INVITED REVIEW

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Improvement of image quality at CT and MRI using deep learning

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Abstract

Deep learning has been developed by computer scientists. Here, we discuss techniques for improving the image quality of diagnostic computed tomography and magnetic resonance imaging with the aid of deep learning. We categorize the techniques for improving the image quality as "noise and artifact reduction", "super resolution" and "image acquisition and reconstruction". For each category, we present and outline the features of some studies.

Keywords Deep learning · Image quality improvement · Computed tomography · Magnetic resonance imaging

Introduction

Most artificial intelligence currently used in the field of medicine is categorized as "machine learning" (ML). In the field of diagnostic radiology, it has long been used for computer-aided diagnosis [1]. Although ML is not a novel technology, advances in the computer infrastructure have led to its wide acceptance. Deep ML has gained attention; it is a technique that uses deep convolutional neural networks (DCNN) [2–5]. The use of support vector machines (SVM), a traditional feature-based approach, is now considered classical ML [6] and this technique continues to be used [7] because it is easy to interpret the output.

The theory underlying the application of ML with its object identification and image quality improvement was developed in the field of computer science before ML was used in diagnostic radiology [3, 6]. The application of image quality improvement techniques to diagnostic imaging reduces radiation exposure and the scanning time.

Here, we focus on image quality improvement techniques using ML. We present an overview of techniques developed in the field of computer science and discuss applications for clinical computed tomography (CT)- and magnetic resonance (MR) imaging studies.

Deep learning-based image quality improvement techniques

Deep learning is a technology developed originally in the computer science field and it has been applied to fields such as digital image processing. Although various applications based on deep learning have been developed, here we focus on techniques that result in the improvement of the quality of diagnostic images.

Noise and artifact reduction

Image noise reduction generally called "image denoising" is the important task for digital imaging. Denoising process is often required as preprocessing for various image processing. In the denoising, the noise component must be removed without degrading the true signal component.

Zhang et al. [8] developed a deep learning-based denoiser, the denoising convolutional neural networks (DnCNNs) that were trained with pairs of noisy- and noise only images. Their denoiser improved the signal-to-noise ratio (SNR) of noisy images by removing noise components. Figure 1 compares an image that includes noise (top) and an image with the noise removed by their DnCNN. The image noise is removed by DnCNN and the edge boundary of structures is maintained. The application of this noise reduction

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Fig. 1 Noise reduction using denoising convolutional neural networks (DnCNNs) [8]

Fig. 2 Comparison of super-resolution techniques. Use of **a** the nearest neighbor, **b** linear interpolation, and **c** DCNN-based super resolution [11]

technique can help to reduce radiation exposure at CT and shorten the imaging time at MR.

High image quality requires the removal of image noise and artifacts. JPEG, a widely used image format, compresses the image irreversibly to reduce the file size. As compression artifacts appear on the image, they must be removed before image processing. Cavigelli et al. [9] developed a JPEG compression artifact remover based on 12-layer DCNN. Their method inputs JPEG images with various compression ratios; the SNR was improved by up to 1.79 dB. Svoboda et al. [10] created a large-scale DnNCC by combining multiple existing DCNNs to remove the JPEG compression noise. They demonstrated that learning occurred in a short time despite the large-scale DCNN, and that the performance for artifact removal was high by the application of an improved algorithm for the learning process. Such artifact reduction techniques can help to reduce artifacts such as motion artifacts on diagnostic images.

Super resolution

Super resolution, a technique that enhances the spatial resolution of the original image, is important for digital image processing. When an image is magnified using simple linear interpolation, blurring of the edge of objects tends to appear. However, the edge sharpness can be retained with advanced super-resolution techniques. Dong et al. [11] developed an image super-resolution technique using a DCNN. They performed three operations, "patch extraction and representation", "non-linear mapping", and "reconstruction". Their DCNN was trained with pairs of low- and high-resolution images and yielded super-resolution images without blurring of the edges encountered with conventional interpolation methods. Figure 2 shows an example of super-resolution images. A jaggy edge is more apparent on the image processed using the nearest neighbor, and blurring occurs at the edge on the image processed by linear interpolation [12]. The DCNN-based super-resolution method of Dong et al. [11] resulted in a close-up image with a sharp edge. The application of their technique for diagnostic imaging can help to restore the slice thickness and shorten the MR imaging time.
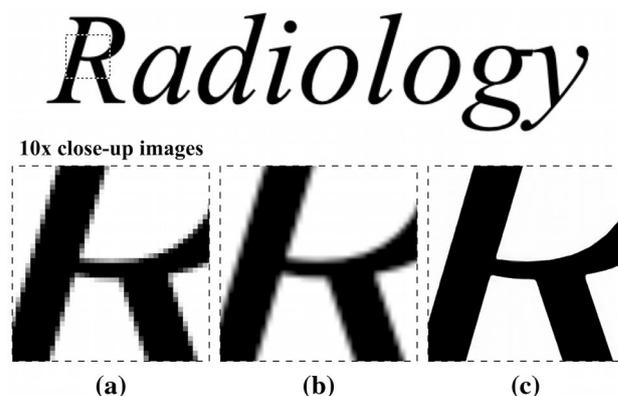
Other techniques

Besides noise removal and super resolution, techniques to improve the image quality have been introduced. Iizuka et al. [13] developed gray-scale image colorization using a DCNN. Their network was trained with 2.3 million photographs that included 205 object classes; it was evaluated with 20,000 test images. Based on qualitative evaluation, 92.6% of the colorized images were considered "natural". Figure 3 shows a colorized image using their method. Although contrast is low, natural color tones can be reproduced. Generally, diagnostic radiology does not tend to use color images, but it may be possible to convert single-energy CT images to images with more information, e.g., dual-energy CT- and photon-counting CT images. Although it may be difficult to convert a non-contrast-enhanced- into a contrast-enhanced CT image, it may be possible to convert contrast-enhanced- into non-enhanced CT images. Ulyanov et al. [14] reported an image restoration technique using a DCNN. It restores the image to which some processing has been applied to its original state. For example, it is possible to remove overlaid text on the image. Also, artifacts due to compression and image noise can be removed. Since there is compensation for missing image information, their method may be useful for removing metal artifacts on CT and MRI scans. However, the truth of the repaired image must be ascertained.

Clinical applications

Because image quality improvement methods using deep learning were developed in the field of computer science, for diagnostic imaging the existing trained networks cannot be used. In most instances, network parameters must be re-configured and the network must be trained
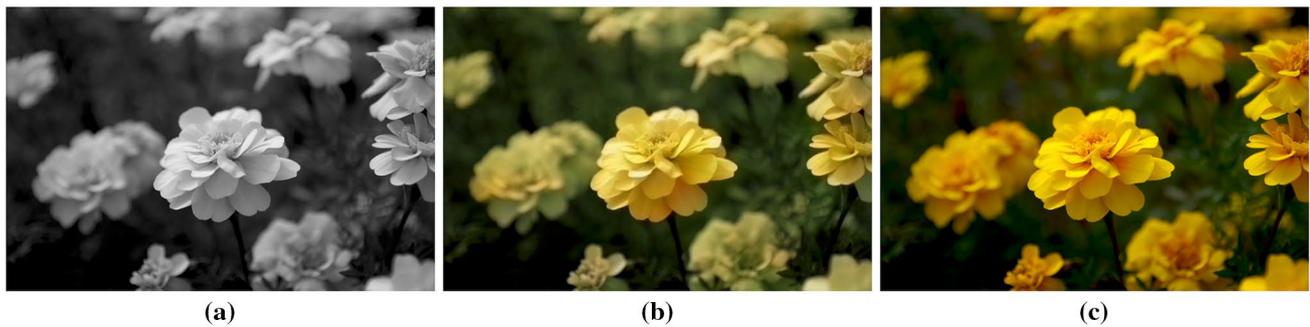
Fig. 3 Deep learning-based colorization [13]. **a** Input gray-scale image, **b** colorized image, **c** base-truth image

with clinical images. The DCNN requires many teaching images and it can be difficult to prepare a sufficient number of such images, e.g., for lesion detection. However, it is possible to include normal images for the application which improves image quality and it is relatively easy to gather a lot of teaching images. Table 1 lists clinical applications for image quality improvements using deep learning.

Noise and artifact reduction

Deep learning applications that reduce the image noise and artifacts are available for diagnostic imaging. For CT studies, radiation exposure can be reduced and for MR,

the acquisition time can be lessened and the image noise can be reduced. Chen et al. [15] who developed a deep learning-based image noise reduction technique acquired the teaching dataset from routine CT studies. Their DCNN was trained with virtual low-dose CT images generated by adding Poisson noise to raw data of teaching images. They trained the CNN in 200 cases; their test of 100 cases yielded the highest SNR compared with other noise reduction methods. Du et al. [16] reported a noise reduction method for low-dose CT using a stacked competitive network (SCN) comprising several successive competitive blocks (CB) that can increase the width of the network and improve the ability of the traditional CNN. They used a publicly available CT image dataset available in

Table 1 Summary of clinical applications of image quality improvement using deep learning

References	Year	Journal	Purpose
Chen et al. [15]	2017	Biomed Opt Express	CT noise reduction
Du et al. [16]	2017	PLoS One	CT noise reduction
Kang et al. [17]	2017	Med Phys	CT noise reduction
Jiang et al. [18]	2018	Jpn J Radiol	MR noise reduction
Zhang et al. [19]	2018	IEEE Trans Med Imaging	CT metal artifact reduction
Kim et al. [20]	2017	Magn Reson Imaging	MR banding artifact reduction
Hauptmann et al. [21]	2018	Magn Reson Med	MR motion artifact reduction
Umehara et al. [22]	2017	J Digit Imaging	CT super resolution
Park et al. [23]	2018	Phys Med Biol	CT super resolution
Liu et al. [24]	2018	Biomed Eng Online	MR super resolution
Wu et al. [25]	2017	IEEE Trans Med Imaging	Image quality improvement for CT reconstruction
Jin et al. [26]	2017	IEEE Trans Image Process	Image quality improvement for under-sampled CT reconstruction
Kida et al. [27]	2018	Cureus	Image quality improvement for corn-beam CT reconstruction
Zhu et al. [28]	2018	Nature	MR direct reconstruction
Han et al. [29]	2018	Magn Reson Med	Image quality improvement for under-sampled MR reconstruction
Golkov et al. [30]	2016	IEEE Trans Med Imaging	MR scan acceleration for multi-parametric image analysis
Nakamura et al. [32]	2018	Radiol Artif Intell	Image quality improvement for CT reconstruction
Tatsugami et al. [33]	2018	Eur Radiol	Image quality improvement for CT reconstruction
Touch et al. [34]	2016	Phys Med Biol	X-ray distortion correction for photon-counting CT
Xiang et al. [35]	2018	Med Image Anal	Image conversion from MR to CT

the Cancer Imaging Archive for teaching data and generated virtual-low-dose CT images by adding Poisson noise to the images. Compared with the other methods, they achieved the highest SNR and the lowest mean square error on images processed with the SCN. Kang et al. [17] proposed a noise reduction method for CT images that incorporates wavelet transform into the DCNN. First, the input image is wavelet transformed and the noise in the wavelet domain is removed by the DCNN. Next, an output image is obtained by the wavelet recomposition process. By applying their method to quarter-dose abdominal CT, they were able to reduce the image noise without degrading visualization of the organ boundary. However, qualitative evaluation by radiologists showed that the texture of the denoised images differed from conventional images. Jiang et al. [18] applied a DCNN-based noise reduction method to brain MR images. Since the DnCNN is a noise reduction DCNN for 2D images, they proposed a multichannel version of DnCNN (MCDnCNN) for 3D denoising. They obtained robust denoising performance when training was with images featuring various image noise levels.

Zhang et al. [19] reported a deep learning-based metal artifact reduction (MAR) method for CT images. They trained their DCNN by generating images with virtually implanted metals. Comparison of virtual- and actual images showed that theirs was superior to other methods. Kim et al. [20] proposed a banding artifact suppression technique for MR imaging based on deep learning. They targeted balanced steady state free precession (bSSFP) sequences and generated virtual images simulating banding artifacts at different phase-cycling angles. Their DCNN was trained on the virtual images. On brain- and knee MR scans, banding artifacts were removed and a high SNR and functional signal changes were maintained. Hauptmann et al. [21] developed a method to suppress spatio-temporal artifacts on cine images obtained during cardiac MR studies. MR scans of the heart, acquired with the bSSFP sequence under the breath-holding, were the teaching images, and artifact-contaminated images applied for training were virtually synthesized. Their DCNN was trained on a 3D image (2D plus time frame) and after the completion of network training, the processing time was short enough to be applicable to real-time images.

Super resolution

Super-resolution techniques have been used in diagnostic imaging studies. By applying such techniques to thick-slice images, it is possible to generate virtual thin-slice images. By converting thick-slice- into thin-slice MR images by post-processing, the acquisition time can be shortened. Umehara

et al. [22] developed a technique to improve the resolution of chest CT images using deep learning. They used routine chest CT images as the teaching data and trained their super-resolution convolutional neural network (SRCNN) using the low-resolution images obtained by downsampling. Comparison with conventional image enlargement techniques such as nearest neighbor and bilinear interpolation with images processed by SRCNN showed that the latter were less blurred and closest to the base-truth images. Park et al. [23] proposed a super-resolution technique along the Z axis using deep learning. They used thin-slice images obtained by routine CT studies as the teaching dataset; their DCNN was trained with thick-slice images. On head CT images, the blur due to the partial volume effect was eliminated especially in the high-contrast region such as the cortical bone. Because thick images were input, the thinned images were less noisy than the real thin images. Liu et al. [24] developed a deep learning-based super-resolution technique for MRI studies. To examine the edge response at different convolution kernel sizes, they employed a multi-scale fusion convolution network (MFCN) that is stacked by a multi-scale fusion unit (MFU). The MFCN was trained on down-sampled brain MR scans. Comparison with actual brain MR scans confirmed that the MFCN recovered detailed information from MR scans and that it outperformed state-of-the-art techniques such as the SRCNN.

Image acquisition and reconstruction

Since image acquisition is time constrained, deep learning is used to supplement missing information. Studies on replacing the image reconstruction process with deep learning have been published. Some of the reports cited here may be categorized as "image noise and artifact reduction" efforts. Wu et al. [25] developed an iterative CT reconstruction method based on priors learned by a k-sparse autoencoder, another kind of neural network. When their method was applied to abdominal CT images acquired at different radiation doses, the image noise was reduced and the object structure was maintained. Application of their method made it possible to reduce the radiation dose to one-sixth of the conventional dose. Jin et al. [26] developed a supplemental deep learning method for inverse problems such as image reconstruction. When solving the inverse problem, it is often impossible to obtain a complete solution due to noise and sparseness of data. They proposed a method to solve this problem with a DCNN. When image reconstruction was with FBPConvNet, a technique that combines FBP and DCNN, high-quality images with less noise could be obtained even from sinograms with a fewer number of views. Kida et al. [27] developed a deep learning technique that improves the image quality for corn-beam CT (CBCT) reconstruction. Artifacts on CBCT images attributable to

scattering were reduced by training their DCNN with pairs of CBCT- and conventional CT images. This process yielded uniform, high-quality images in a short processing time. Zhu et al. [28] directly reconstructed MR scans using a DCNN that applied various k-space sampling methods. It could also apply to PET reconstruction. Accurately reconstructed MR images were obtained even with sparse sampling. Furthermore, their PET images were of the high quality yielded by iterative reconstruction (IR). However, as a large memory is required for processing, the reconstruction of high-resolution CT images remains difficult. Han et al. [29] reported an image quality improvement method that applies deep learning to the reconstruction of sparsely sampled MR scans. They proposed a domain-adaptation scheme that employs a pre-trained DCNN involving a large number of CT or synthesized radial MR scans. For fine-tuning, they used a few radial MR datasets. When the amount of radial MR data was sufficient, their DCNN provided good restoration results. Golkov et al. [30] created a scan-acceleration method for diffusion-weighted MR using deep learning. As analysis by, for example, diffusion kurtosis imaging (DKI) and neurite-orientation dispersion and density imaging (NODDI) to diffusion-weighted MR requires many images obtained with different scan parameters, the scanning time is very long. By applying deep learning, they were able to reduce the number of images required for DKI analysis from 288 to 12, and the number of images necessary for NODDI analysis from 158 to 12.

In collaboration with Canon Medical Systems Corp., our group also developed a deep learning-based image noise reduction technique [31–33] called deep learning-based reconstruction (DLR). We trained our DCNN with a pair of low- and high-quality CT images. The former were obtained with low-radiation doses and subjected to hybrid IR, and the latter at routine doses and reconstructed with a customized MBIR algorithm. Nakamura et al. [32] who evaluated images acquired in patients with hypovascular hepatic tumors found that DLR improved the image quality. Tatsugami et al. [33] confirmed that with DLR the image noise on coronary CT angiograms was reduced without reducing spatial resolution. Figures 4, 5, and 6 are low-dose CT images of the abdomen, chest, and coronary artery, respectively, that were reconstructed with DLR. The image noise was consistently lower on the DLR- than the hybrid IR images, and the image quality was improved by DLR without degradation of spatial resolution. As shown in Fig. 4, the low-frequency noise on the hybrid IR image of the abdomen was suppressed on the DLR image and the image quality was drastically improved. The DLR can also be applied to MR images (Fig. 7). Compared with the conventional image, on the image reconstructed with the DLR, image noise is reduced without blurring.

Fig. 4 Comparison of CT image reconstruction techniques applied to low-dose abdominal CT. Close-up views are shown in the bottom row. **a** Hybrid iterative reconstruction, **b** deep learning-based reconstruction

(a)   (b)

Fig. 5 Comparison of CT image reconstruction techniques applied to low-dose chest CT. Close-up views are shown in the bottom row. **a** Hybrid iterative reconstruction, **b** deep learning-based reconstruction
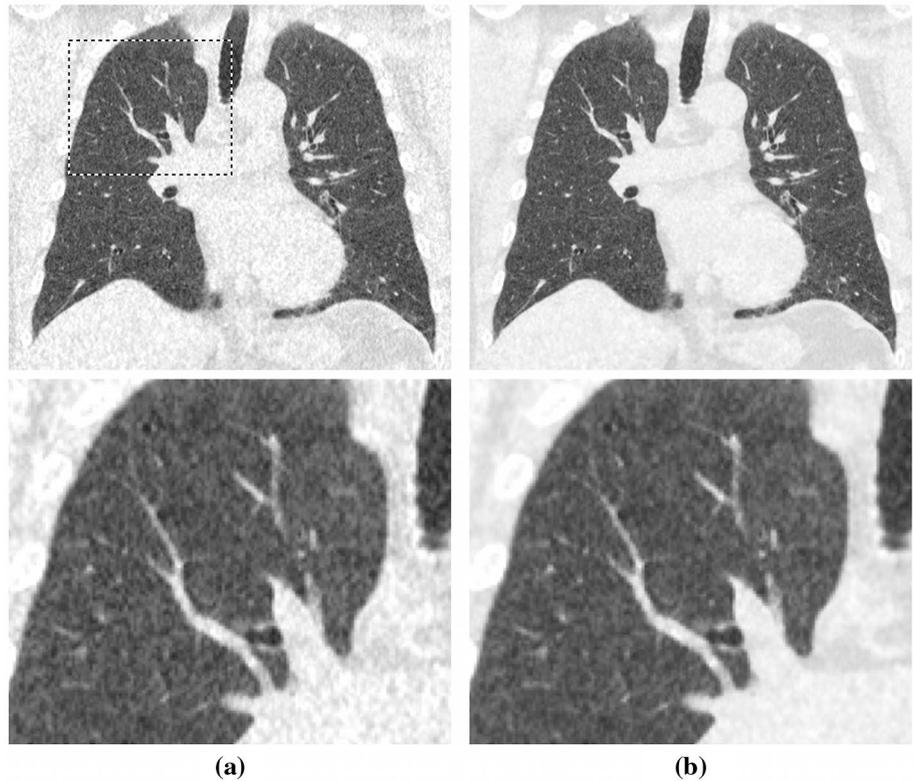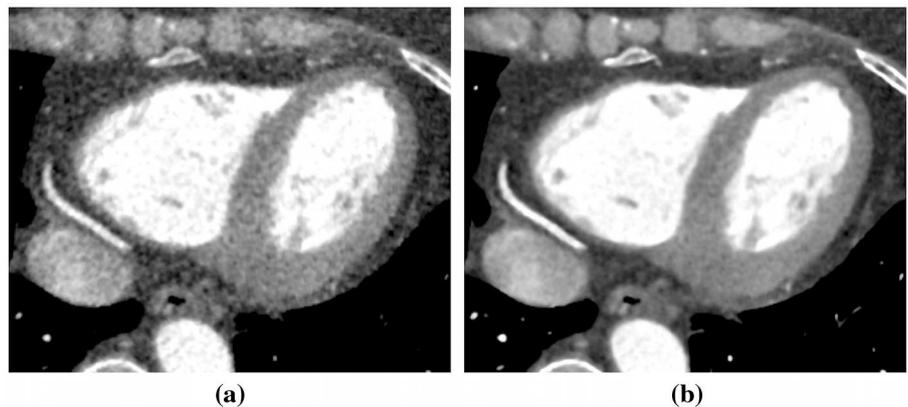

(a)   (b)

Fig. 6 Comparison of CT image reconstruction techniques applied to low-dose coronary CT angiography. **a** Hybrid iterative reconstruction, **b** deep learning-based reconstruction


(a)   (b)

Other techniques

Other methods to improve the image quality with deep learning techniques have been reported. Touch et al. [34] developed a spectral distortion correction method for photon-counting CT (PCCT). Unlike conventional CT, it decomposes the X-ray energy spectrum. However, they encountered problems with the X-ray detector; the noise was higher and the X-ray energy spectrum was distorted. Nevertheless, they confirmed that the accuracy of material decomposition on prototype PCCT images was improved after spectral distortion correction with deep learning. Xiang et al. [35] reported a method in which deep learning converts T1-weighted MRI scans into CT images. They trained a deep-embedding convolutional neural network (DECNN) using aligned CT and MR scans. On brain- and prostate images, their DECNN converted MR into CT scans in a short time. However, the noise present in their training data and artifacts due to image misalignment were a problem.

Fig. 7 Comparison of MR image reconstruction techniques applied to T2WI of the brain. Close-up views are shown in the bottom row. **a** Conventional reconstruction, **b** deep learning-based reconstruction

(a)   (b)
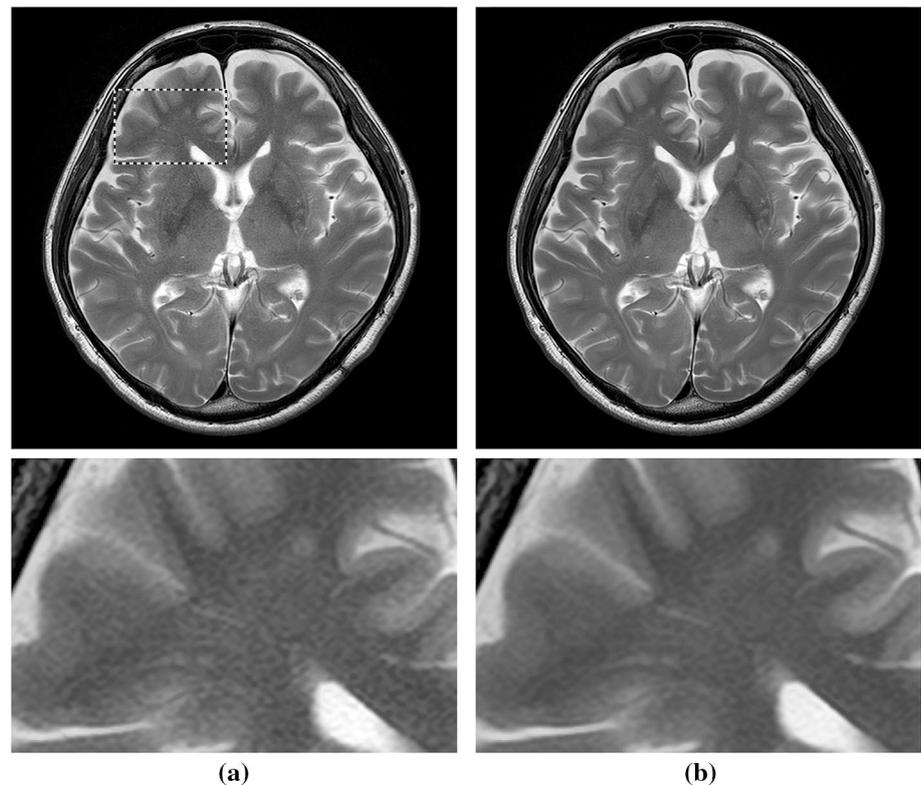
Conclusion

Most deep learning techniques were developed by computer scientists. We presented a review of image quality improvements that applied deep learning to CT and MR studies. With respect to clinical applications, we categorized the techniques for improving the image quality as "noise and artifact reduction", "super resolution", and "image acquisition and reconstruction". Noise and artifact reduction is expected to help decrease the radiation exposure at CT studies and to shorten the MR scanning time. Super resolution may increase diagnostic ability by improving the resolution of thick-slice images and shorten the imaging time required for MR studies. Many of the image acquisition- and reconstruction techniques we discussed reduce the noise and artifacts attributable to incomplete data acquisition and could be classified as noise and artifact reduction techniques. Among innovative techniques, we discussed a method for directly reconstructing raw data into image data using a DCNN. Although deep learning is expected for various clinical applications, additional hardware such as a graphical processing unit (GPU) is necessary for application since the calculation cost is high. Also, since it is completely nonlinear processing, it should be carefully used as it is difficult to predict behaviors as compared to the linear processing conventionally used. Image quality improvements strongly benefit patients regardless of their disease, and further advances are expected.

Compliance with ethical standards

Conflict of interest The other authors declare that they have no conflict of interest.

Ethical statement None.

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