Complex Relationship Between Artificial Intelligence and CT Radiation Dose

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Concerns over need for CT radiation dose optimization and reduction led to improved scanner efficiency and introduction of several reconstruction techniques and image processing-based software. The latest technologies use artificial intelligence (AI) for CT dose optimization and image quality improvement. While CT dose optimization has and can benefit from AI, variations in scanner technologies, reconstruction methods, and scan protocols can lead to substantial variations in radiation doses and image quality across and within different scanners. These variations in turn can influence performance of AI algorithms being deployed for tasks such as detection, segmentation, characterization, and quantification. We review the complex relationship between AI and CT radiation dose.

BACKGROUND

The turn of new millennium brought both challenges and solutions to radiology. While the initial years raised alarms over rising contributions of CT scanning to overall medical radiation doses, technologic innovations brought solutions to these challenges and opened new avenues for research and clinical applications. Among the new technologies, none is deemed more impactful than the reemergence of artificial intelligence (AI) which has the potential of touching every aspect of radiology from the selection of the right test and imaging protocol to the final interpretation of radiology exams for a growing list of findings. AI refers to a broad field in computation technology that aims to perform complex tasks that traditionally require human intelligence. Machine Learning (ML), a subset of AI, involves training computer algorithms to recognize, and learn patterns in processing inputs to outputs from large datasets in order to perform certain tasks.

There are several hundred AI algorithms in the commercial and research space. The United States Food and Drug Administration (FDA) has cleared several AI algorithms. Some cleared algorithms help in CT radiation dose optimization which, given the critical role, and increasing use of CT as a leading tool for medical diagnosis, remains a safety priority (1).

Just in the United States, over 70 million CT procedures were performed in the year 2019 alone (2). Such use of CT triggered concerns over the potential of radiation-induced cancer from CT and led to calls for optimizing and regulating radiation doses (3). While the subject of cancer induction from low radiation doses from CT remains controversial, there is no debate that when needed CT must be performed at as low as reasonably achievable (ALARA principle) radiation doses. The achievability should refer to the ability of the resulting dose-optimized or reduced-dose CT images to provide the needed diagnostic information for specified clinical indications in patients of different ages and body habitus. Improved detector efficiency, automatic tube potential selection and tube current modulation techniques, and iterative reconstruction (IR) help optimize radiation doses (4).

Despite clinical and technological progress in radiation dose optimization, need for further dose reduction, and optimization persists. Expanding applications of CT and the need for higher resolution in both spatial (thinner slices for smaller details) and spectral (dual-energy) domains make dose optimization important. New AI reconstruction and denoising algorithms have started to make an impact on enabling CT radiation dose optimization. At the same time, AI algorithms that help in triage, detection, characterization, or quantification of findings and structures on CT must prove that they can provide generalizable and reproducible performance over a substantive heterogeneity in scan protocols, radiation doses,

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and image reconstruction options. In this article, we review the complex relationship between AI algorithms, and CT radiation dose.

IMPACT OF AI ON CT RADIATION DOSE

The buildup of concerns over the rising use of CT and its increasing contribution to medical radiation doses led to several technologic improvements in both CT hardware and software technologies. From the hardware perspective, the newer CT models have improved x-ray tube design and power (e.g. higher mA at low kVp), x-ray beam filtration (such as the beam shaping filter and tin filter), x-ray beam collimation (to reduce over-scanning), and detector efficiency when compared to older models. These features help reduce unnecessary x-rays and radiation dose from reaching the patient's body and enable the use of a greater proportion of x-ray beams for generating images (5). Among the software side of innovations, CT vendors introduced IR techniques to improve image quality and lower artifacts, which allow users to reduce radiation doses compared to filtered back projection (FBP) techniques (6,7). However, most IR techniques come at cost of three limitations: firstly, IR is vendor- and scanner-specific and not generalizable to other scanners or vendors; secondly, they require intensive computational costs due to multiple projections and back projection steps; thirdly, dependence on regularization function form and other settings often result in cartoon-like appearance of IR images (8). Such limitations provide opportunities for improvements in image reconstruction with AI-based approaches.

In this section, we discuss how AI algorithms are helping in efforts to optimize radiation doses associated with CT (Table 1). Most AI research regarding CT dose reduction involves the use of Deep Learning (DL), a class of ML that makes use of artificial neural networks with multiple layers, inspired by the human brain. These neural networks can perform complex, cognitive tasks which are beyond the capabilities of human beings (9,10). Next, we discuss the impact of

TABLE 1. Summary of patient studies on application of AI algorithms for optimizing radiation dose. (Key: # patients – number of patients; DLIR – deep learning-based image reconstruction)

AI domain	Authors (publication year) # patients	Remarks
Acquisition - AI-assisted centering	Saltybaeva (2018) (*n* = 120) [14]	Automatic centering (offset 5 ± 3 mm) improved patient centering compared to manual positioning by technologists (19 ± 10 mm)
Acquisition- AI-assisted centering	Booij (2019) (*n* = 677) [15]	Automatic centering (13.2 [IQR, 17.0] mm) improved centering compared to manual positioning (6.1 [IQR, 7.0] mm)
Acquisition- AI-assisted centering	Gang (2021) (*n* = 127) [17]	Automatic centering (29 ± 7 sec; 15.6 ± 8.3 mm; 13.3 ± 2.4 mGy) is faster, more precise, and has lower dose compared to manual positioning (40 ± 11 sec; 40.5 ± 24 mm; 14.9 ± 2.3 mGy).
AI-based reconstruction	Kim (2021) (*n* = 58) [32]	At low-dose chest CT (CTDIvol 1.1 mGy), DLIR images had lower noise and better signal-to-noise (SNR) and contrast-to-noise ratios (CNR) compared to iterative reconstruction (ASIR-V). Lesion detection was not performed.
AI-based reconstruction	Bernard (2021) (*n* = 296) [35]	Despite lower radiation dose, DLIR images (CTDIvol 7 ± 3 mGy) had 49-51% higher better CNR and SNR for cardiac CT compared to iterative reconstruction (AIDR 3D - 11.5 ± 2.2 mGy). Lesion assessment was not performed.
AI-based reconstruction	Singh (2020) (*n* = 59) [36]	Low radiation dose DLIR images (CTDIvol 2.1 ± 0.8 mGy) had acceptable image quality and lesion detection both chest and abdomen CT as compared to standard dose iterative reconstruction (AIDR 3D, 13 ± 4.4 mGy).
AI-based reconstruction	Nakamura (2021) (*n* = 72) [38]	DLR reconstructed low-dose abdomen CT (11-18 mGy) had superior image quality scores compared to standard dose images (16-25 mGy) with iterative reconstruction (ADIR 3D). Lesion evaluation was not conducted.
AI-based reconstruction	Zeng (2021) (*n* = 207) [39]	Low-dose abdominal CT DLIR (CTDIvol 4.4 ± 0.7 mGy) had comparable quality and lesion detection to standard dose iterative reconstruction (KARL 3D, 9 ± 1.3 mGy).
AI-based reconstruction	Parakh (2021) (*n* = 50) [84]	Standard dose (CTDIvol 12 ± 5 mGy) CTs with DLIR were preferred over iterative reconstruction (ASIR-V) for better image quality. No lesion assessment was conducted.
AI-based image denoising and processing	Wang (2021) (*n* = 251) [40]	Low-dose abdomen CT (CTDIvol 3.3 ± 0.2 mGy) images post-processed with a DL algorithm had similar lesion detection for liver metastases as compared to standard dose filtered back projection images (6.4 ± 1.6 mGy).

AI on CT dose reduction into three specific targets including CT image acquisition, image reconstruction, and denoising tasks.

AI in CT Image Acquisition

Patient centering in CT gantry isocenter is important for making sure that there is no under- or over-radiation exposure to patients on modern scanners that use beam shaping filters and anatomic automatic exposure control for modulating tube current. Several prior studies have reported radiation dose and image quality penalties of patient off-centering (11,12). Using the information provided by a mounted 3D depth camera, AI algorithms can help in automatic patient centering (13). The algorithm creates a 3D avatar of patient's surface and contour from the 3D depth camera data and then estimates key anatomic structures to determine patient position, body regions, and iso-centering. In this manner, AI helps to automatically re-center the patient if needed by adjusting table height. Furthermore, recognition of anatomic landmarks in different body regions helps the AI to prescribe scan range based on the specified CT protocols. Recent studies have reported encouraging results with AI-based automatic patient positioning as compared to manual positioning by CT technologists which is prone to operator dependency and adds to the imaging time (14,15). Booji et al reported that the extent of table height deviation from the isocenter was more than 50% less with the 3D camera-assisted body contour detection than with manual positioning by CT technologists (15). AI-based automatic positioning method from another CT vendor was 99% accurate compared to 92% accuracy for manual positioning; this resulted in a 16% reduction in radiation dose and 9% noise reduction (16). AI-based solutions for automatic patient centering are now commercially offered by several vendors (13,16,17). A head-to-head comparison of these AI algorithms across multiple CT vendors is not available at the time of manuscript preparation.

Another data-driven AI algorithm (myExam Companion, Siemens Healthcare GmBH, Forchheim, Germany) automates selection of patient specific scan and image reconstruction parameters for a large number of clinical indications (13). No published data were available at the time of manuscript preparation on the impact of this algorithm on CT dose reduction. To achieve this, the algorithm uses decision trees based on large training patient datasets with several patient characteristics, and assigned CT protocols. Such automation can again help reduce operator variations and potential errors in prescribing the optimal scan parameters and radiation doses.

AI-Based CT Image Reconstruction

The traditional FBP-based method provides efficient image reconstruction with good image quality. However, at reduced radiation dose, high image noise and artifacts in FBP images limit diagnostic information and confidence. In the last two decades, various CT vendors introduced iterative reconstruction (IR) techniques to overcome the limitations of the FBP method. IR images have lower noise and artifacts compared to FBP but there are concerns over changes in overall image appearance and loss of small anatomic details (18). Despite these limitations, several studies have reported a substantial radiation dose reduction with the use of IR for both adult and pediatric patients (19,20). From an analytic method (FBP), CT image reconstruction moved to IR and now to data-driven or DL-based image reconstruction to improve issues related to resolution accuracy and reconstruction times (21). The latter uses deep neural networks trained on large training data to obtain superior tomographic reconstruction (22). The strength of DL based reconstruction lies in its ability to learn complex greater prior information than the traditional IR methods, and thus recover missing details and/or enhance the quality of output images. The DL reconstruction approaches can be classified based on one or more of the four steps (data enhancement, domain transform, data-driven fitting, and image refinement) in image reconstruction (22).

Prior studies have reported on several DL approaches and frameworks in the space of both single and dual-energy CT image reconstruction and post-processing (23-26). CT vendors apply DL algorithms both by training neural networks to reconstruct reduced dose images and through the optimization of existing IR algorithms in order to improve image quality. (27-29). The data-driven AI methods learn transference of raw signal inputs directly into the output images or perform image post-processing to reduce noise and artifacts (30). Most such algorithms perform post-processing on the image domain when the conditioned inputs of conditional generative adversarial networks (GAN) are limited from noise, artifacts, or low resolution. Unfortunately, there are no reliable methods for comparing different AI algorithms other than with human observers or image analysis tasks.

One such commercial DL Image Reconstruction (DLIR, TrueFidelity, GE Healthcare) algorithm uses a deep neural network (DNN) trained with large clinical datasets of high-quality CT images reconstructed with FBP to differentiate image noise from signal (Fig. 1-4). The algorithm targets reconstructed high-quality images from a reduced dose sinogram. In a phantom study, Greffier et al reported that DLIR images had better image quality than both FBP and IR techniques (31). The authors conducted a task-based image quality assessment of texture, noise power spectrum, spatial resolution, and detectability index across different image reconstruction methods. DLIR produced the highest quality images at the lowest dose, with texture, and image appearance similar to that of high dose FBP images. Their findings indicated potential for radiation dose reduction by up to 17% with low-strength of DLIR and by up to 56% at higher strength compared to the vendor's IR (adaptive statistical iterative reconstruction- V (ASiR-V) at 50% strength, GE Healthcare). Given the considerable variations in quality and reconstruction methods in different commercial IR methods

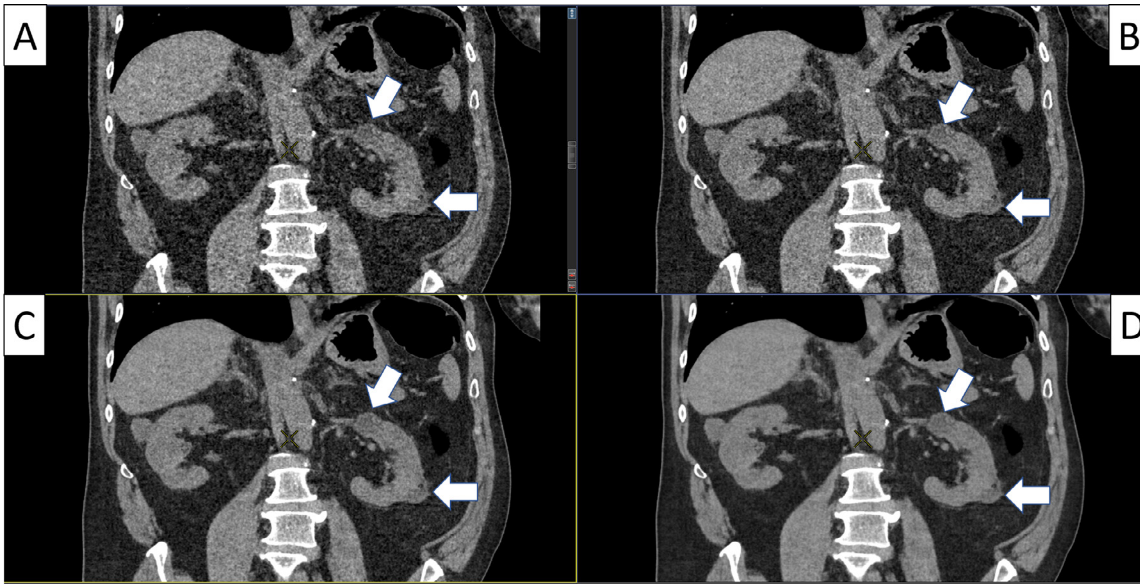


Figure 1. A 72-year-old man underwent non-contrast, low-dose CT for evaluation of abdominal pain at CTDIvol of 2.6 mGy (DLP 157 mGy. cm). Coronal images were reconstructed with iterative reconstruction (A: ASiR-V 40%, GE Healthcare) and DL-based image reconstruction (DLIR at low (B), medium (C) and high (D) settings). Note better delineation of left renal cysts (arrows) and lower image noise with increasing strength of DLIR from low to high (B-D), as compared to ASiR-V image (A). Despite lower image noise, the DLIR images do not demonstrate any pixilation or altered image texture.

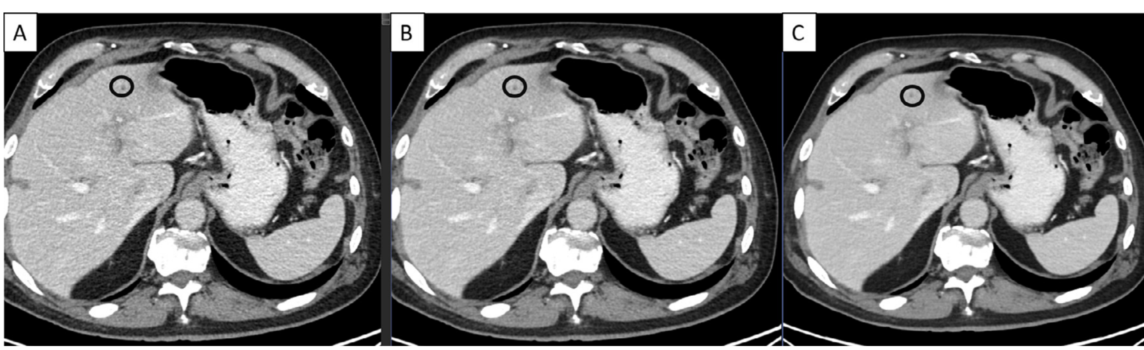


Figure 2. A 78-year-old woman (weight 86 Kg) underwent contrast-enhanced abdomen CT with standard department protocol (CTDIvol 13 mGy). Reconstructed 1.25 mm images demonstrate a tiny hypodensity in the left hepatic lobe which is more conspicuous on iterative reconstruction image (ASIR-V, A) than on the DLIR (low [B] and medium [C] settings). However, there is lower noise, and better image texture in the DLIR images than in the ASIR-V image.

from other vendors, such dose reductions may not be achievable, generalizable, or even possible on sinogram data from other scanners.

Kim et al evaluated chest CTs of 58 patients and concluded that DLIR images had higher contrast and lower noise as compared to the same vendor-specific IR (ASiR-V at 30% strength) (32). Other investigators have also reported similar findings for use of DLIR in low-dose CT for lung cancer screening (27,32–34).

The other commercial DL algorithm for image reconstruction from Canon (Advanced Intelligent Clear-IQ Engine - AiCE) integrates DL within the process of reconstruction. Instead of FBP, this algorithm was trained with large sets of model-based IR images to differentiate image noise and signal with an objective of enhancing signal and decreasing noise. The resulting AiCE images have improved quality and spatial resolution with retained diagnostic information. Bernard et al compared radiation doses and image quality of coronary CT angiography images reconstructed with the vendor-specific IR (AIDR3D, Canon) and AiCE in 296 patients (35). AiCE improved signal-to-noise and contrast-to-noise ratios by about 51% and 49%, respectively, compared to the assessed IR; an improvement which enabled radiation dose reduction of up to 40%. In a much smaller study with 59 patients, Singh et al evaluated AiCE in sub-millisievert chest and abdomino-pelvic CTs (36). They found that the radiologists detected all 31 significant abdominal lesions and all 39 of the pulmonary nodules on low-dose AiCE images, identical to their performance on standard dose CTs. Compared to low-dose FBP and IR techniques (AIDR3D and FIRST, Canon), AiCE

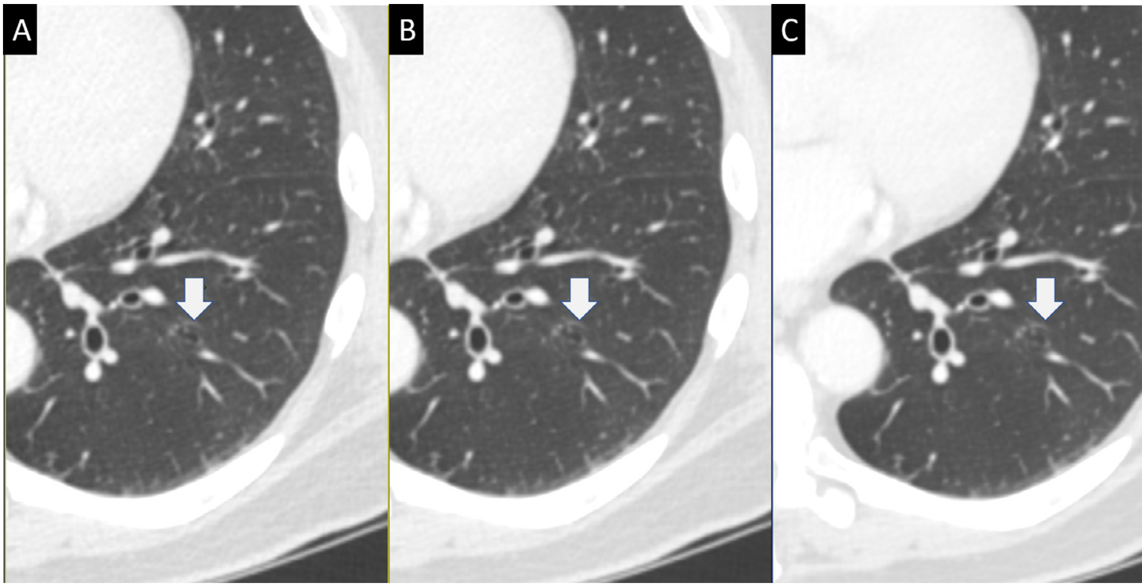


Figure 3. Zoomed-in lung window images of a 78-year-old woman (weight 86 Kg) who had a contrast-enhanced abdomen CT for cancer staging (CTDIvol 13 mGy). Reconstructed 1.25 mm images demonstrated that focal bronchiectasis in the left lower lobe (arrow) and some of the blood vessels are less conspicuous on DLIR images (low [B] and medium [C] settings) compared to the iterative reconstruction image (ASIR-V, A). However, there is lower image noise in the DLIR images than in the ASIR-V image.

provided better image quality with acceptable diagnostic confidence in most reduced-dose chest CTs. Similarly, other investigations on AiCE have also reported reduced noise and higher contrast to noise ratio (CNR) compared to vendor-specific hybrid and model-based IR techniques (37,38).

Two other CT vendors also have commercially available DL algorithms, DELTA (United Imaging) (39) and NeuAI (Neusoft Medical) (40). Aside from the commercially available DL algorithms for image reconstruction, there are reports on several other DL-based image reconstruction techniques for noise reduction, and preserved image quality at reduced doses (41,42). For example, Cao et al reported that DL-reconstructed contrast-enhanced abdominal CT images had substantially lower image noise and better contrast-to-noise ratio with a potential to reduce radiation dose by up to 76% (from 3.2 ± 0.45mSv to 0.8 ± 0.1 mSv) (43).

Despite clear progress on DLIR in the last five years (32-43), most publications on DLIR have limited sample size, single-institutional data, and no inter-vendor comparison on different techniques. Likewise, substantial differences and subjectivity in the evaluation of image quality across various DLIR studies confound estimation of actual dose reduction and image quality improvement potential of reported DLIR and image denoising AI algorithms.

Image Denoising With AI

Prior attempts at image denoising with noise reduction filters to enable CT radiation dose reduction were often met with loss of image details and altered image appearance compared to baseline, unprocessed FBP images (44). Recently, some AI-based image denoising methods have attained commercial availability (45). These methods use convolutional neural networks to enhance image quality of CT images reconstructed with FBP or IR techniques. Although initial publications report promising results (44-48), these studies are limited by small sample size and a lack of comparison to DLIR.

ClariCT.AI is one such commercial AI algorithm (ClariPi) that reduces image noise and improves image quality of low-dose CT images. The algorithm uses a modified U-net type convolutional neural network (CNN) model to predict and subtract noise from CT images. Lim et al compared this denoising algorithm with a commercial IR technique (iDose 4, Philips Healthcare) in 43 patients who underwent abdomen-pelvis CT exam at a median CTDIvol of 1.7 mGy; image quality was similar between the two techniques (46).

Another image denoising method (PixelShine, AlgoMedica) uses a DL-based algorithm trained with large datasets of high-dose and low-dose CT images at a pixel level to detect and differentiate patterns of image noise and relevant anatomic structures. The algorithm helps reduce image noise in reconstructed CT images. Rozema et al reported substantial improvement in image quality upon image denoising with the algorithm on face CT images acquired with about 60% lower dose (dose length product (DLP) 21 mGy.cm versus 54 mGy.cm) (47). In 33 patients who underwent pelvic arterial phase CT at 70 kV, Tian et al reported a 30% lower image noise with PixelShine denoising algorithm on ASiR-V (GE Healthcare) CT images as compared to images without the denoising algorithm (48).

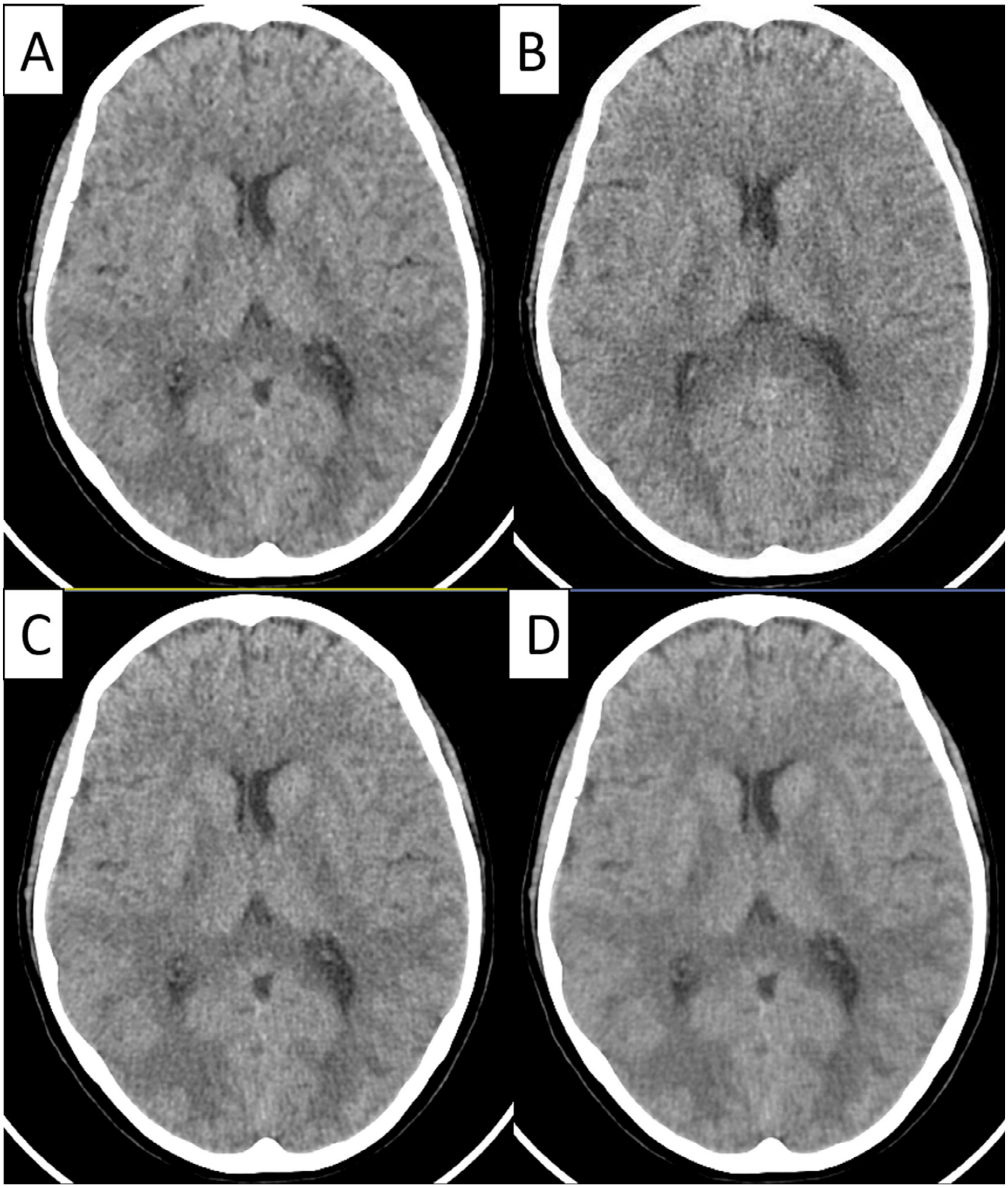


Figure 4. Non-contrast head CT in a 25-year-old woman with headaches performed on a 256-detector-row CT scanner (CTDIvol 35 mGy) and reconstructed with iterative reconstruction (ASIR-V at 70%, A) and DLIR (at low [B], medium [C] and high [D] settings). The ASIR-V image had higher noise compared to the DLIR images. Although high DLIR images had the least image noise, they also exhibited the lowest gray-white matter differentiation compared to other images.

Limitations and Future Needs

While there is little doubt that commercial DL-based algorithms help in efforts to optimize CT radiation dose, there are some concerns over their use. Most research on the application of DL algorithms to enable dose reduction is retrospective analysis with a small number of patients scanned at a single institution on a limited number of scanners, scan parameters settings, and anatomical regions of interest. These limitations make it difficult to infer reproducibility and generalizability of these DL algorithms.

Unfortunately, as noted for automatic exposure control (49), the pursuit of commercial interest and need to stand out has led to limited information on how the commercial DL-based reconstruction techniques work and operate. Standardization is crucial to ensure the generalizability of the AI algorithms.

From the perspective of DL-based image reconstruction, we observed some loss of fidelity or sharpness of small osseous, and pulmonary structures with use of DL-based image reconstruction as compared to images generated from IR at identical radiation doses (CTDIvol and DLP) (Fig 1). As a result, despite better image denoising with DL algorithms, FDA-cleared status, and availability on clinical scanners at our institutions, we do not use these algorithms in our institution for chest CT examinations. Furthermore, these algorithms are available on only few state-of-the-art scanners. More work is therefore needed to optimize the DL algorithms so that diagnostic information and equivalence to the current standard of care IR techniques are not lost. Future studies should include focus on making the promising DL algorithms available for use across different CT scanners including the older units in common clinical use.

Reliable detection or delineation of small structures or lesions requires statistical fidelity of their signal at the detector level (pre-reconstruction). In other words, there exists a minimum signal-to-noise ratio (SNR_{min}) for delineating or detecting lesions (in a given patient scanned on a given scanner) in the raw data/sinogram domain below which a reliable detection of the lesion is not possible or optimum. This SNR_{min} is associated with a minimum dose level ($Dose_{min}$). Below such $Dose_{min}$, there is an unrecoverable loss of information regardless of the image reconstruction algorithm (i.e. less dose=less information). Statistical fidelity plays a huge role in hardcore science such as nuclear particle physics where a strict "5-sigma" rule must be satisfied to confirm discovery of new particles (such as Higgs boson) (50). In radiology, lack of such strict rules for statistical fidelity of lesion or structure detection makes it difficult to establish objective criteria for radiation dose optimization.

The hype and the promise of commercial IR techniques introduced into clinical practice in 2008 can be simply phrased as: Decrease the dose of FBP protocols and recover any lost information with IR. Strictly speaking, this can be achieved only under assumption that degradation of low contrast detectability (LCD) in the raw data/sinogram domain caused by FBP reconstruction (due to noise propagation and artifacts) is worse than the corresponding degradation of LCD in IR images (i.e. $LCD_{RAW} - LCD_{FBP} > LCD_{RAW} - LCD_{IR}$). However, images cannot contain more information than the sinogram from which they are reconstructed. This implies that LCD in the image domain, regardless of the reconstruction technique, cannot exceed LCD measured in the sinogram domain. It can only (asymptotically) approach it. Another important thing to keep in mind is that improved CNR due to denoising does not necessarily translate into better LCD (51,52). According to Von Falck et al (52), LCD can be only estimated with comparison of multiple human readers' observations, various statistical analyses, or experimental models simulating human vision with model observers.

For the assumption $LCD_{RAW} - LCD_{FBP} > LCD_{RAW} - LCD_{IR}$ to hold, LCD_{IR} should be better than LCD_{FBP} at an equal dose level. Although controversial, evidence from multiple publications suggests that IR does not improve LCD compared to FBP at equal dose levels (53-57). Mileto et al (54) found that, for each radiation level and CT platform, variance in LCD performance across observers was greater than that across FBP and IR indicating that IR has "limited radiation optimization potential in detectability of small low-contrast hypoattenuating focal lesions". Jensen et al (55) reported compromised detection of colorectal liver metastases with modest radiation dose reduction and IR use. Omigbodum et al (57) also discovered that area under the curves (AUCs) for IR images was slightly worse than those for FBP. Likewise, Yu et al (58) reported inferior performance of 120 mAs IR in small lesions (3mm) compared to LCD_{FBP}, both for human observers (drop from 79.8% ± 2.8% to 68.8 ± 3.0%) and model observer (drop from 78.3% ± 4.1% to 77.4% ± 3.8%). Sidky et al (59) attribute the loss of performance to "overregularization" (such as for aggressive denoising) by IR which favors removal of subtle details in the image and attempts to quantify this loss of LCD through the image reconstruction process.

Even though the promise of IR to fully recover the information at reduced dose has NOT really been fulfilled, it did play an important role in reducing the overall radiation dose burden across different imaging tasks and different institutions. A major reason for IR success in reducing the dose is because it could restore radiologists' confidence in making a diagnosis at reduced dose levels compared to the original (higher) dose levels with FBP protocols. This confidence largely depends on radiologist's perception of such image characteristics as average noise, noise pattern, and edge sharpness. To some degree, IR managed to restore these characteristics at reduced dose levels and, by doing that, return radiologists to their "comfort zone", despite certain loss of information associated with the dose reduction. The key factor we should consider: Whether this loss of information was clinically relevant for a given imaging task? Could this lost information be critical for making a confident diagnosis? Definitive answers to these questions would require consensus among experts in each clinical field. For example, experts in urolithiasis would have to decide which renal stone size is clinically relevant and, hence, should not be missed due to insufficient radiation dose.

The promise of AI in further CT dose reduction using DL reconstruction can be formulated the same way: Drop the dose of IR protocols and recover the same information with DL reconstruction. Not surprisingly for the readers, all the arguments stated previously remain valid. Studies like those in (53-57) must be replicated to ensure that LCD_{DLR} can be better than $LCD_{FBP/IR}$ at an equal dose level. Any further dose reduction (with respect to IR protocols) will result in additional loss of information. The decision whether this loss of information is clinically relevant for a given imaging task will again have interobserver and inter-institutional differences. The potential for further CT dose reduction will depend on the ability of DL reconstruction to restore radiologists' confidence in making a diagnosis at radiation doses below the

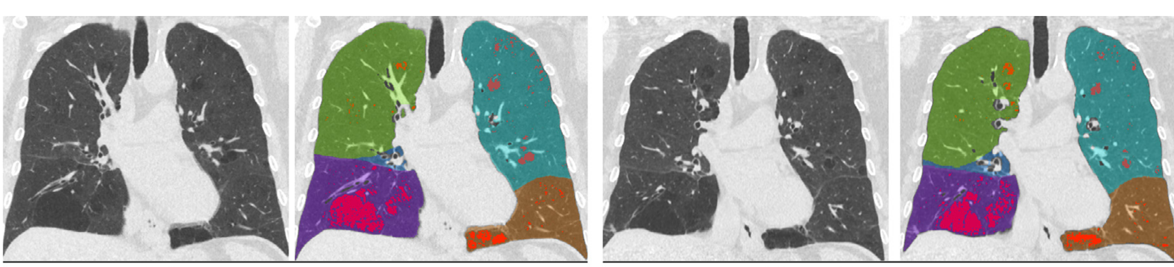
IR protocols. The early DLR literature published up to date provides evidence that this is possible (60,61). The most notable factor with DL reconstruction is aggressive denoising compared to IR without the penalty of "plastic" image appearance. Recent studies on two commercial DL reconstructions (GE True Fidelity (60), Canon AiCE (61)) reported significant improvements in radiologists' confidence for detecting small lesions compared to IR. Larger studies are needed to determine if DL reconstruction can reduce dose compared to IR or retain the IR dose levels with image quality improvement.

IMPACT OF VARIATIONS IN CT DOSES ON AI

In this section, we will discuss how variations in radiation dose or use of low-dose CT influence performance of AI algorithms. Variations in radiation doses resulting from or associated with changes in scan and reconstruction parameters impact image quality and appearance of normal and abnormal structures. Prior studies report adverse effects of variation in CT radiation doses and reconstruction parameters on reproducibility of radiomics (62). For AI algorithms, such variations imply need to verify generalizability and reproducibility of AI performance across a spectrum of CT radiation doses and reconstruction parameters besides the imperative age, gender, race, socioeconomic status, and lesion type and severity. Because differences in doses can change both qualitative and quantitative content in CT images, AI algorithms trained and validated on detection, diagnosis, quantification, and/or segmentation tasks at standard or regular dose CT images may not perform similarly at different radiation dose levels.

Schwyzer et al assessed the performance of an AI algorithm to detect pulmonary infection in 100 patients at regular dose (1.4 ± 0.5 mSv) and at 20-fold reduced dose (0.07 ± 0.03 mSv) chest CT examinations. The authors reported a drop in sensitivity to 71% at reduced dose CT as compared to 83% on regular dose CT (63). In a phantom study for detection and quantification of lung nodules using four AI algorithms, Fu et al noted a decrease in detectability of lung nodules at reduced dose CT or with change in reconstruction kernel with two of the four AI algorithms (64). Likewise, Su et al reported substantial variations in measurement of CT attenuation values of pulmonary nodules with change in radiation dose and reconstruction kernel when using a commercial volumetric software (65). The lung volume estimate did not vary for nodules between 5-10 mm but dose reduction led to substantial change in volume estimation in solid lung nodules less than 5 mm in size (65). Multiple AI algorithms are available for quantifying emphysema on low-dose CT. Gierada et al reported higher emphysema indexes at reduced dose CT (effective tube current of 30-60 mAs) as compared to regular dose chest CT (100-250 mAs) images (66) (Fig 5). However, the overestimation of emphysema with reduced dose CT was less than 3% compared to regular dose CT.

There is an increasing interest in application of radiomics, both with and without AI-aid, for predicting patient outcome and differentiating different disease patterns (benign versus malignant as well as cancers associated with mutations).



Volumetric Measurements

	LA Volume (cc)	Total Volume (cc)	LA Volume Ratio (%)
BL	320.7	5236.3	6.1
RL	184.5	2716.4	6.8
RUL	41.9	1055.3	4
RML	18.9	316	6
RLL	123.6	1345	9.2
LL	136.3	2520	5.4
LUL	47.5	1257	3.8
LLL	88.8	1263	7

Volumetric Measurements

	LA Volume (cc)	Total Volume (cc)	LA Volume Ratio (%)
BL	261.2	5214.9	5
RL	167.8	2728.7	6.1
RUL	34.5	1060.9	3.3
RML	12.6	299.7	4.2
RLL	120.7	1368	8.8
LL	93.4	2486.2	3.8
LUL	28.7	1230.7	2.3
LLL	64.7	1255.5	5.2

Figure 5. A 54-year-old male (body weight 87 kg) underwent baseline (A- CTDIvol 3.5 mGy) and follow-up (B- CTDIvol 0.9 mGy) non-contrast chest CT examinations for evaluation of lung nodules over a 3-month interval. CT data processing with an emphysema quantification AI algorithm (Coreline, South Korea) demonstrate minor variations in estimation of emphysema in both lungs as well as for individual lung and lobe between chest CTs performed at the two dose levels. Red color on coronal color overlay images correspond to low attenuation areas (<950 HU). The tables summarize quantification of emphysema and lung volumes. Keys: Low attenuation (LA); Both lungs (BL); Right lung (RL); Right upper lobe (RUL); Right middle lobe (RML); Right lower lobe (RLL); Left lung (LL); Left upper lobe (LUL); Left lower lobe (LLL) (Color version of the figure is available online.)

Emaminejad et al reported a need for caution with use of radiomics based on a comprehensive phantom study with changes in CT acquisition and reconstruction settings (62). The investigators reported that most radiomics are not reproducible over different CT acquisition and reconstruction parameters. Conversely, other studies reported on robustness of AI performance despite variations in radiation doses in emphysema quantification as well as in use of radiomics for lung nodule assessment (67,68). Several investigators have also reported on high performance of different AI algorithms on low-radiation dose CT (36,69-72). In the recent COVID-19 pandemic, Gieraerts et al reported that AI-assisted analysis of pulmonary involvement on sub-milli-Sievert low-dose CT outperforms visual assessment without AI-aid (73).

Limitations and Future Needs

Based on the presented evidence, there is variation in AI performance of at least some AI algorithms with changes in CT acquisition parameters, radiation doses, and reconstruction settings. Most AI algorithms (based on CT or other imaging modalities) cleared in Europe or in the US, lack transparency on how these algorithms were validated (74). Wu et al reported that most AI algorithms with FDA-cleared status had limited validation datasets (75). It is not clear how many of these algorithms were assessed or were generalizable across different scanners, radiation dose levels, and reconstruction settings. Upon review of 254 publications on use of AI algorithms in COVID-19 pneumonia, Roberts et al came to a disturbing conclusion (76). Of the 762 "best" AI algorithms, not a single algorithm was suitable for clinical use due to limitations in how the algorithms were trained, tested, and validated! Such systemic reviews highlight the problems associated with bias in the evaluation of AI algorithms where subjective preferences of a few human observers are often recorded rather than an objective metric such as number of detected lesions. These reports suggest a need for a post-market or real-world surveillance of cleared AI algorithms (77).

Future studies should focus on comprehensive evaluation of AI algorithms across large variations in radiation dose and reconstruction settings. Indeed, the regulators should issue guidance on how such assessments should be performed and made available to the medical community in an accessible and transparent way. Although such evaluation will set a higher and expensive bar for the AI vendors, it will also improve the quality and safety of their AI algorithms, and help the AI vendors to convince end-users and reimbursement agencies to adopt AI algorithms as part of their standard of care.

Like its autonomous use for interpreting retinal scans and PAP smears, it is anticipated that autonomous AI will enter imaging, whether in acquisition, reconstruction, triage, or interpretation domain. Should and when that happens, validation across a host of radiation doses and image reconstruction settings, specifically for CT images, should be comprehensive.

We also believe that the applications of AI in CT radiation dose will continue to increase with time. There are research reports on how AI can help in selecting the right exam (need for CT and other imaging examinations) based on clinical indication and other parameters (78). Such decision support with AI algorithms can help decrease the frequency of unnecessary or unjustified use of CT. Likewise, there is ongoing work in the sphere of AI-assisted image quality evaluation for CT. Lee et al reported use of a CNN to predicting minimal diagnostic quality for chest CT (79). Recent studies have also reported on use of AI for accurate organ mapping and organ-specific dose estimation for CT radiation dose (80,81). The deep neural network in combination with empirical mode decomposition techniques can help predict individual radiation doses in very short timeframe (80). With prospective prediction of organ dosimetry, which is better indicator of actual patient doses than the current CT dose descriptors in plastic phantom, perhaps CT protocols, and doses can be personalized prospectively (81). The most important questions that future algorithms and studies on CT radiation dose pose remain unanswered. Can second-read AI algorithms help reduce the subjective variations in image quality preferences between different radiologists? Can autonomous AI algorithms, when available and approved, drive radiation dose lower or at the very least avoid unindicated use of high-dose CT examinations and protocols? Should one or both things happen, concerns over CT radiation dose would find a big respite! Recently, Rampado et al reported on the potential of an unsupervised cluster analysis method for identifying scan parameters associated with increased patient dose from a large database of patient doses (82). Meineke et al also found that AI can help identify chest CTs with potential for dose optimization although results needed an adjudication from an expert human observer (radiologist or radiation physicist) to avoid false-positive findings (83).

CONCLUSIONS

In summary, several AI algorithms aid in optimizing, and reducing radiation dose associated with CT scanning. These applications are expected to keep expanding given the lingering concerns over safety of CT radiation dose. At the same time, variations in CT radiation doses can influence performance of AI algorithms. The reciprocal relationship between AI and CT radiation dose should be understood and investigated to ensure reproducible and generalizable performance of AI.

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