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Research Article

Differences in Image Quality Between Different Deep Learning Algorithms in Chest CT Scans

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Abstract

Background: Lately, however, deep learning reconstruction (DLR) technologies have emerged as a viable technical option for reducing radiation dose because they can effectively reconstruct images developed at a low radiation dose to create clear and interpretable images for diagnostic and clinical use.

Objectives: This study explores the possibility of using DLR algorithms in healthcare imaging by comparing image quality between vendor-specific DLR algorithms like TrueFidelityTM and vendor-non-specific DLRs to improve the diagnostic quality of ultra-low-dose CT scans in lung imaging.

Methods: The study involved studying past CT scans of 50 patients who had undergone CT scans between January and February of 2021. Two reconstructed images for each patient were submitted to experienced radiographers from whom reconstruction details had been hidden for qualitative assessment. The assessors rated the images on a scale of 1 to 4 for the noise, resolution, and distortion properties and gave their preferred choice between the two images for each case. Quantitatively, one experienced radiographer assessed the signal-to-noise ratio (SNR) and Edge-Rise-Distance (ERD) for each image.

Results: Non-tuberculous lung diseases, precisely, were the main, accounting for 62% (n = 31). The other conditions included atelectasis (12%, n = 6), pneumonia including COVID-19 (18%, N = 9), and active tuberculosis (8%, n = 4). For subjective noise, TrueFidelity™ scored higher than ClariCT.AI. On the qualitative noise assessment scale, the former scored 3.72, whereas the latter scored an average of 3.22. On resolution, whereas TrueFidelity™ had a score of 3.66, ClariCT.AI recorded an average score of 3.49. In terms of Image distortion, TrueFidelity™ had a score of 3.46, while ClariCT.AI recorded an average score of 3.51. the average preference rate for TrueFidelity™ was 72%, while for ClariCT.AI was 28%. Quantitatively, whereas the SNR for TrueFidelity™ was 22.65 ± 2.84, that for ClariCT.AI was 25.95 ± 5.82. While the ERD for TrueFidelity™ was 0.97 ± 0.19, that for ClariCT.AI was 1.48 ± 0.19.

This study confirmed that vendor-specific DLR algorithms were generally more effective at delivering quality images, confirming the need to develop more specific DLR for the different CT scanners available in the market.

Keywords: Iterative Reconstruction (IR); Signal-To-Noise Ratio (SNR); Edge-Rise-Distance (ERD)

Introduction

Iterative reconstruction (IR) techniques have been utilized in CT practice for many years to restore the quality of images developed at low radiation doses while maintaining their usability in clinical setups [1]. It was possible to significantly reduce the dose of radiation administered to patients during imaging procedures by employing these technologies. While these were initially considered effective and gained wide application, they were noticed to cause defects in imaging. For instance, IRs altered the texture and characteristics of the image, increasing noise and adjusting the spatial resolution and image contrast in response to dose variations. Through numerous studies aimed at assessing the effectiveness of IR algorithms in image reconstruction, it has been proven that the image quality obtained by these IR algorithms is compromised, altered, and smoothed. Such affects the diagnostic quality and usability of such technologies.

Additionally, the use of IR techniques necessitates the development of new measurements that are compatible with their properties. To accomplish this, a task-based image quality evaluation is frequently conducted using measurements such as the signal to noise ratio to assess the texture and intensity of noise, the pixel density under various contrast and dose conditions, and the detection range index to approximate the radiographers' capacity to detect specific abnormalities [1]. This measurable image quality evaluation has tremendous promise for evaluating the performance of CT scans and adjusting the dose in clinical settings [2]. However, a subjective examination of the image quality by an experienced radiographer is complementary and permits the radiologists' preferences for the obtained pictures.

While CT scanning is a regularly utilized imaging method in clinical cases, it is unavoidably associated with the risk of high radiation exposures, which may be harmful to the patients. In response, Iterative Reconstruction (IR) has been developed as a technology aimed at decreasing radiation exposure doses in CT scans while ensuring the highest possible level of diagnostic and imaging accuracy [2]. Lately, however, deep learning reconstruction (DLR) technologies have emerged as a viable technical option for reducing radiation dose because they can effectively reconstruct images developed at a low radiation dose to create clear and interpretable images for diagnostic and clinical use [3].

DLR algorithms have received significant attention in the past and are proving to have a significantly promising capability to meet the objective of reducing radiation dose while maintaining the diagnostic quality and accuracy of CT scans [3]. For instance, TrueFidelity™, a DLR developed by GE Healthcare, was confirmed to lower radiation exposure by 36–50 percent while also lowering image signal-to-noise ratio (SNR) and facilitating more accurate detection of lesions [4]. However, because TrueFidelity™ is vendor-specific, it is only usable on CT equipment manufactured by GE Healthcare and not any other machines. Such may prove challenging because many other companies manufacture CT scanners that utilize such highly effective DLR algorithms [4]. The need to develop an exposure reduction method that is adaptable to any contemporary CT scanner has been confirmed by the COVID-19 pandemic, which has increased demand for chest CTs [3]. As a result, developing and evaluating the effectiveness of non-specific algorithms that improve image quality while reducing radiation dose is a critical and necessary research area.

CT scanning is often the most beneficial imaging technology for evaluating lung lesions in the majority of clinical scenarios due to its high spatial and temporal resolution and short acquisition time. Lately, the use of CT imaging technology has shown its efficacy in reducing early deaths when used as a cancer screening tool in clinical trials, and the number of CT scans performed worldwide has been rapidly rising secondary to this documented efficiency [5]. With this, the need for reduced radiation doses to limit exposure continues to stand out. For instance, the currently acceptable level of radiation exposure for low dosage CT imaging is around 1.5 mSv [6]. This is significantly low compared to other CT tests used in the medical profession, it is around tenfold that of two-view chest radiography and about 50 times that of a single posterior-anterior chest radiograph [6]. Because many lung illnesses need continuous monitoring, the exposure dose used in imaging remains a significant concern for most physicians. As a result, using ultralow-dose scans may be helpful in some circumstances. While they only use a fraction of the radiation dose used in ordinary CT scans, these ultralow approaches have been shown to perform well in the detection of lung lesions when combined with various IR techniques [7]. Regrettably, the efficiency and distortion levels were unsatisfactory, especially when studying delicate tissues. Low-dose CT remains the preferred imaging modality in most clinical settings, particularly lung imaging investigations.

Using DLR systems is a promising approach for improving the quality of these imaging systems. Currently, machine learning systems are reported to perform well in various diagnostic imaging applications, most notably lesion recognition, categorization, and image reconstruction [8]. Notably, TrueFidelity™ — a commercial DLR technology developed by GE Healthcare Systems – was recently used to remove picture noise from CT scans acquired from a single vendor [9]. However, vendor specialization limits the approach's widespread adoption. If a supplier-independent DLR algorithm improved the image quality in ultralow-dose CTs, radiation dose reduction would improve significantly in the majority of clinical situations [10]. Thus, this study explores the possibility of using DLR algorithms in healthcare imaging by comparing image quality between vendor-specific DLR algorithms like TrueFidelityTM and vendor-non-specific DLRs to improve the diagnostic quality of ultra-low-dose CT scans in lung imaging.

Methodology

Patient

The study involved studying past CT scans of patients who had undergone CT scans between January and February of 2021. Being a retrospective study involving only past scans, the ethical requirements for informed consent were waived by the Institutional Review Board.

The study, in totality, included 50 patients selected consecutively from 1st January 2021. The average age of the patients was 57 years with a deviation of 12 years (age range 45 – 69 years). Of the 50, 16 were men, whereas 34 were female. All these had undergone an ultra-low dose chest CT scan.

Model used

The vendor-specific deep learning image reconstruction system used in this study was True Fidelity, developed by GE Healthcare and designed for specific CT systems. On the other hand, the vendor-agnostic deep learning model used in this study was ClariCT.AI and was primarily designed as a denoiser for CT images.

Acquisition and reconstruction of images

All the CT scans were scanned by an ultra-low dose multidetector set to detect images with the following features: a tube voltage of 120kVp, noise index of 70.7, a gantry rotation of 280ms, and detector pitch of 1.53. They were then reconstructed to 1.25mm slice thicknesses using the algorithms considered in this study.

Image quality assessment

Assessment of Image quality was done qualitatively and quantitatively. Qualitative image quality assessment was done by experienced radiologists specializing in thoracic imaging. In each case, two sets of reconstructed images were sent to the evaluator from whom other image details and reconstruction details were hidden. The images were also made anonymous. The assessment focused on image noise, resolution, and artifacts or distortion. The assessors were required to select the most preferred algorithm out of the five sets of images sent to them and score them on a subjective scale of 1-4, where 1 meant the least preferred and 4 was the most preferred. Table 1 below summarizes the criteria for qualitative image assessment. One radiographer with 6-year experience in interpreting thoracic images did the quantitative assessment of images. This was mainly done by calculating the signal-to-noise ratio (SNR) and Edge-Rise-Distance (ERD).

Property	Score	Meaning	Interpretation
Noise	1	Severe noise	Non-diagnostic image
	2	Moderate noise	Some diagnostic value
	3	Some noise	Minimum diagnostic difficulty
	4	No noise	Excellent image
Resolution	1	Mostly invisible fissures/severe blurring	Non-diagnostic image
	2	Moderate blurring and invisible	Some diagnostic value
	3	Fissures can be identified/ minimal blurring	Minimum diagnostic difficulty
	4	All fissures are clear, with clear edges	Excellent image
Distortion/ presence of artifacts	1	Severely distorted image	Non-diagnostic image
	2	Moderate image distortion	Some diagnostic value
	3	Minimal recognizable distortion	Minimal diagnostic difficulty
	4	No recognizable distortion	Excellent image

Table 1: Criteria for qualitative image assessment.

Data analysis

The analysis of the data collected was primarily accomplished by calculating averages for the different scores assigned by the quantitative and qualitative assessors of images. These averages allowed comparison between the two panels of images considered for analysis. To measure overall preference between the sets of images, percentages were calculated to determine which of the two reconstruction methods was preferred.

Results

Indications for low-dose chest CT

Doctors primarily ordered the ultra-low CT scans of the chest to assess known lung diseases. Non-tuberculous lung diseases, precisely, were the main, accounting for 62% (n = 31). The other conditions included atelectasis (12%, n = 6), pneumonia including COVID-19 (18%, N = 9), and active tuberculosis (8%, n = 4). The average dose of radiation administered was 0.24 ± 0.036 mSv.

Quality assessment of image quality

The assessors scored for subjective noise, spatial resolution, distortion artifacts, and the overall image quality. For subjective noise, TrueFidelity™ scored higher than ClariCT.AI. On the qualitative noise assessment scale, the former scored 3.72, whereas the latter scored an average of 3.22. On this scale, 1 stood for most noise while 4 stood for the least. Thus, the vendor-specific DLR algorithm was preferred by the radiographers at reducing signal-to-noise ratios of images.

On resolution, the findings were similar to those noted for noise assessment - TrueFidelity™ scored higher than ClariCT.AI. Whereas TrueFidelity™ had a score of 3.66, ClariCT.AI recorded an average score of 3.49. On this, whereas the findings were significantly close, it was observable, again, that the vendor-specific DLR algorithm appeared to report better image resolution when used to assess lung lesions.

Image distortion was the third feature considered in the qualitative image assessment by the experienced radiographers that assessed the DE identified images. Here, distortion is used to refer to the presence of image artifacts. TrueFidelity™ had a score of 3.46, while ClariCT.AI recorded an average score of 3.51. This implied that the vendor-agnostic technique was marginally better, though the difference was insignificant.

Overall, the qualitative assessment of images by experienced radiographers confirmed that the panels of images were averagely good for use in clinical diagnoses. When asked about their preference out of the two panels of images, the qualitative assessors believed that TrueFidelity™ was a better choice in terms of its image quality according to their experience and preferences. This was confirmed by the fact that the average preference rate for TrueFidelityTM was 72% out of the sets. Table 2 below summarizes the qualitative assessment scores.

Property	TrueFidelity™	ClariCT.AI
Noise	3.72	3.22
Resolution	3.66	3.49
Distortion	3.46	3.51
Overall preference	72%	28%

Table 2: Summary of qualitative assessment scores.

Quality image assessment

Quantitatively, the results were significantly consistent with the findings of the qualitative assessment. Here, TrueFidelity™ showed the least edge-rise-distance (ERD) and SNR. The findings are summarized in table 3 below.

Property	TrueFidelity™	ClariCT.AI
Signal-to-Noise Ratio	22.65 ± 2.84	25.95 ± 5.82
Edge-Rise-Distance	0.97 ± 0.19	1.48 ± 0.19

Table 3: Summary of quantitative assessment results.

Discussions

CT scans are generally preferred for assessing lung lesions, among other health issues, because of their image quality [11]. This explains why many physicians have considered them effective for assessing lesions. However, because of the high rate of radiation exposure, especially when repeated imaging is needed, there is a need to reduce exposure to radiation doses while maintaining the quality of images [12]. Thus, IRs and DLRs have been developed to overcome the challenge of declining image quality with reduced radiation doses. So far, it has been proved that DLRs are more promising than IRs [13]. Therefore, this study's goal was to compare the image qualities between vendor-specific and vendor-non-specific DLRs. TrueFidelity™ was the vendor-specific DLR, whereas ClariCT.AI was the non-specific algorithm considered.

The reasons for ordering lung CT were mainly non-tuberculous. These accounted for 62% (n = 31). This was consistent with Putman., *et al*. [14], who had noted that non-tuberculous lung injuries, especially interstitial injuries, were the main reason for the clinical ordering of lung CT scans. Further, Hatabu., *et al*. [15] also agreed that the other conditions included for ordering lung CTs would be atelectasis, pneumonia, and active tuberculosis. Lately, COVID-19 has also become a common reason for ordering CT scans. According to Radpour., *et al*. [16], COVID19 has particularly increased the demand for low-dose lung CT scans to assess the extent of lung injury as both a diagnostic and prognostic tool in studying the disease's progress and severity. With such use becoming common, it is justified that the need to reduce exposure doses is also becoming more common because of the repeated exposures to which patients are exposed. Such increases the need for imaging algorithms like IRs and DRLs to limit dosage levels.

The findings of this study showed notable qualitative differences in the qualities of the images as assessed by the experienced radiographers. Generally, the scores for subjective image noise were good. Whereas TrueFidelity™ scored, 3.72 ClariCT.AI scored an average of 3.22. This finding was generally consistent with Kim., *et al*. [17], who had established that DLR algorithms were excellent at reducing image noise and improving the diagnostic value of CT scans obtained under low radiation doses. Studying image quality differences between IRs and DLRs by assessing mediastinal window images, Hata., *et al*. [18] showed that DLRs had a better image quality compared to IRs. This study, however, considered two different DLRs. Nam., *et al*. (2021) studied image noise differences between vendor-specific and vendor-agnostic DLRs and confirmed that the vendor-specific versions were more effective at reducing image noise, which was consistent with this study's findings.

Image resolution and distortion were also interest areas for this study. Resolution and artifacts are important considerations for image interpretations because they determine how accurately a radiographer can derive meaningful information from the CT scan [9]. However, whereas Nam., *et al*. [9] noted that vendor-specific DLR algorithms had a higher defect in terms of resolution and artifacts, this study proved otherwise, concluding that vendor-specificity was an important determinant of improved image quality. Hata., *et al*. [8] also agreed with Nam., *et al*. [9], who concluded that vendor-specific algorithms produced poor image resolution and distortion results.

The quantitative findings also promoted this general finding that vendor-specific algorithms were better than vendor-agnostic algorithms. Quantitatively, whereas the SNR for TrueFidelity™ was 22.65 ± 2.84, that for ClariCT.AI was 25.95 ± 5.82. While the ERD for TrueFidelity™ was 0.97 ± 0.19, that for ClariCT.AI was 1.48 ± 0.19. These findings generally agreed with Nam., *et al*. [9], who had confirmed the effectiveness of vendor-specific DLR algorithms in improving image quality.

The two types of deep learning reconstructions and data pretreatment methods addressed in this article, TrueFidelity™, and ClariCT.AI, were developed to address various technical goals in image preprocessing. TrueFidelity™ was developed to manage the whole reconstruction process, from photon starvation compensation to beam hardness correction, sinogram to CT image translation, and noise management. Because TrueFidelity™ is a vendor-specific approach, it may take advantage of vendor-specific system characteristics during image reconstruction. ClariCT.AI, on the other hand, was developed as a vendor-neutral solution with the sole objective of conducting noise reduction on filtered-back-projection (FBP)-reconstructed CT images, leaving the remainder of the reconstruction to vendor-specific FBP. Because the whole network nodes in a deep learning architecture must be adjusted and reweighted concurrently to achieve the specified objective, it is believed that the network would perform better when the task is simple rather than difficult [19]. TrueFidelity™'s better quality, which comprised noise reduction without texture distortion, resolution preservation, and reader acceptance in this inquiry, might be attributed to its exclusive concentration on noise reduction.

Given that FBP reconstruction is a mature technology that has been fine-tuned for each vendor's unique system details, it makes sense for a vendor-independent deep learning algorithm to prioritize noise reduction tasks to achieve the highest overall reconstruction effectiveness, particularly for ultralow-dose scans. ClariCT.AI's most critical characteristic is vendor compatibility; consequently, this technology may be utilized to improve the quality of CT scans acquired from numerous manufacturers [9]. However, since this study focused only on a single CT scanner manufactured by a single manufacturer, a more comprehensive investigation of a vendor-neutral technique for additional manufacturers and scan protocols is required.

This study is notable because we created new objective measures that accurately represent subjective image quality. Prior research assessing the image quality of various CT imaging techniques has mostly been subjective, with objective evaluations limited to SNR only [20,21]. ERD refers to edge sharpness, while skewness refers to inhomogeneous image distortion. These parameters might be significantly improved and used in future studies assessing the quality of CT scan images. This research's diagnosis accuracy was not evaluated, which is a significant issue. Numerous studies have shown good diagnostic accuracy of ultralow-dose CT images utilizing iterative reconstruction methodologies for nodule identification, ground-glass nodule evaluation, and assessment of diffuse lung illnesses such as lung infections and cystic fibrosis [22,23]. However, further study is necessary to establish this since deep learning-based algorithms may include unintended visual distortion, impairing detection accuracy. To increase the clinical utility of ultralow-dose CT and reduce the radiation dose imposed on patients, it is required to compare the picture quality and diagnostic performance of the deep learning algorithm-reconstructed ultralow-dose CT to traditional traditional low-dose CT. Additional prospective studies testing the algorithms' efficacy in real-world clinical settings are required, and our results may serve as a springboard for future studies.

Additionally, this study has serious limitations. First, even though we collected consecutive cases, there is a possibility of selection bias due to the study's retrospective nature. Second, only photos with a thin section thickness (1.25 mm) were assessed, although numerous readers prefer images with a 2.5 mm thickness for regular use. Third, the mean effective dose used in our ultralow-dose CT scans was 0.20 0.036 mSv, somewhat higher than the 0.12-0.21 mSv range previously described [24]. Ernst., *et al*. [25] investigated ultralow-dose CT with an effective dose of around 0.05 mSv for a specific patient group. It should be tried to further minimize the radiation dose. Finally, readers in this study were given a separate option. Because we surveyed just three readers, further study may be necessary to determine the optimal method.

Conclusion

Compared to vendor-agnostic DLR, a vendor-specific DLR produced the highest overall image quality, and more than two out of three readers preferred it. This points to a need for CT manufacturers to develop specific DLR algorithms to improve image quality when low-dose radiation is used for imaging. However, more study is needed to verify diagnostic performance and image quality in clinical setups.

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