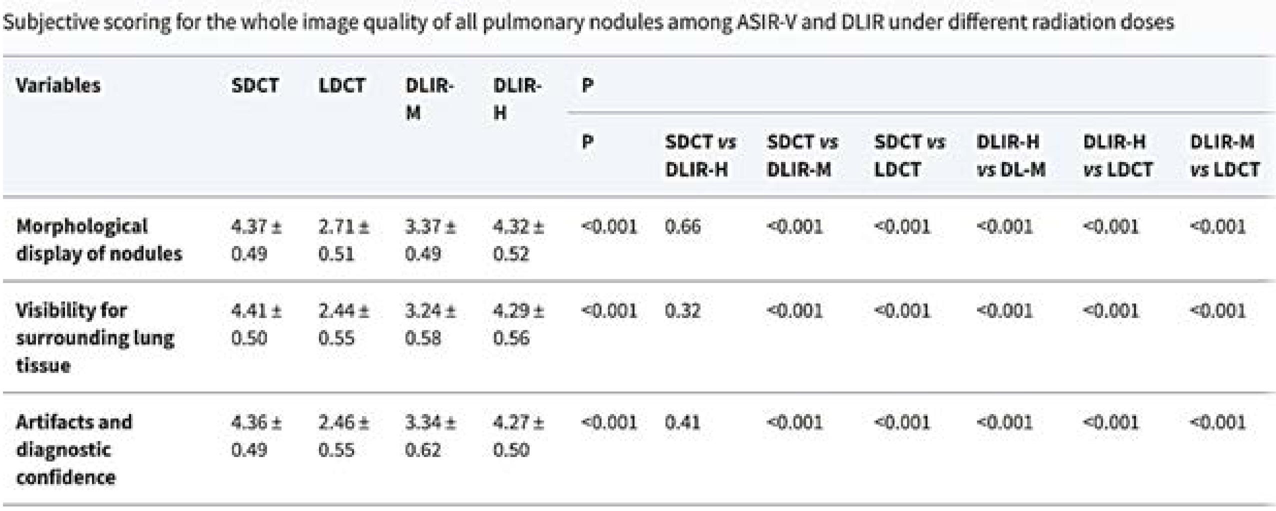

Subjective scoring for the whole image quality of all pulmonary nodules among ASIR-V and DLIR under different radiation doses

Variables	SDCT	LDCT	DLIR-M	DLIR-H	P						
					P	SDCT vs DLIR-H	SDCT vs DLIR-M	SDCT vs LDCT	DLIR-H vs DL-M	DLIR-H vs LDCT	DLIR-M vs LDCT
Morphological display of nodules	4.37 ± 0.49	2.71 ± 0.51	3.37 ± 0.49	4.32 ± 0.52	<0.001	0.66	<0.001	<0.001	<0.001	<0.001	<0.001
Visibility for surrounding lung tissue	4.41 ± 0.50	2.44 ± 0.55	3.24 ± 0.58	4.29 ± 0.56	<0.001	0.32	<0.001	<0.001	<0.001	<0.001	<0.001
Artifacts and diagnostic confidence	4.36 ± 0.49	2.46 ± 0.55	3.34 ± 0.62	4.27 ± 0.50	<0.001	0.41	<0.001	<0.001	<0.001	<0.001	<0.001

Table 2: the table elaborates the subjective analysis of how DLR is better in appearance of nodules [57]. Another figure demonstrating how DLR enhances the appearance of nodules compared to AIR is presented below in **Figure 3.3.4.4**.

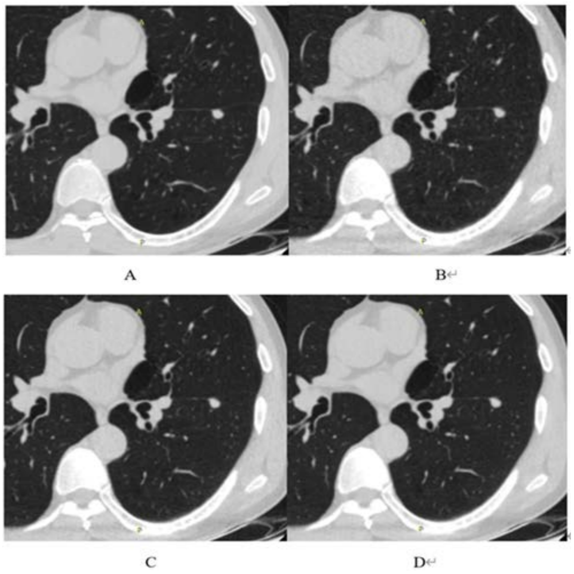

Figure 11: Comparison of chest CT scan in axial soft tissue window images of lung in 42-year-old male. Images were (A), ASIR-V40% at SDCT; (B), ASIR-V40% at LDCT; (C), DLIR-M at LDCT; and (D), DLIR-H at LDCT. There was no significant difference in the detection rate of nodules among the different reconstructions however, the appearance was clear in DLR-H [57].

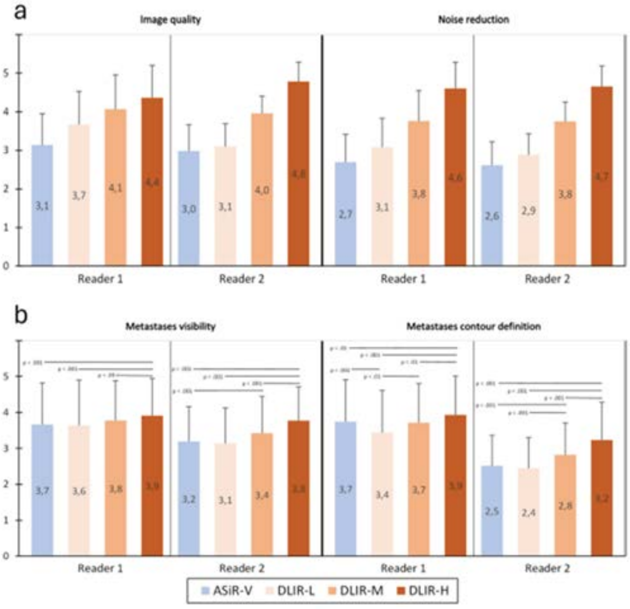

Figure 12: Subjective CT image quality and noise evaluation showed significant differences across all comparisons, with hepatic metastases also differing significantly (p-values indicated) [60].

especially for subsolid nodules, hepatic metastases, and lung nodules [52].

Clinical Implications

The integration of Deep Learning Image Reconstruction (DLIR) in clinical oncology offers substantial advantages, particularly in reducing cumulative radiation exposure without compromising diagnostic precision. Oncology patients frequently undergo repeated CT imaging, increasing their risk of radiation-induced complications [75]. Studies indicate that DLIR enables a dose reduction of 40–75% while preserving or even improving image clarity, making it an ideal reconstruction method for patients requiring frequent follow-up scans. Furthermore, DLIR enhances lesion characterization by improving contrast-to-noise ratios, thereby increasing diagnostic confidence in tumor detection and treatment monitoring [75][33]. The clinical transition from AIR to DLIR not only aligns with modern radiation safety principles but also improves patient outcomes by providing high-quality imaging at significantly lower radiation doses [33]. As healthcare institutions increasingly prioritize low-dose imaging protocols, the adoption of DLIR is expected to play a pivotal role in the future of oncology.

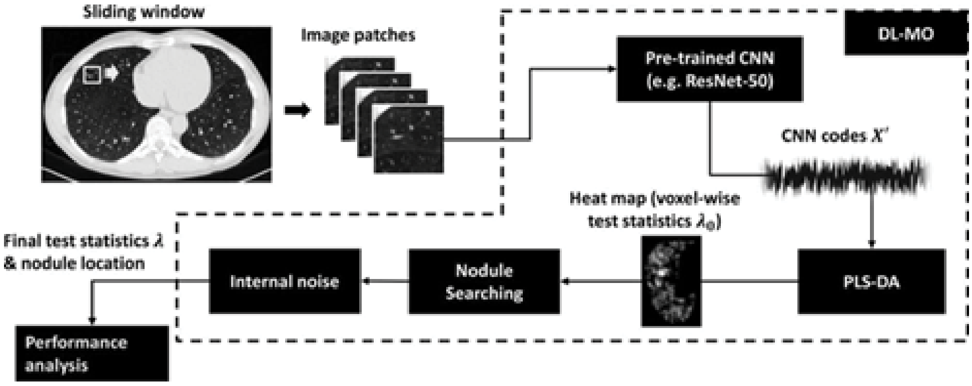

Figure 13: Framework for a deep learning–based model observer (DL-MO), which includes a pretrained deep CNN, a partial least squares regression discriminant analysis (PLS-DA), and a nodule-searching process, as well as an internal noise component.

Discussion: Interpretation of Findings (Comparison of DLR and AIR performance, Clinical implications for oncology imaging).

Recent advancements in CT reconstruction have positioned deep learning-based reconstruction (DLR) as a promising alternative to adaptive iterative reconstruction (AIR). Comparative evaluations highlight notable differences in their performance regarding radiation dose reduction and diagnostic image quality [65].

Comparison of DLR and AIR Performance: Radiation Dose Reduction

DLR demonstrates substantial potential in lowering CT radiation doses [58]. Canon's AiCE, for instance, achieved a 40% reduction compared to AIR 3D while preserving image quality [63][76], and other studies report reductions up to 75% [60]. In contrast, AIR—though more effective than traditional FBP—offers more modest improvements. ASIR reduces noise under low doses but doesn't match DLR's reductions [81].

Comparison of DLR and AIR Performance: Diagnostic Image Quality

DLR generally outperforms AIR in diagnostic image quality, particularly in ultra-low-dose CT scans [33]. It improves anatomical clarity, noise suppression, and contrast-to-noise ratio (CNR), supporting superior lesion detection [3][67][68][76]. While AIR methods improve upon FBP, their enhancements are less pronounced than those seen with DLR [69][70][81].

Clinical Implications for Oncology Imaging:

DLR's combination of reduced radiation exposure and maintained or enhanced image quality makes it ideal for oncology patients requiring frequent imaging. These benefits help minimize long-term radiation risks while supporting accurate tumor detection and monitoring [65][61][38][66]. The current evidence affirms DLR's superiority over AIR in both dose reduction and image quality [58][59].

Strengths and Limitations

Methodological strengths of the review

This systematic review employed a comprehensive search strategy across multiple databases including PubMed, EMBASE, Cochrane CENTRAL, Elsevier, and Google Scholar, coupled with clearly defined inclusion/exclusion criteria. Dual independent reviewers ensured objectivity. These steps reinforce the reliability and reproducibility of the findings.

Limitations of included studies and review process.

Despite methodological rigor, heterogeneity in study designs, imaging protocols, and outcome metrics limited direct comparability. Variability in DLR implementations and lack of standardization hinder generalizability [72]. Additionally, limited data on long-term clinical outcomes and small or unspecified sample sizes in some studies further constrain the conclusions [73][74].

Comparison with Other Studies: Alignment or differences with previous literature.

Recent literature consistently supports DLR's effectiveness in both dose reduction and diagnostic improvement [75][6][77]. Studies show DLR enhances detection of small hypo-vascular liver lesions [1][82] and improves image quality in dual- and single-energy CT [15][78]. Findings from [71][55] and [35] confirm that AiCE and similar algorithms outperform AIDR 3D and FIRST in noise reduction while avoiding excessive image smoothing. Though [85] focused on abdominal imaging and low-dose applications, [62][78][76] further validate DLR's clinical utility, with improvements in CNR and noise texture more aligned with FBP. Although model-based IRs may offer higher spatial resolution, DLR matches or exceeds them in performance for low-contrast tasks [80][81][82][83][84][86][87]. Moreover, [60] highlighted DLR's ability to reduce radiation dose by up to 75% while maintaining diagnostic quality in lung nodule

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detection. Studies [70][79][85] confirm DLR's superior noise suppression and dose efficiency. Collectively, the literature [86][87][88][89] reinforces that DLR offers marked advantages over traditional IR methods—enabling significant dose reductions without sacrificing, and often improving, diagnostic image quality.

Future Research Directions:

Advancements in deep learning-based image reconstruction (DLIR) hold significant potential for minimizing radiation exposure during CT scans while preserving image quality [90]. Nonetheless, additional research is essential for its comprehensive adoption in clinical settings, particularly concerning oncology patients. Critical areas for future exploration are included in **Table 4.4.1.**

Table 3: Future Research Directions: Areas for further investigation, including long-term outcomes.

Long-Term Clinical Outcomes:	Evaluating the impact of reduced radiation exposure through DLIR on patient prognosis, treatment effectiveness, and survival rates [90].
Standardization &Validation:	Establishing standardized protocols and validation techniques to guarantee consistent performance across various CT systems and patient demographics [92] [91].
Integration with Other Imaging Modalities:	Investigating how DLIR can enhance the capabilities of other imaging technologies, such as MRI and PET, for more thorough diagnostic assessments [93[94] [95].
Patient-Specific Optimization:	Customizing DLIR protocols based on individual patient characteristics to maximize image quality and minimize radiation dose [96] [97].
Cost-Effectiveness Analysis:	Analyzing the economic implications of DLIR in clinical environments to guide healthcare policy decisions [98] [99].
Training &Education:	Ensuring that healthcare professionals receive adequate training to utilize DLIR technologies effectively for optimal outcomes. These areas of research will help optimize DLIR's integration and improve patient care in oncology imaging [100].

Conclusion

Deep learning-based image reconstruction (DLR) represents a transformative advancement in oncologic CT imaging, offering substantial benefits over traditional adaptive iterative reconstruction (AIR) techniques. This systematic review demonstrates that DLR consistently achieves superior or comparable diagnostic image quality while enabling significant reductions in radiation dose ranging from 40% to 75% without compromising lesion detectability or image clarity. High-strength DLR methods (e.g., DLR-H, AiCE) provide enhanced contrast-to-noise and signal-to-noise ratios, realistic noise textures, and sharper delineation of anatomical structures, thereby improving diagnostic confidence and supporting safer long-term imaging protocols.

Given the cumulative radiation risks faced by oncology patients undergoing repeated CT examinations, DLR provides a critical solution that aligns with modern principles of radiation protection. Furthermore, its clinical reliability across various imaging conditions, including low-dose protocols and complex anatomical scenarios, underscores its utility in routine cancer care.

To maximize the potential of DLR in clinical settings, future research should focus on standardizing implementation across vendors, assessing long-term clinical outcomes, and exploring integration with other imaging modalities. In parallel, comprehensive training of radiology professionals and cost-effectiveness evaluations will support broader adoption.

In conclusion, DLR is poised to become a cornerstone technology in oncologic imaging enhancing patient safety, diagnostic precision, and overall care quality in an era of personalized and low-dose imaging.

Key Terms: AI in Radiology; Noise Reduction in CT; AI Based Reconstruction; Radiation Dose Reduction Strategies; Quantitative Image Analysis; Noise Equivalent Dose

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Conflicts of Interest

The authors declare no conflict of interest.

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