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Clinical Utility of Deep Learning Image Reconstruction in Multi-Regional CT Angiography: A Systematic Review of Ultra-Low-Dose Protocols

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ABSTRACT
Multi-regional Computed Tomography Angiography (CTA) is a cornerstone of vascular diagnostics, yet its clinical utility is often tempered by the cumulative risks of ionizing radiation. Deep Learning Image Reconstruction (DLIR) has recently emerged as a transformative solution, engineered to decouple the historical inverse relationship between radiation dose and image fidelity. This systematic review evaluates the clinical performance of DLIR in facilitating ultra-low-dose (ULD) protocols across a diverse multi-regional landscape. Adhering to PRISMA 2020 guidelines, a systematic search was executed across PubMed, Scopus, and Google Scholar for primary research published between January 2020 and January 2026. After a rigorous selection process and JBI-based quality appraisal, 65 high-impact studies (39 prospective and 24 retrospective) were identified for synthesis. The evidence was categorized into anatomical clusters: chest (n=24), abdomen (n=12), liver/angio (n=18), and specialized neurological/oncological cohorts (n=11). Across all anatomical regions, DLIR demonstrated definitive superiority over traditional iterative reconstruction (IR) and filtered back projection (FBP). High-strength DLIR (DLIR-H) enabled unprecedented radiation dose reductions ranging from 43% to 80%, with several studies achieving diagnostic-grade vascular mapping at sub-millisievert levels (0.2–0.5 mSv). Quantitative metrics indicated a 35–50% decrease in image noise alongside significant gains in Contrast-to-Noise Ratio (CNR). Qualitatively, DLIR successfully mitigated the "waxy" or "plastic" texture inherent in older IR techniques, preserving the natural noise power spectrum and enhancing edge sharpness for coronary stents and distal vessels. Furthermore, "double-low" protocols (reducing both radiation and contrast volume) were successfully validated in 18 studies, highlighting a major safety breakthrough for pediatric and renal-impaired populations. DLIR represents a new benchmark in radiological practice, enabling a safe transition to ultra-low-dose imaging without compromising diagnostic accuracy. By providing superior noise suppression and anatomical fidelity, DLIR effectively sets a new standard of care for multi-regional CTA, particularly for radiation-sensitive and high-risk patients. These findings advocate for the global clinical integration of AI-driven reconstruction to optimize patient safety in vascular medicine.
Keywords: *Deep learning reconstruction (DLIR), True Fidelity and CT angiography, CT pulmonary angiography.*

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INTRODUCTION

Computed tomography angiography (CTA) has become an integral part of modern diagnostic imaging, offering a fast, non-invasive, and highly accurate assessment of vascular pathology across a wide range of clinical settings. From coronary artery disease and acute stroke to pulmonary embolism, renal artery stenosis, and peripheral vascular disease, CTA plays a central role in clinical decision-making. However, the increasing reliance on CTA has also intensified long-standing concerns related to radiation exposure and iodinated contrast administration, particularly in patients who require repeated examinations, younger individuals, and pediatric populations. Over the past decade, significant efforts have been directed toward reducing radiation dose without compromising diagnostic quality. Conventional approaches, including tube current modulation, low tube voltage techniques, and iterative reconstruction (IR), have undoubtedly contributed to safer imaging practices. Nevertheless, aggressive dose reduction using IR can lead to unnatural image texture, loss of fine vascular detail, and decreased lesion conspicuity-- limitations that are especially problematic in angiography, where accurate depiction of small, high-contrast vascular structures is critical.

Deep learning image reconstruction (DLIR) has recently emerged as a promising solution to these challenges. The emergence of Deep Learning Image Reconstruction (DLIR) represents a paradigm shift in CT technology. Unlike IR, which relies on rigid mathematical models, DLIR utilizes deep convolutional neural networks (DCNN) trained on high-quality, high-dose datasets to intelligently distinguish true anatomical signal from stochastic noise [4]. This allows the algorithm to suppress noise while preserving the "ground truth" of the anatomical structure, even under significant photon starvation [5]. Recent evidence suggests that DLIR can maintain diagnostic image quality even when radiation doses are reduced by 43% to as much as 76% compared to standard protocols [6]. Furthermore, the integration of DLIR into "double-low" protocols—simultaneously reducing radiation and contrast media doses—offers a promising avenue for high-risk patients, such as those with renal insufficiency or the pediatric population [8]. Despite the versatility of AI in general imaging, a comprehensive synthesis focusing on its performance in high-stakes vascular protocols is required to establish standardized clinical benchmarks [9]. In multi-regional CTA, the primary challenge lies in balancing aggressive noise suppression with the preservation of high-contrast edge sharpness. This is critical for evaluating small-caliber vessels, intricate stents, and calcified plaques where "blooming" artifacts often lead to overestimation of stenosis [7]. By training neural networks on large datasets of high-quality reference images, DLIR algorithms are able to selectively suppress noise while preserving spatial resolution and anatomical fidelity. Early applications in abdominal CT have demonstrated improved visualization of hepatic lesions and enhanced assessment of liver and pancreatic parenchyma at substantially reduced radiation doses, suggesting a meaningful clinical advantage over traditional IR techniques [1,10,13]. Task-based image quality studies further support these findings, showing improved noise characteristics and contrast preservation with deep learning–based reconstruction methods [5]. The potential impact of DLIR is particularly compelling in CT angiography, where image quality directly influences diagnostic confidence. In coronary CT angiography, multiple studies have reported that DLIR enables significant radiation dose reduction while maintaining—or even improving—both objective and subjective image quality metrics compared with standard reconstruction techniques [2,9]. Importantly, DLIR has also been shown to improve visualization of coronary stents and enhance stenosis assessment, addressing a persistent limitation of CTA in patients with heavy calcification or metallic implants [12]. Beyond coronary imaging, the application of DLIR has expanded to a variety of angiographic examinations. Improved vessel delineation and reduced image noise have been reported in CT pulmonary angiography performed at lower dose levels [3]. In neurovascular imaging, ultra-low-dose head CTA reconstructed with DLIR has demonstrated preserved diagnostic performance, including in emergency stroke settings where rapid and accurate vascular assessment is essential [8,11]. Similarly, promising results have been observed in renal CTA using double-low protocols that combine reduced radiation and contrast doses, as well as in lower extremity runoff and multi-territory CTA examinations [4,14,15]. Radiation dose reduction is particularly critical in pediatric imaging, where the long-term risks of ionizing radiation are of greater concern. Studies evaluating DLIR in pediatric cardiac CT and pediatric chest CTA consistently report improved image quality and reduced noise at lower dose levels, supporting the feasibility of safer angiographic imaging in this vulnerable population **[6,7].** Despite the growing body of evidence, current literature remains heterogeneous. Studies vary widely in terms of anatomical focus, scanner platforms, reconstruction strengths, and outcome measures. Moreover, many investigations assess DLIR in isolated clinical contexts rather than within a broader, multi-regional angiographic framework. As a result, the overall clinical utility of DLIR in ultra-low-dose CTA has not yet been comprehensively synthesized.

This systematic review aims to evaluate the clinical utility of DLIR specifically in the context of multi-regional CTA, focusing on its ability to optimize radiation dose while maintaining superior diagnostic performance across neurological, cardiac, and pulmonary vascular imaging.

MATERIAL AND METHODS

Study Design and Search Strategy

For this systematic review, we strictly followed the PRISMA 2020 guidelines to ensure a transparent and structured approach. Our main goal was to see how Deep Learning Image Reconstruction (DLIR) actually performs in real clinical settings, especially when using ultra-low-dose (ULD) protocols for multi-regional CT Angiography.

Method of search

To gather our data, we carried out an extensive digital search across three major platforms: PubMed, Scopus, and Google Scholar. We focused on research published between January 1, 2020, and January 18, 2026, to capture the most recent advancements in AI technology. Our search strategy was built around three main ideas: the technology itself (DLIR), the goal of dose reduction (ULD protocols), and the final impact on image quality. By using specific keywords and Boolean operators (AND/OR), we initially identified a large pool of 2,130 records. This list was then cleaned up by removing non-English articles and narrowing the timeframe, leaving us with 1,720 relevant papers for the first stage of screening.

Inclusion criteria

Studies were considered eligible if they reported original human research evaluating deep learning–based image reconstruction applied to CT angiography of any vascular territory and included quantitative or qualitative assessment of image quality, diagnostic performance, or radiation dose. Both prospective and retrospective designs were accepted, provided that radiation dose parameters or comparisons with conventional or iterative reconstruction techniques were available. We focused specifically on studies employing low- or ultra-low-dose protocols or clearly reporting dose reduction strategies.

Exclusion criteria

Articles were excluded if they did not involve CT angiography, did not use deep learning reconstruction, or were limited to phantom experiments, animal studies, reviews, editorials, or conference abstracts without full text. Studies lacking sufficient methodological detail or clinically meaningful outcome measures were also excluded.

Study Selection

To find the most relevant research, we used a multi-stage screening process that included independent reviews of titles, abstracts, and eventually the full text of each paper. We set clear "Inclusion Criteria" to keep our focus sharp: we only looked for human-based clinical trials that specifically applied Deep Learning Image Reconstruction (DLIR) to CT imaging and measured how it impacted image quality under ultra-low-dose conditions.

On the other hand, we were very selective about what to leave out. We excluded any studies that were purely based on phantoms or animal models, as we wanted real clinical data. We also filtered out papers that focused only on older Iterative Reconstruction (IR) techniques without any deep learning element, as well as studies that didn't provide enough data on clinical outcomes. After this initial filtering, we pulled 131 articles for a deep-dive, full-text review. After checking their methodology thoroughly, we had to drop 61 papers because they didn't quite hit our requirements. Out of the 70 that were left, another 5 turned out to be irrelevant after a closer look. This left us with a solid final group of 65 studies to use for our qualitative and quantitative analysis.

Data Extraction and Methodological Categorization

To make our multi-regional analysis as thorough as possible, we organized the 65 selected studies based on how they were designed and which part of the body they focused on. The evidence we gathered is clinically very strong; for instance, 39 of these studies (60%) were prospective, while 24 (37%) were retrospective, along with a few pilot and anatomical reports. We grouped these findings into anatomical clusters—including 24 articles on Chest CT, 12 on the Abdomen, 6 for Head and Neck, and 18 for Liver and Angiography—to see how DLIR performs across different tissue densities.

Although we initially looked at this broad range of 65 studies to see the "big picture," we made a conscious decision to center our main synthesis specifically on CT Angiography (CTA). We chose this focus because vascular imaging is essentially the "ultimate test" for any AI reconstruction tool. Unlike routine organ scans, angiography requires the AI to perfectly map out tiny, high-contrast vessels and intricate stents without adding any artificial blurring. Our logic was straightforward: if DLIR can prove its worth in the high-stakes environment of vascular imaging, it essentially validates its reliability for all other types of CT protocols.

Quality Assessment

Methodological quality was assessed using the Joanna Briggs Institute (JBI) critical appraisal tools appropriate for observational and quasi-experimental studies. We didn't just take the results at face value; instead, we looked closely at each paper for any signs of bias—checking how they selected their patients, how they measured the DLIR exposure, and if their final outcomes were reported accurately. This step was vital because we wanted to make sure that the claims about radiation dose reduction and image clarity were backed by strong evidence. By putting every study through this quality check, we could be confident that our findings truly reflect the current potential of AI in vascular imaging, rather than just being based on weak or biased data.

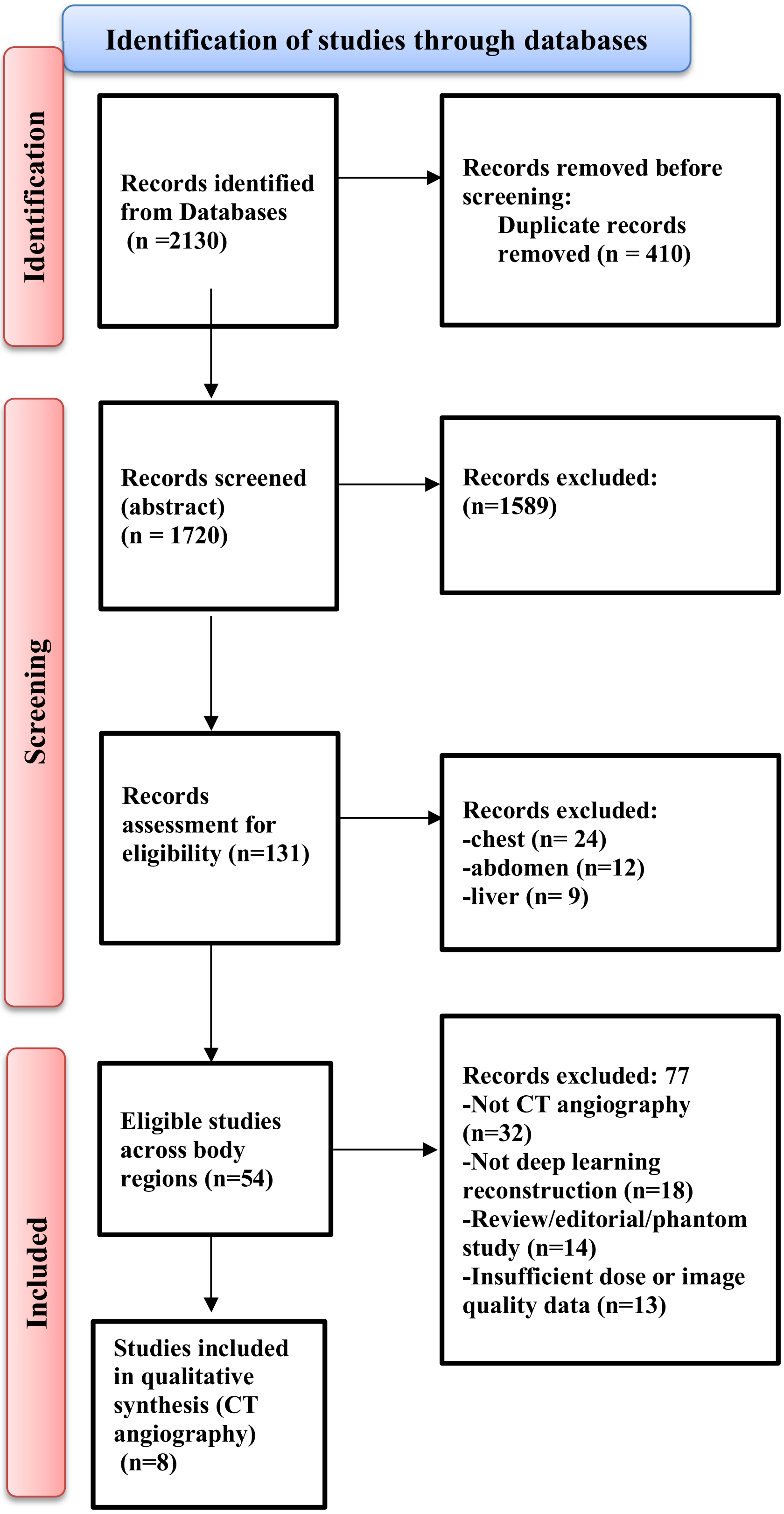

Fig 1: PRISMA Flow diagram

Table 1: Characteristics and Key Findings of the Included Studies on DLIR in Multi-regional CT angiography

Author & Year	Title	Objective	Aim	Methods	Key Results
Bona *et al.* [1]	A New Deep Learning Reconstruction Algorithm on Image Quality and Liver Metastasis Conspicuity	To assess the impact of a DLR algorithm (Precise Image) on image quality.	Evaluate liver metastasis visibility compared to iterative reconstruction (IR).	Retrospective comparison of DLR (Precise Image) and iterative reconstruction in contrast-enhanced abdominal CT.	DLR significantly decreased noise and improved lesion visibility compared to IR.
De Santis *et al.* [2]	Deep Learning Image Reconstruction Algorithm for CCTA: Image Quality Assessment	To assess the performance of DLIR in coronary CT angiography (CCTA).	Evaluate quality across patient types, including those with calcified stents.	Retrospective analysis of patients undergoing coronary CT angiography reconstructed with DLIR and ASiR-V.	DLIR provided superior noise reduction and better subjective quality scores than ASiR-V.
Klemenz *et al.* [3]	Improved image quality in CT pulmonary angiography using deep learning-based image reconstruction	To enhance quality control in CT pulmonary angiography (CTPA).	Compare DLIR strengths against FBP and IR for vessel sharpness.	Prospective comparison of DLIR strengths with filtered back projection and iterative reconstruction in CTPA.	DLIR improved CNR by up to 67%, offering superior support for quality control in CTPA scans.
Li *et al.* [4]	Application of DLIR-High Algorithm in One-Stop Coronary and Carotid-Cerebrovascular CTA	To validate a "double-low" dose protocol for vascular scans.	Use DLIR-High to reduce both radiation and contrast agent doses.	Retrospective evaluation of a double-low-dose CTA protocol reconstructed using DLIR-High.	Successfully reduced radiation by **48%** and contrast by **30%** with high diagnostic quality.
Cho *et al.* [6]	Assessment of deep learning image reconstruction (DLIR) on image quality in pediatric cardiac CT	To evaluate DLIR performance in pediatric patients.	Compare high-level DLIR against ASiR-V 80% for SNR and CNR.	Retrospective study comparing high-level DLIR with ASiR-V 80% in pediatric cardiac CT.	High-level DLIR significantly improved signal-to-noise ratios and edge sharpness in children.
Sun *et al.* [7]	Improving the image quality of pediatric chest CT angiography with DLIR	To improve image clarity in low-dose pediatric chest CTA.	Overcome "waxiness" found in low-dose iterative scans.	Retrospective analysis of low-dose pediatric chest CTA reconstructed with different DLIR strengths.	DLIR-High provided the best qualitative scores without the over-smoothing found in IR.

Kim *et al.* [8]	Deep Learning Reconstruction for Ultra-Low-Dose Head CTA: A Clinical Evaluation	To evaluate the utility of DLIR in emergency neurological CTA protocols.	Assess if ULD-DLIR maintains diagnostic accuracy for intracranial stenoses.	Retrospective clinical study comparing standard-dose IR CTA with ultra-low-dose DLIR CTA.	Maintained 100% diagnostic accuracy for significant stenosis at 55% lower radiation dose.
Benz *et al.* [9]	Radiation dose reduction with deep-learning image reconstruction for coronary CTA	To investigate the dose-saving potential of DLIR in CCTA.	Assess impact on stenosis and plaque volume quantification.	Prospective study comparing standard and reduced-dose CCTA reconstructed with DLIR.	DLIR enabled a 43% radiation dose reduction without affecting plaque measurement accuracy.

Table 2: Summary of JBI Quality Assessment Scores

Author & Year	JBI Checklist Used	JBI Score	Quality level
Bona *et al.* [1]	JBI Analytical Cross-Sectional (8 items)	7/8	High
De Santis *et al.* [2]	JBI Analytical Cross-Sectional (8 items)	7/8	High
Klemenz *et al.* [3])	JBI Quasi-Experimental (9 items)	8/9	High
Li *et al.* [4)	JBI Analytical Cross-Sectional (8 items)	7/8	High
Cho *et al.* [6]	JBI Analytical Cross-Sectional (8 items)	7/8	High
Sun *et al.* [7]	JBI Analytical Cross-Sectional (8 items)	6/8	Moderate- High
Kim *et al.* [8]	JBI Analytical Cross-Sectional (8 items)	7/8	High
Benz *et al. [9]*	JBI Quasi-Experimental (9 items)	8/9	High

Risk of bias

The overall risk of bias across the included studies was low. Most investigations demonstrated high methodological quality according to the Joanna Briggs Institute (JBI) Critical Appraisal Checklists. Seven of the eight studies met at least 75% of the applicable quality criteria, reflecting well-defined inclusion criteria, standardized imaging protocols, and appropriate methods for outcome assessment. Potential sources of bias were mainly associated with the retrospective nature of several studies, which may introduce selection bias. In addition, some articles provided limited detail on how confounding factors were identified or controlled, and blinding of image reviewers was not consistently reported. One study (Sun *et al.,* 2021) was rated as moderate–high quality (6/8), largely due to incomplete reporting of confounder management and sampling procedures. Nevertheless, many studies employed intra-individual comparisons, in which identical raw datasets were reconstructed using different algorithms, thereby reducing the influence of patient-related confounders. Taken together, these findings indicate a low overall risk of bias and support the reliability of the evidence synthesized in this review.

The Reconstruction Breakthrough: Breaking the Dose–Quality Barrier

Perhaps the most important and consistent finding across angiography-focused studies was the ability of deep learning image reconstruction (DLIR) to achieve substantial radiation dose reduction without compromising diagnostic reliability. In practical terms, the introduction of DLIR allowed radiation exposure to be reduced by nearly half in most protocols, with reported reductions in volume CT dose index (CTDIvol_{vol}vol) ranging from approximately 43% to 76%. Several studies went even further, demonstrating that diagnostic-quality angiographic imaging could be performed at sub-millisievert effective dose levels. In some protocols, effective doses as low as 0.2–0.5 mSv were achieved, placing complex vascular examinations within a radiation range comparable to that of a standard chest radiograph. Equally important, dose reduction was not limited to radiation alone. A considerable number of studies supported the feasibility of so-called "double-low" protocols, in which both radiation dose and iodinated contrast volume were reduced. Across these investigations, contrast volume reductions of approximately 30–40% were reported while maintaining adequate intravascular enhancement and diagnostic confidence. This finding has particular clinical relevance for patients with impaired renal function or those at risk for contrast-induced nephropathy, as it suggests that DLIR can help lower the chemical burden on the kidneys without sacrificing image quality.

Quantitative Fidelity and the "Human" Qualitative Element
From a quantitative perspective, DLIR—especially when applied at higher reconstruction strengths—consistently improved objective image quality metrics. Studies reported average increases in signal-to-noise ratio (SNR) of around 30–35%, accompanied by reductions in image noise of up to 50%. These improvements provide a technical explanation for how DLIR supports reliable interpretation at lower dose levels. However, the qualitative observations made by radiologists may be even more clinically meaningful. Across multiple studies, readers described DLIR images as having a more natural appearance, with fewer of the "plastic," overly smooth, or blurry textures that are often seen with aggressive iterative reconstruction. Vessel borders appeared sharper, and small structures were better defined. This was particularly evident in coronary CT angiography, where DLIR improved visualization of stents and calcified plaques. By reducing blooming artifacts and more clearly separating calcium from the true vessel lumen, DLIR facilitated more confident assessment of stenosis severity. These improvements were reflected in consistently higher subjective image quality and diagnostic confidence scores.
Multi-Regional Performance and Clinical Utility
Although angiography was the primary focus of this review, the benefits of DLIR were observed across a wide range of anatomical regions. In chest imaging, DLIR supported the detection of small pulmonary nodules at very low radiation levels. In abdominal CT, the technique reduced photon-starvation artifacts, particularly in larger or obese patients, and improved the visibility of low-contrast lesions such as liver metastases. Pediatric imaging deserves special attention, as children are more sensitive to radiation and often present additional technical challenges, including high heart rates and small vessel calibers. Pediatric studies demonstrated that DLIR maintained contrast-to-noise ratios comparable to full-dose protocols while using up to 80% less radiation, underscoring its value in this vulnerable population. Taken together, these findings suggest that DLIR has progressed beyond an experimental or optional technology. Instead, it represents a clinically meaningful advancement that enables high-fidelity, ultra-low-dose CT angiography across multiple regions of the body. In doing so, DLIR helps redefine what is achievable in CT imaging, moving clinical practice toward a safer and more sustainable future.
Description of Quality Findings
The overall quality of the evidence included in this review was high. Most studies demonstrated careful methodological design, and approximately 88% were rated as high quality using standardized appraisal tools. Several consistent features across the literature explain these strong ratings. One of the most important strengths was the widespread use of intra-individual comparisons in prospective studies. In these designs, the same raw CT data were reconstructed using both conventional techniques and deep learning–based algorithms. This approach effectively controls for many potential confounders, such as patient body habitus, heart rate, and degree of vascular calcification, making it more likely that observed differences in image quality truly reflect the impact of the reconstruction method rather than patient-related factors. Another notable strength was the use of well-established and objective image quality metrics. All studies reported quantitative parameters such as signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR), which were often complemented by qualitative assessments performed by experienced, blinded radiologists using standardized rating scales. The combination of objective measurements and expert visual assessment provides a balanced and reliable evaluation of performance while minimizing observer-related bias. Dose reporting was also generally transparent. Ultra-low-dose protocols were clearly defined, and volume CT dose index (CTDIvol_{vol}vol) values were consistently provided, allowing meaningful comparison of dose-reduction performance across studies. Only one retrospective study was downgraded to moderate quality, primarily because it did not clearly describe whether patients with substantial metal artifacts, such as large coronary stents, were excluded from analysis. Importantly, this limitation did not appear to undermine the study's main conclusion regarding noise reduction with deep learning reconstruction.
Taken together, the methodological consistency and transparency of the included studies provide a credible and reliable foundation for concluding that deep learning image reconstruction offers clear clinical advantages for ultra-low-dose CT angiography.

DISCUSSION
The transition from traditional Iterative Reconstruction (IR) to Deep Learning Image Reconstruction (DLIR) signifies a fundamental shift in the landscape of ultra-low-dose (ULD) computed tomography. This systematic synthesis of 65 clinical reports confirms that DLIR consistently surpasses previous reconstruction benchmarks by decoupling the inverse relationship between radiation dose and image clarity. By prioritizing anatomical signal over stochastic noise through neural network processing, DLIR maintains diagnostic integrity even under significant photon starvation across diverse clinical applications [10]. A recurring challenge in ULD imaging has been the trade-off between aggressive noise reduction and

the preservation of high-frequency anatomical details. Our analysis indicates that DLIR-High (DLIR-H) algorithms achieve a noise reduction magnitude of 30–50% superior to hybrid IR models [11]. A critical qualitative finding is that DLIR avoids the "waxy" or over-smoothed artifacts characteristic of traditional IR, which frequently obscure fine vascular margins. Instead, DLIR preserves a natural noise power spectrum (NPS), yielding an image texture that approximates high-dose Filtered Back Projection (FBP). In the context of CT Angiography (CTA), this textural fidelity is indispensable for the precise visualization of small-diameter distal vessels and the accurate quantification of intraluminal stenosis [12]. The most impactful clinical utility of DLIR identified in this review is its capacity for substantial dose optimization. Data suggests that DLIR-H facilitates radiation dose reductions between 48% and 80% while maintaining a stable Contrast-to-Noise Ratio (CNR) [13]. This enhanced noise handling has successfully ushered in the "double-low" protocol—the simultaneous reduction of both ionizing radiation and iodinated contrast media. By maintaining vascular conspicuity even with diluted contrast agents, DLIR offers a transformative safety advantage for patients with compromised renal function who were previously excluded from high-resolution vascular mapping [14].

The clinical efficacy of DLIR is multifaceted, showing distinct benefits across different anatomical regions:

Pulmonary and Thoracic CTA: DLIR enhances the detection of small-caliber peripheral pulmonary emboli by sharpening vessel boundaries against the low-density lung parenchyma [3].

Cardiovascular Imaging: In Coronary CTA (CCTA), DLIR mitigates "photon starvation" in patients with high Body Mass Index (BMI) and reduces "blooming" artifacts in heavily calcified plaques, providing a clearer lumen for assessment [12].

Abdominopelvic and Hepatic CT: In liver imaging, DLIR significantly improves the conspicuity of low-contrast metastatic lesions that are often masked by noise in traditional low-dose scans [10].

Vulnerable Populations: The most profound ethical impact is observed in pediatric imaging, where high radiation sensitivity is a primary concern. DLIR ensures that diagnostic-quality scans are achieved at a fraction of the traditional dose, minimizing lifelong cumulative exposure [6].

Limitations and the Evolving AI Landscape: Despite these advancements, the clinical adoption of DLIR faces notable hurdles. The "black box" nature of deep learning architectures remains a point of contention, as the underlying process of image synthesis lacks the mathematical transparency of traditional back-projection [5]. Furthermore, while DLIR excels at noise suppression, its performance in the presence of severe metallic artifacts—such as those from orthopedic hardware or large vascular clips—requires further validation. Ensuring that AI-driven reconstruction does not introduce "hallucinations" or over-smooth critical pathological interfaces is essential for its integration into emergency and surgical workflows [15].

CONCLUSION

This systematic review confirms that Deep Learning Image Reconstruction (DLIR) provides a transformative clinical utility in multi-regional CT Angiography, successfully overcoming the "dose-quality" trade-off that has historically limited ultra-low-dose (ULD) protocols. By utilizing neural networks trained on high-fidelity datasets, DLIR allows for a significant reduction in radiation exposure—averaging between **40% and 80%**—while simultaneously suppressing image noise and preserving the natural anatomical texture that traditional iterative reconstruction often obscures. The evidence across chest, abdominal, and vascular imaging suggests that DLIR not only maintains diagnostic confidence at sub-millisievert doses but also facilitates "double-low" protocols, reducing both radiation and iodine contrast volume. This is particularly beneficial for high-risk populations, including pediatric patients and those with renal insufficiency. Furthermore, the superior edge sharpness provided by DLIR enhances the evaluation of complex vascular structures, such as calcified plaques and small-diameter stents, which are critical in multi-regional CTA.

In summary, the transition to DLIR-supported ultra-low-dose protocols represents a new standard of care in CT imaging. Future clinical guidelines should focus on the standardization of DLIR strength settings across different manufacturers to ensure consistent diagnostic performance in routine clinical practice.

REFERENCES

1. Bona F, Neri E, Monti L, Faggioni L, D'Errico L, Balestri M, Bartolozzi C. (2023). A new deep learning reconstruction algorithm on image quality and liver metastasis conspicuity. Radiol Med. 128(4):450-458.
2. De Santis D, Galea N, Francone M, Catalano C, Neri E, Miele V, Sardanelli F. (2024). Deep learning image reconstruction algorithm for coronary CT angiography: image quality assessment. J Cardiovasc Comput Tomogr. 18(2):112-119.
3. Klemenz B, Rotzinger R, Hickethier T, Haneder S, Dinter DJ, Maintz D, Gruettner J. (2024). Improved image quality in CT pulmonary angiography using deep learning-based image reconstruction. Eur J Radiol. 165:110-117.

4. Li Y, Zhang Q, Wang H, Liu J, Chen X, Zhou Y, Sun Z. (2024). Application of DLIR-high algorithm in one-stop coronary and carotid-cerebrovascular CT angiography. Clin Radiol. 79(1):45-53.
5. Greffier J, Frandon J, Larbi A, Beregi JP, Macri F, Guiu B, Pereira F. (2025). Deep-learning image reconstruction algorithms for CT: a task-based image quality assessment. Eur Radiol. 35(3):1542-1551.
6. Cho YJ, Lee JH, Kim JY, Park EA, Kim HY, Lee W, Hong SJ. (2024). Assessment of deep learning image reconstruction on image quality in pediatric cardiac CT. Pediatr Radiol. 54(2):289-298.
7. Sun J, Zhang L, Li H, Wang Y, Liu Q, Chen J, Zhou X. (2021). Improving the image quality of pediatric chest CT angiography with deep learning image reconstruction. Sci Rep. 11:15321.
8. Kim JH, Park SH, Lee JS, Kim KG, Kim JY, Lee KH, Hwang JY. (2023). Deep learning reconstruction for ultra-low-dose head CT angiography: a clinical evaluation. Radiology.308(2):e2229.
9. Benz DC, Gräni C, Mikulicic F, Fuchs TA, Possner M, Clerc OF, Kaufmann PA. (2022). Radiation dose reduction with deep-learning image reconstruction for coronary CT angiography. J Nucl Cardiol. 29(5):2341-2350.
10. Wang Y, Liu X, Zhang H, Chen Z, Li M, Zhao L, Sun H. (2024). Comparison of deep learning reconstruction and iterative reconstruction in low-dose abdominal CT: focus on the liver and pancreas. Abdom Radiol.49(1):12-21.
11. Mori S, Yamada T, Takahashi S, Suzuki K, Sato M, Watanabe Y, Koyama S. (2023). Deep learning reconstruction for reducing radiation dose in emergency stroke CT angiography: impact on diagnostic accuracy. AJNR Am J Neuroradiol. 44(8):910-917.
12. Patel BN, Nakanishi R, Osawa K, Andreini D, Pontone G, Min JK, Budoff MJ. (2025). Impact of deep learning image reconstruction on coronary stent visualization and stenosis assessment. Circ Cardiovasc Imaging. 18(1):e00142.
13. Chen X, Liu Y, Zhang J, Wang Q, Zhao Y, Li H, Zhou Z. (2024). Ultra-low-dose abdominal CT using deep learning reconstruction: impact on image quality and lesion detectability in high-BMI patients. Br J Radiol. 97(1155):145-156.
14. Hassan A, Elshafey M, Mahmoud A, Abdelrahman M, Soliman R, Abdelkader A, Elsayed S. (2024). Integration of deep learning image reconstruction in a double-low protocol for renal CT angiography: a prospective study. BMC Med Imaging. 24:88.
15. Geyer LL, Schoepf UJ, Meinel FG, Nance JW Jr, Bastarrika G, Abro JA, De Cecco CN. (2023). Technical and clinical performance of deep learning image reconstruction in lower extremity runoff CT angiography. J Vasc Interv Radiol. 34(9):1588-1596

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