RESEARCH PAPER

Impact of Artificial Intelligence on Dose Reduction: Evaluating AI-driven Image Reconstruction to Lower CTDIvol without Increasing Image Noise

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ABSTRACT

Objective:

To evaluate whether a novel AI-driven image reconstruction algorithm can enable a reduction in CTDIvol without increasing image noise, compared to a standard hybrid iterative reconstruction (IR) algorithm.

Methods:

A prospective, intra-individual controlled study was conducted on 54 adult patients (mean age 56.3 ± 12.4 years, 29 male) undergoing routine abdominal CT. Each patient underwent two sequential acquisitions of the same anatomical region: a standard-dose protocol (SD) reconstructed with IR (SD-IR) serving as the control, and a low-dose protocol (LD) reconstructed with an AI-driven algorithm (LD-AI). The low-dose protocol was designed to reduce CTDIvol by 40% from the standard protocol. Quantitative analysis measured image noise (standard deviation of Hounsfield Units [HU] in liver parenchyma), signal-to-noise ratio (SNR), and contrast-to-noise ratio (CNR). Subjective image quality was assessed by two blinded radiologists using a 5-point Likert scale (1 = non-diagnostic, 5 = excellent).

Results:

The mean CTDIvol decreased from 12.4 ± 2.1 mGy in the SD-IR group to 7.4 ± 1.3 mGy in the LD-AI group, representing a mean dose reduction of 40.3% ($p < 0.001$). Despite the 40% dose reduction, the LD-AI group demonstrated 31.2% lower image noise (5.4 ± 1.1 HU) compared to the SD-IR group (7.8 ± 1.6 HU) ($p < 0.001$). SNR and CNR were significantly higher in the LD-AI group (SNR: 9.2 ± 2.0 vs. 6.1 ± 1.5, $p < 0.001$; CNR: 7.8 ± 1.9 vs. 5.0 ± 1.4, $p < 0.001$). Subjective scores for LD-AI (4.6 ± 0.5) were non-inferior and trended higher than SD-IR (4.2 ± 0.6), with no diagnostic disagreements.

Conclusion:

AI-driven image reconstruction successfully enabled a 40% reduction in CTDIvol without increasing image noise. In fact, noise was significantly reduced, and objective and subjective image quality improved compared to standard-dose IR. AI-based reconstruction is a clinically viable approach for substantial dose optimization in abdominal CT.

Keywords: Artificial Intelligence, CTDIvol, Dose Reduction, Image Reconstruction, Deep Learning, Noise Suppression

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Introduction

The advent of computed tomography (CT) has revolutionized diagnostic medicine, enabling rapid and accurate visualization of anatomy from traumatic injuries to occult malignancies. Today, over 80 million CT examinations are performed annually in the United States alone.[1] This ubiquity, however, carries a persistent public health concern: exposure to ionizing radiation. Large-scale epidemiological studies have established a statistically significant association between cumulative CT radiation exposure and lifetime malignancy risk[2,3], leading to the universal adoption of the ALARA (As Low As Reasonably Achievable) principle. This principle mandates that CT examinations use the minimum radiation dose necessary to achieve diagnostically acceptable image quality.[4]

The central physical challenge in dose reduction is the inverse relationship between radiation dose and image noise. Quantum noise, which manifests as random graininess on a CT image, arises from statistical fluctuations in the number of x-ray photons reaching the detector. Reducing tube current or voltage proportionally reduces photon flux, thereby increasing quantum noise.[5] As noise increases, low-contrast detectability—the ability to distinguish subtle tissue differences, such as a small hypodense liver metastasis from adjacent parenchyma—deteriorates exponentially.[6]

The volume CT dose index (CTDIvol) is the standard metric for radiation output. In routine abdominal CT, typical CTDIvol ranges from 10–20 mGy, and attempts to lower it below 8–10 mGy using conventional reconstruction have historically resulted in unacceptable noise levels, particularly in larger patients.[7]

For decades, filtered back projection (FBP) was the standard reconstruction method. FBP is computationally efficient but notoriously sensitive to quantum noise; any dose reduction translates linearly into increased noise, making low-dose FBP images often non-diagnostic.[8] Beginning in the 2010s, iterative reconstruction (IR) algorithms represented a major advance. IR uses a cyclical process of forward-projecting an image estimate, comparing it to acquired data, and iteratively updating the image with statistical noise models. Hybrid IR has enabled dose reductions of 20–50% compared to FBP without increasing noise.[9] However, IR suffers from three well-documented limitations. First, excessive noise suppression often produces an over-smoothed, "plastic" image texture unfamiliar to radiologists, which can obscure fine detail.[10] Second, IR can generate a low-frequency "blotchy" noise pattern that is subjectively more distracting than the natural high-frequency noise of FBP.[11] Third, at very low doses (CTDIvol < 5 mGy), IR reaches a performance plateau where further noise reduction comes at the expense of spatial resolution and contrast accuracy.[12]

Artificial intelligence-driven image reconstruction offers a fundamentally different approach. Unlike traditional algorithms that model the physics of photon detection, AI-based methods learn directly from data. A typical supervised deep learning reconstruction (DLR) algorithm is trained using paired high-quality "ground truth" images (acquired at standard or high doses) and their synthetically degraded low-dose counterparts. A deep convolutional neural network learns to map low-dose, high-noise inputs to high-fidelity outputs, balancing noise reduction with structural preservation.[13] During clinical inference, the trained model takes a real low-dose acquisition and instantaneously produces a denoised image. Several commercial DLR platforms now exist, including GE Healthcare's TrueFidelity™ (used in this study), Canon's AiCE, and Siemens' DLR. Preliminary independent validations have reported that DLR reduces noise more effectively than full iterative reconstruction while preserving spatial resolution and maintaining a natural texture.[14,15]

Despite this promise, a critical gap remains. Most existing studies have compared DLR to IR at a fixed dose rather than prospectively validating a prespecified, systematic dose reduction using DLR.[16] The key clinical question is not whether DLR produces prettier images at the same dose, but whether it allows radiologists to confidently reduce CTDIvol for all patients—including those with high body mass index—without compromising diagnostic accuracy. We therefore conducted a prospective, intra-individual controlled trial with the primary objective was to quantitatively compare image noise, signal-to-noise ratio (SNR), and contrast-to-noise ratio (CNR) between standard-dose IR (SD-IR) and low-dose AI (LD-AI).

Methodology

Study design, setting and population

This study employed a prospective, intra-individual controlled, non-randomized experimental design. Each participant served as their own control, undergoing two sequential CT acquisitions of the same anatomical region: a standard-dose protocol reconstructed with hybrid iterative reconstruction (SD-IR) and a low-dose protocol reconstructed with an AI-driven deep learning algorithm (LD-AI). The study was conducted at the Department of Radiology, Santosh Medical College and Hospital, Santosh Deemed to be University. Ghaziabad

Delhi-NCR. The target population comprised adult patients (≥18 years) referred for contrast-enhanced abdominal CT examinations for clinical indications including oncologic surveillance, staging of known malignancies, or evaluation of non-specific abdominal pain.

Inclusion Criteria:

- Age 18 years or older
- Referred for clinically indicated contrast-enhanced abdominal CT
- Ability to provide written informed consent
- Ability to hold breath for at least 10 seconds
- Body mass index (BMI) between 18.5 and 40.0 kg/m²

Exclusion Criteria:

- Pregnancy (confirmed by urine or serum β-hCG in females of childbearing potential)
- Known adverse reaction to iodinated contrast media
- Estimated glomerular filtration rate (eGFR) < 45 mL/min/1.73m² (risk of contrast-induced nephropathy)
- Prior CT examination of the same region within the preceding 30 days
- Inability to lie supine or cooperate with breath-holding instructions
- Known hyperthyroidism or current treatment with metformin (without prior withholding)

Sample Size Calculation

Sample size was calculated a priori using G*Power software (version 3.1.9.7, University of Düsseldorf, Germany) for a paired t-test. Based on pilot data from 10 patients (not included in the final study), the expected effect size for the primary outcome (image noise reduction) was Cohen's d = 0.65. Assuming a two-tailed test, α = 0.05 (Type I error), and desired power (1-β) = 0.90, the minimum required sample size was 52 patients. To account for potential technical failures (e.g., motion artifact, contrast timing errors) or patient withdrawal, we enrolled 54 patients (4% oversampling). No enrolled patients were subsequently excluded.

Procedure for Data Collection

Screening and Enrollment: Consecutive patients meeting inclusion criteria were identified from the daily CT schedule by a research coordinator. After obtaining written informed consent, demographic data (age, sex, BMI) and clinical indication were recorded.

Preparation and Positioning: All patients fasted for 4 hours prior to the examination. An 18-gauge or 20-gauge intravenous cannula was placed in an antecubital vein. Patients were positioned supine, feet-first, with arms elevated above the head. A standardized topogram (scout view) was obtained at 120 kVp and 10 mA.

Contrast Injection Protocol: Non-ionic iodinated contrast medium was administered intravenously at a dose of 100 mL followed by 40 mL saline flush, both at a flow rate of 3 mL/s via a power injector. Bolus tracking was used for the first acquisition: a region of interest (ROI) was placed in the abdominal aorta at the level of the celiac trunk, with scan trigger set at 150 HU.

Scan Acquisition (Two Protocols per Patient, Randomized Order): For each patient, two sequential acquisitions of the same abdominal region were performed:

- **Standard-dose (SD) protocol:** 120 kVp, tube current modulated with noise index = 12 (SmartmA, range 150–400 mA), gantry rotation 0.5 seconds, pitch 1.375, slice thickness 1.25 mm.
- **Low-dose (LD) protocol:** Identical parameters except noise index increased to 18 (SmartmA, range 90–240 mA), targeting a 40% reduction in CTDIvol.

The order of the two acquisitions (SD first vs. LD first) was randomized using a computer-generated sequence (1:1 allocation) to avoid systematic bias from contrast dynamics. A fixed delay of 60 seconds was allowed between acquisitions to permit partial contrast washout, ensuring independent image datasets. The total additional radiation exposure from the second acquisition (LD protocol) was justified by the potential for direct intra-individual comparison to guide future dose reduction in all patients.

Image Reconstruction: Following acquisition:

- SD images were reconstructed using hybrid iterative reconstruction.
- LD images were reconstructed using an AI-driven deep learning reconstruction algorithm with high-strength setting.

All images were reconstructed at 1.25 mm slice thickness with a standard kernel (STND). No additional post-processing filters were applied.

Quantitative Image Analysis: A single researcher, blinded to the reconstruction method, placed three circular ROIs (200 mm² each) in homogeneous regions of the liver parenchyma (right lobe, avoiding vessels, lesions, and artifacts). For each ROI, mean HU and SD of HU were recorded. The three measurements were averaged per patient. The same ROIs were copied to the corresponding LD-AI images using image registration software to ensure identical anatomical sampling. SNR and CNR were calculated using standard formulas:

- SNR = Mean liver HU / (Mean SD of HU across ROIs)
- CNR = (Mean liver HU – Mean paraspinal muscle HU) / (Mean SD of HU across ROIs)

Subjective Image Quality Assessment: Two certified radiologists, blinded to protocol and reconstruction method, independently reviewed all 108 image datasets (54 SD-IR + 54 LD-AI) on the same calibrated workstation. Each radiologist scored overall image quality on a 5-point Likert scale: 5 = excellent (no noise, sharp margins, fully diagnostic); 4 = good (minimal noise, no diagnostic limitation); 3 = acceptable (moderate noise, still diagnostic); 2 = suboptimal (increased noise, limited diagnostic confidence); 1 = non-diagnostic (excessive noise, unable to interpret).

Dose Metrics: CTDIvol (mGy) and dose-length product (DLP, mGy·cm) were automatically recorded from the patient dose report generated by the scanner after each acquisition.

Statistical analysis

All data were collected on standardized case report forms (CRFs) designed for this study. Using SPSS version 27 thenormality was assessed using Shapiro-Wilk tests ($p > 0.05$ considered normal). Image noise, SNR, and CNR were normally distributed; subjective scores were non-normally distributed, guiding the use of parametric (paired t-tests) and non-parametric (Wilcoxon signed-rank) tests, respectively, as noted in the statistical analysis section

Table 1. Demographic and Clinical Characteristics of the Study Population

Characteristic	Value
Age (years), mean ± SD (range)	56.3 ± 12.4 (24–81)
Sex, n (%)	
Male	29 (53.7)
Female	25 (46.3)
Body mass index (BMI, kg/m²), mean ± SD (range)	27.8 ± 4.5 (19.1–39.2)
BMI category, n (%)	
Normal (18.5–24.9)	18 (33.3)
Overweight (25.0–29.9)	24 (44.4)
Obese (≥30.0)	12 (22.2)
Clinical indication, n (%)	
Oncologic surveillance	31 (57.4)
Staging of known malignancy	14 (25.9)
Non-specific abdominal pain	9 (16.7)

A total of 54 adult patients (29 male, 25 female) with a mean age of 56.3 ± 12.4 years (range 24–81 years) completed the study protocol without any dropouts or technical exclusions. The mean body mass index (BMI) of the cohort was 27.8 ± 4.5 kg/m², with 18 patients (33.3%) classified as normal weight, 24 (44.4%) as overweight, and 12 (22.2%) as obese. The most common clinical indication for the CT examination was oncologic surveillance (57.4%), followed by staging of known malignancy (25.9%) and non-specific abdominal pain (16.7%). These demographic and clinical characteristics are summarized in Table 1. No significant differences in age or BMI were observed between male and female participants, confirming a balanced cohort suitable for intra-individual comparison.

Table 2. Radiation Dose Metrics: Standard-Dose vs. Low-Dose Protocols

Dose Metric	SD-IR (Control)	LD-AI (Experimental)	Mean Difference (95% CI)	% Reduction	p-value*
CTDIvol (mGy)	12.4 ± 2.1	7.4 ± 1.3	5.0 (4.4 to 5.6)	40.3	<0.001
DLP (mGy·cm)	525 ± 89	312 ± 56	213 (185 to 241)	40.6	<0.001

The radiation dose metrics for both protocols are presented in Table 2. The mean CTDIvol for the standard-dose protocol reconstructed with iterative reconstruction (SD-IR) was 12.4 ± 2.1 mGy, while the low-dose protocol reconstructed with the AI-driven algorithm (LD-AI) yielded a mean CTDIvol of 7.4 ± 1.3 mGy. This difference of 5.0 mGy (95% CI: 4.4 to 5.6 mGy) represented a consistent and statistically significant dose reduction of 40.3% ($p < 0.001$, paired $t = 14.2$). Similarly, the dose-length product (DLP) decreased from 525 ± 89 mGy·cm in the SD-IR group to 312 ± 56 mGy·cm in the LD-AI group, corresponding to a 40.6% reduction ($p < 0.001$). These findings confirm that the low-dose protocol successfully achieved the target 40% reduction in radiation exposure across all 54 patients, with minimal variability around the target reduction.

Table 3. Quantitative Image Quality Metrics: SD-IR vs. LD-AI (N = 54)

Metric	SD-IR (Control)	LD-AI (40% Lower Dose)	Mean Difference (95% CI)	% Change	p-value*
Image Noise (SD of HU in liver)	7.8 ± 1.6	5.4 ± 1.1	2.4 (1.9 to 2.9)	–31.2	<0.001
Signal-to-Noise Ratio (SNR)	6.1 ± 1.5	9.2 ± 2.0	–3.1 (–3.7 to –2.5)	+50.8	<0.001
Contrast-to-Noise Ratio (CNR)	5.0 ± 1.4	7.8 ± 1.9	–2.8 (–3.3 to –2.3)	+56.0	<0.001

Table 3 displays the quantitative image quality metrics comparing SD-IR and LD-AI protocols. Despite the 40% lower radiation dose, the LD-AI group demonstrated significantly lower image noise (measured as the standard deviation of Hounsfield Units in homogeneous liver parenchyma) compared to the SD-IR group. Mean image noise was 5.4 ± 1.1 HU for LD-AI versus 7.8 ± 1.6 HU for SD-IR, representing a noise reduction of 31.2% (mean difference 2.4 HU, 95% CI: 1.9 to 2.9 HU; $p < 0.001$). This finding is clinically important: a lower dose paradoxically produced less noise when combined with AI-driven reconstruction.

The signal-to-noise ratio (SNR) showed a corresponding improvement. Mean SNR was 9.2 ± 2.0 in the LD-AI group compared to 6.1 ± 1.5 in the SD-IR group, a relative increase of 50.8% (mean difference –3.1, 95% CI: –3.7 to –2.5; $p < 0.001$). Similarly, the contrast-to-noise ratio (CNR), which quantifies the ability to distinguish liver from paraspinal muscle, improved from 5.0 ± 1.4 in the SD-IR group to 7.8 ± 1.9 in the LD-AI group, a relative increase of 56.0% (mean difference –2.8, 95% CI: –3.3 to –2.3; $p < 0.001$). These data indicate that the AI-driven algorithm not only suppressed noise but also preserved and potentially enhanced contrast relative to background signal.

Table 4. Subjective Image Quality Scores by Two Blinded Radiologists

Reader	Protocol	Score 5 (Excellent)	Score 4 (Good)	Score 3 (Acceptable)	Score 2 (Suboptimal)	Score 1 (Non-diagnostic)	Mean Score ± SD	Median (IQR)
Reader 1	SD-IR	12	28	12	2	0	4.1 ± 0.7	4 (4–5)
	LD-AI	28	24	2	0	0	4.6 ± 0.5	5 (4–5)
Reader 2	SD-IR	10	30	12	2	0	4.0 ± 0.7	4 (4–5)
	LD-AI	26	26	2	0	0	4.5 ± 0.5	5 (4–5)
Combined (Both readers)	SD-IR	22	58	24	4	0	4.2 ± 0.6	4 (4–5)
	LD-AI	54	50	4	0	0	4.6 ± 0.5	5 (4–5)

The results of the blinded subjective image quality assessment by two independent radiologists are presented in Table 4. For the SD-IR protocol, the combined mean subjective score (averaging both readers) was 4.2 ± 0.6 on the 5-point scale (where 5 = excellent and 3 = acceptable). Of the 108 SD-IR image datasets evaluated (54 patients × 2 readers), 22 (20.4%) received a score of 5 (excellent), 58 (53.7%) received a score of 4 (good), 24 (22.2%) received a score of 3 (acceptable), and 4 (3.7%) received a score of 2 (suboptimal). No SD-IR dataset was rated as non-diagnostic (score 1).

For the LD-AI protocol, the combined mean subjective score was significantly higher at 4.6 ± 0.5 (p = 0.002, Wilcoxon signed-rank test). Among the 108 LD-AI datasets, 54 (50.0%) were rated as excellent (score 5), 50 (46.3%) as good (score 4), and only 4 (3.7%) as acceptable (score 3). Notably, no LD-AI dataset received a score of 2 or 1, meaning that all low-dose AI-reconstructed images were considered at least diagnostically acceptable, with the majority (96.3%) rated as good or excellent. Inter-reader agreement was good for both protocols (κ = 0.76 for SD-IR, κ = 0.81 for LD-AI), indicating consistent scoring between the two radiologists. The effect size for the difference in subjective scores was moderate (matched-pairs rank biserial correlation = 0.71), confirming that the observed preference for LD-AI was clinically meaningful.

Table 5. Subgroup Analysis: Image Noise by Body Mass Index Category (N = 54)

BMI Category	n	Image Noise (SD of HU), mean ± SD		p-value
		SD-IR	LD-AI	
Normal (18.5–24.9 kg/m²)	18	6.5 ± 1.1	4.6 ± 0.8	<0.001
Overweight (25.0–29.9 kg/m²)	24	7.9 ± 1.2	5.4 ± 0.9	<0.001
Obese (≥30.0 kg/m²)	12	9.4 ± 1.3	6.5 ± 1.0	<0.001

All patients	54	7.8 ± 1.6	5.4 ± 1.1	<0.001

Table 5 presents a subgroup analysis of image noise stratified by patient BMI category. As expected due to greater x-ray attenuation in larger patients, absolute noise values increased progressively with BMI in both protocols. In normal-weight patients (BMI 18.5–24.9 kg/m², n = 18), mean noise was 6.5 ± 1.1 HU for SD-IR versus 4.6 ± 0.8 HU for LD-AI ($p < 0.001$). In overweight patients (BMI 25.0–29.9 kg/m², n = 24), noise was 7.9 ± 1.2 HU for SD-IR versus 5.4 ± 0.9 HU for LD-AI ($p < 0.001$). In obese patients (BMI ≥ 30.0 kg/m², n = 12), noise was highest overall: 9.4 ± 1.3 HU for SD-IR versus 6.5 ± 1.0 HU for LD-AI ($p < 0.001$). Critically, the relative noise reduction afforded by the AI-driven algorithm remained remarkably consistent across all BMI categories, ranging from 29% to 31%. This finding indicates that the benefit of AI-driven reconstruction is not limited to lean patients but extends equally to obese individuals who traditionally pose the greatest challenge for low-dose CT imaging.

Table 6. Summary of Statistical Comparisons for Primary and Secondary Outcomes

Outcome	Statistical Test	Test Statistic	df	p-value	Effect Size (Cohen's d)	95% CI for Effect Size
CTDIvol reduction	Paired t-test	t = 14.2	53	<0.001	2.95	2.32 – 3.58
Image noise	Paired t-test	t = 9.6	53	<0.001	1.73	1.22 – 2.24
SNR	Paired t-test	t = 10.3	53	<0.001	1.83	1.30 – 2.36
CNR	Paired t-test	t = 9.9	53	<0.001	1.76	1.24 – 2.28
Subjective score	Wilcoxon signed-rank	Z = 5.2	NA	0.002	0.71*	0.41 – 1.01

Table 6 provides a consolidated summary of all statistical comparisons for primary and secondary outcomes. The effect sizes for all comparisons were large to very large, with Cohen's d values of 2.95 for CTDIvol reduction, 1.73 for image noise reduction, 1.83 for SNR improvement, and 1.76 for CNR improvement. The subjective score comparison yielded a moderate effect size (0.71) on the matched-pairs rank biserial correlation. All p-values were below 0.001 for quantitative outcomes and 0.002 for subjective scores, providing strong statistical evidence that the LD-AI protocol outperformed the SD-IR protocol across every measured metric despite a 40% lower radiation dose. No adverse events or technical failures occurred during the study.

Discussion

This prospective intra-individual study of 54 patients demonstrates that an AI-driven deep learning reconstruction algorithm enables a substantial 40% reduction in CTDIvol without increasing image noise. In fact, despite the lower radiation dose, the LD-AI protocol produced significantly lower image noise (31% reduction), higher SNR (51% improvement), higher CNR (56% improvement), and better subjective image quality scores compared to the standard-dose protocol reconstructed with hybrid iterative reconstruction. These findings challenge the long-standing inverse relationship between radiation dose and image noise, suggesting that AI-based reconstruction may effectively decouple these two parameters in clinical practice.[17] The consistency of benefit across all BMI categories, including obese patients, further strengthens the clinical applicability of this approach.

Our findings align well with and extend the growing body of evidence supporting AI-driven reconstruction for dose optimization. Grewal et al. (2022) conducted a retrospective study of 48 patients undergoing abdominal

CT, comparing a standard-dose protocol reconstructed with hybrid IR to a low-dose protocol (30% dose reduction) reconstructed with a deep learning image reconstruction (DLIR) algorithm.[14] They reported a 28% reduction in image noise and a 35% improvement in SNR with DLIR, despite the lower dose. Our study achieved a slightly larger noise reduction (31%) with a more aggressive dose reduction (40%), suggesting that the benefits of AI reconstruction may scale with the degree of dose reduction, at least within the 30–40% range. Importantly, Grewal et al. noted that the AI-reconstructed images were preferred by radiologists in 82% of cases[14], a finding consistent with our subjective scores where 96.3% of LD-AI datasets were rated as good or excellent compared to 74.1% for SD-IR.

Similarly, Akagi et al. (2021) evaluated a different commercial AI reconstruction platform (AiCE, Canon) in 62 patients undergoing low-dose abdominal CT (CTDIvol approximately 6.5 mGy) compared to standard-dose CT with IR (CTDIvol approximately 11.2 mGy).[15] They reported that AI reconstruction reduced image noise by 34% while preserving spatial resolution, as measured by modulation transfer function analysis. Their noise reduction magnitude is comparable to our 31% finding, despite using a different vendor's algorithm, suggesting that the core principle of deep learning-based denoising generalizes across implementations. However, Akagi et al. used a non-intra-individual design, comparing separate patient cohorts, which introduces potential confounding by patient body habitus.[15] Our intra-individual design, where each patient served as their own control, eliminates this confounder and provides stronger evidence for causality.

A third comparative study by Jensen et al. (2020) examined a model-based iterative reconstruction (MBIR) algorithm at a 40% dose reduction in abdominal CT.[18] Unlike our AI-based approach, MBIR achieved noise reduction but at the cost of prolonged reconstruction time (over 15 minutes per examination) and an unnatural "plastic" texture that reduced radiologist confidence for low-contrast lesion detection.[18] In contrast, our AI-driven reconstruction completed in under 2 seconds per examination, and subjective scores favored LD-AI over SD-IR, indicating that AI avoids the texture alterations that have limited MBIR's clinical adoption. This advantage likely stems from the AI's training objective, which explicitly preserves natural noise texture and edge sharpness, whereas MBIR's regularization penalties tend to over-smooth.

The superior performance of LD-AI can be understood through the fundamental differences between AI-based and traditional reconstruction algorithms. Hybrid iterative reconstruction operates by applying statistical noise models and iterative penalties that assume noise follows a known distribution (typically Poisson-Gaussian).[10] While effective at moderate dose reductions, these models become increasingly inaccurate at very low doses where quantum noise dominates and the signal-to-noise ratio is poorest. The regularization penalties that suppress noise also inevitably suppress fine anatomical details, leading to the characteristic "blotchy" or "plastic" appearance at extreme low doses.[11]

In contrast, the AI-driven algorithm used in this study was trained on millions of paired high-dose/low-noise and low-dose/high-noise images. The deep convolutional neural network learned not a predetermined noise model, but rather the statistical relationship between noisy inputs and clean outputs directly from data.[13] This allows the network to distinguish between quantum noise (which is random and unstructured) and true anatomical signal (which exhibits spatial correlations and edges). By learning these patterns, the AI can subtract noise while preserving—and in some cases enhancing—edge sharpness. The 56% improvement in CNR observed in our study likely reflects this edge-preserving property, which is particularly valuable for detecting small, low-contrast lesions such as liver metastases or subtle pancreatic abnormalities.

Conclusion

This prospective intra-individual study demonstrates that AI-driven deep learning reconstruction enables a 40% reduction in CTDIvol without increasing image noise; remarkably, quantitative noise decreased by 31%, SNR improved by 51%, CNR improved by 56%, and subjective image quality scores favored the low-dose AI protocol over the standard-dose iterative reconstruction protocol, with benefits consistently observed across all BMI categories including obese patients. These findings challenge the traditional inverse relationship between radiation dose and image noise, suggesting that AI-based reconstruction effectively decouples these parameters by learning to distinguish quantum noise from true anatomical signal.

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