

# World Journal of *Clinical Cases*

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Editorial Board Member of *World Journal of Clinical Cases*, Alessandro Leite Cavalcanti, DDS, MSc, PhD, Associate Professor, Department of Dentistry, State University of Paraiba, Campina Grande 58429500, Paraiba, Brazil. alessandrouepb@gmail.com

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## Advances in deep learning for computed tomography denoising

Sung Bin Park

**ORCID number:** Sung Bin Park 0000-0002-4155-9260.

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**Sung Bin Park**, Department of Radiology, Chung-Ang University Hospital, Seoul 06973, South Korea

**Corresponding author:** Sung Bin Park, MD, PhD, Chief Physician, Full Professor, Department of Radiology, Chung-Ang University Hospital, 102, Heukseok-ro, Dongjak-gu, Seoul 06973, South Korea. [psungbin@paran.com](mailto:psungbin@paran.com)

### Abstract

Computed tomography (CT) has seen a rapid increase in use in recent years. Radiation from CT accounts for a significant proportion of total medical radiation. However, given the known harmful impact of radiation exposure to the human body, the excessive use of CT in medical environments raises concerns. Concerns over increasing CT use and its associated radiation burden have prompted efforts to reduce radiation dose during the procedure. Therefore, low-dose CT has attracted major attention in the radiology, since CT-associated x-ray radiation carries health risks for patients. The reduction of the CT radiation dose, however, compromises the signal-to-noise ratio, which affects image quality and diagnostic performance. Therefore, several denoising methods have been developed and applied to image processing technologies with the goal of reducing image noise. Recently, deep learning applications that improve image quality by reducing the noise and artifacts have become commercially available for diagnostic imaging. Deep learning image reconstruction shows great potential as an advanced reconstruction method to improve the quality of clinical CT images. These improvements can provide significant benefit to patients regardless of their disease, and further advances are expected in the near future.

**Key Words:** Denoising; Deep learning; Computer-assisted imaging processing; Iterative reconstruction; Radiation dose

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**Core Tip:** Early application of deep learning techniques have shown success in the denoising of computed tomography (CT) images, especially low-dose CT images, and future advances are expected to provide additional benefit.

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## INTRODUCTION

In radiography, decreases in radiation dosage result in the debasement of image quality, basically due to an increment in image noise[1]. Increased image noise can compromise the diagnostic performance of computed tomography (CT) images. Hence, much exertion has been invested in designing image processing techniques that reduce image noise. By applying data handling and image reconstruction methods that diminish image noise whereas keeping up spatial resolution, it is conceivable to move forward the quality and diagnostic value of low-dose CT (LDCT) images, which are inherently noisy[2]. Recently, deep learning (DL) techniques have been increasingly applied to many aspects of medical imaging and are showing promise as an effective solution for the problem of noise[3-5]. This is particularly true in their application to denoising CT images, where DL techniques have appeared noteworthy performance in moving forward imaging quality by noise suppression, structural preservation, and lesion detection[1,6].

## CT USE AND RADIATION HAZARD

CT has seen a rapid increase in use in recent years[2,7,8]. Radiation from CT accounts for a significant proportion of total medical radiation. However, given the known harmful impact of radiation exposure to the human body, the excessive use of CT in medical environments raises concerns[7]. Concerns over increasing CT use and its associated radiation burden have prompted efforts to reduce radiation dose during the procedure[9-11].

## LDCT IMAGING

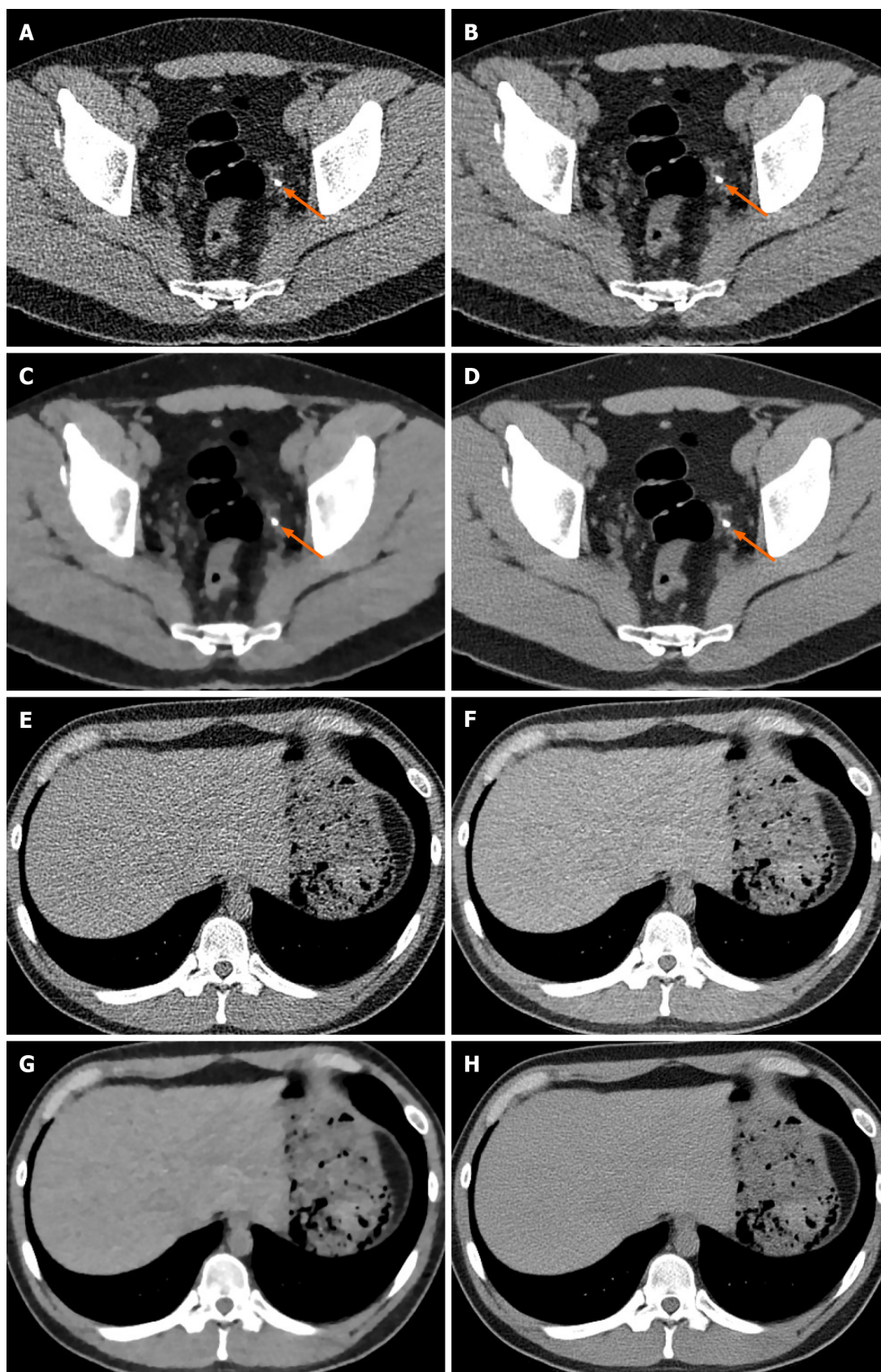
Recently, LDCT has attracted significant interest in the radiography community[8,12,13]. Several approaches can be used to reduce radiation exposure as follows: avoiding unnecessary examinations and superfluous acquisitions; optimizing CT acquisition parameters (*i.e.*, lowering tube voltage or current and pitch); routinely using size adaptation techniques, such as automatic tube current modulation; and progressing the postprocessing and reconstruction of CT images[2]. In any case, the diminishment of radiation dosage increases noise and presents artifacts in reconstructed images[7,8]. In other words, reductions in radiation dose lead to decreases in image quality, which may adversely affect diagnosis using LDCT images[1,8]. Therefore, much exertion has been made to plan better image processing techniques that can further diminish image noise after image capture[1].

## DENOISING OF CT IMAGING

Image noise reduction, generally called “image denoising,” is an important but challenging task. In the midst of the denoising handle, the noise component must be expelled without debasing the true signal component[14]. Clinical applications with characteristic high-contrast abnormalities (*e.g.*, CT for urolithiasis, CT enterography) can accomplish noteworthy dosage decreases by applying denoising strategies (Figure 1)[2,12]. In low-contrast cases, such as detection of metastases in solid organs, dose reduction is considerably more restricted by loss of lesion conspicuity due to a loss of low-contrast spatial resolution and coarsening of noise texture[2].

Noise reduction algorithms for LDCT can be categorized into three types: (1) Handling the raw data gotten from sinogram (projection space denoising); (2) Iterative reconstruction (IR) strategies; and (3) Handling reconstructed CT image (image space denoising)[2,8,13].

In projection space denoising, the noise expulsion algorithm is connected to the CT sinogram information gotten from low-dose CT. These strategies join system physics



**Figure 1** Representative low-dose computed tomography images at 100 kV and 30 mAs (dose length product, approximately 93.4 mGy·cm; effective radiation dose, approximately 1.401 mSv) using four image reconstruction techniques: Filtered back projection; iDose4, hybrid iterative reconstruction; iterative model reconstruction, fully iterative reconstruction; ClariCT, deep learning based image reconstruction. The arrows point to a left distal ureter stone of 5-mm diameter. The noise in the images produced by FBP (A, E), iDose4 (B, F), IMR (C, G) and ClariCT (D, H) is decreased and the image quality, improved. An unfamiliar plastic-looking noise texture is observed in the high-level iterative reconstruction (C, G).



On the other hand, deep learning-based image reconstruction (D, H) sharpened structural margins and produced favorable images.

and photon statistics to diminish both image noise and artifacts. In any case, this process uses an algorithm supplied by the vendor. These strategies too require get to sinogram information, which isn't accessible for commercial CT scanners. At last, these procedures ought to be actualized within the scanner reconstruction system, which increments the taken a toll of denoising[2].

IR strategies refer to another group of techniques to make strides the image quality of LDCT. For the past 30 years, filtered back-projection (FBP) has been the prevailing strategy of reconstruction due to its computational proficiency and precision. FBP requires noteworthy amounts of high-quality projection data to get precise reconstructions[15]. At low-dose settings, challenges emerge with increased image noise and artifacts. Thus, IR was presented to overcome these restrictions of FBP (Figure 1). These methods consider the system model geometry, photon counting statistics, as well as the x-ray beam spectrum. They generally beat projection space denoising strategies. They can expel artifacts and give great spatial resolution. Be that as it may, like projection space denoising, they require get to the projection information, are vendor subordinate, and ought to be actualized on the reconstruction system of the scanner. Additionally, images with high reconstruction strength levels (Figure 1) have a waxy, plastic-looking unfamiliar noise texture or blotchy, unnatural appearance[2,15,16]. It influences the assessment of CT scan images, and apparently, the interpretation of imaging findings[17].

In contrast to these first two strategies, image space denoising algorithms don't require raw projection information. They work straightforwardly on the reconstructed CT images and are by and large quick, free of the scanner vendor and can be effectively coordinates into a workflow. They get a low-dose CT image as an input and foresee the normal-dose CT image as the yield[2].

## DL IMAGING RECONSTRUCTION

Recently, promising results in low-dose CT denoising have been achieved using DL-based algorithms, especially convolutional neural networks (CNNs) and generative adversarial network architectures[7,8]. With the rapid development of CNNs, denoising models have achieved impressive denoising results for LDCT[3,6,7,18]. DL has recently appeared the potential for making stride image reconstruction in CT since it can oversee a higher number of models and parameters more successfully and proficiently than statistics-based reconstruction methods[15]. DL-based image reconstruction (DLIR) can incorporate complex models and a gigantic number of parameters through training processes, overcoming the modeling restrictions of IR [15]. As of late, several clinical studies on deep CNN-based reconstruction methods have detailed that DLIR yields favorable noise texture, prevalent image quality, and significantly reduced image noise (Figure 1)[15].

Currently, two available vendor-specific DLIR technologies, TrueFidelity (GE Healthcare) and Advanced intelligent Clear-IQ Engine (AiCE, Canon Medical System) have been trained with high-quality FBP or statistical IR images produced with high-level X-ray dose[11,14-16].

ClariCT (ClariPi, Seoul, South Korea) is based on the CNN algorithm noise reduction approach and features digital imaging and communications in medicine (DICOM)-based sinogram blend and crossover IR. It offers the advantage in terms of denoising from both projection and image space[1,19,20].

The crossover algorithm in ClariCT is completed taking after a special handle. The primary stage is forward projection of CT image from FBP to form a synthesized sinogram, which is similar to other crossover reconstruction technologies. The geometry of the CT system is determined indirectly from the DICOM header and related data. In the second stage, the algorithm investigates the synthesized sinogram and recognizes the noisiest portion of sinogram (*i.e.*, the photon-starved area). This can be taken after by a removal of noise sinogram through an iterative handle. At last, the denoised image is adaptively mixed with the original FBP image utilizing the local noise statistic. This acts to limit the waxy appearance of the handled image that is due to over-the-top noise subtraction. Thus, overall noise is decreased without over-smoothing and loss of details in the image (Figure 1). Extraordinary in ClariCT, the forward projection and FBP reconstruction steps are carried out as it were utilizing

DICOM information; subsequently, the whole crossover IR is performed in a vendor neutral way[20].

Although DLIR algorithms appear to be exceedingly compelling for moving forward image quality, there are a few issues or obstacles to be talked about. Firstly, further external validation of DLIR is vital. Secondly, actual radiation dose reduction in the clinical practice because of altering procurement parameters whereas performing diagnostic investigations has yet to be affirmed. Thirdly, the decision-making process of trained algorithms may be a black box to human discernment[21].

## CONCLUSION

The use of DLIR methods employing deep CNNs has been proposed to encourage dose reduction whereas keeping up the image quality and diagnostic performance of CT imaging.

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