The use of deep learning methods in low-dose computed tomography image reconstruction: a systematic review

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Abstract
Conventional reconstruction techniques, such as filtered back projection (FBP) and iterative reconstruction (IR), which have been utilised widely in the image reconstruction process of computed tomography (CT) are not suitable in the case of low-dose CT applications, because of the unsatisfying quality of the reconstructed image and inefficient reconstruction time. Therefore, as the demand for CT radiation dose reduction continues to increase, the use of artificial intelligence (AI) in image reconstruction has become a trend that attracts more and more attention. This systematic review examined various deep learning methods to determine their characteristics, availability, intended use and expected outputs concerning low-dose CT image reconstruction. Utilising the methodology of Kitchenham and Chartier, we performed a systematic search of the literature from 2016 to 2021 in Springer, Science Direct, arXiv, PubMed, ACM, IEEE, and Scopus. This review showed that algorithms using deep learning technology are superior to traditional IR methods in noise suppression, artifact reduction and structure preservation, in terms of improving the image quality of low-dose reconstructed images. In conclusion, we provided an overview of the use of deep learning approaches in low-dose CT image reconstruction together with their benefits, limitations, and opportunities for improvement.

Keywords Deep learning (DL) · Artificial intelligence (AI) · Low-dose computed tomography (LDCT) · Systematic review

Introduction

The main purpose of computer tomography (CT) imaging in clinical practice is to provide detailed information about the inside of the body, and it has been found to have more and more important functions in screening, diagnosis, staging, and management decision-making. On the other hand, excessive use of CT will expose patients to excessive radiation, especially women, the elderly, and children. Therefore, when performing a CT scan, the ALARA (as low as reasonably achievable) concept must be followed. There are two commonly used methods to reduce CT radiation dose. The first is the reduction of X-ray exposure by changing the tube current or reducing the exposure time to X-ray source, thereby reducing the CT radiation; the second is to reduce the estimated number of scan trajectories. However, both options will reduce resolution, and increase noise and artifacts, thereby reducing image quality and leading to unreliable diagnostic results. To improve the reconstructed image quality, several reconstruction algorithms have been proposed. Filtered back projection (FBP) was used until the early 2010s, and iterative reconstruction (IR) was later used. These are two algorithms that have been frequently used since the advent of computed tomography.

FBP technology is the most used method to reconstruct CT images with measured projection data. It performs high-pass filtering on the sinogram data obtained from multiple angles before back-projecting. The high-pass filter is an essential part of the blur suppression and sharpness enhancement of the
image. The FBP algorithm has simple mathematical methods and high computational efficiency and can reconstruct images of acceptable quality in a short time. On the other hand, FBP reconstructed images are susceptible to the influence of the projection dose, reducing the dose can easily lead to higher image noise and fringing artifacts, especially when treating patients who are obese due to photon starvation. With the improvement of industrial computing power and graphics processing power, the traditional FBP methods are finally replaced by iterative reconstruction (IR).

IR methods are superior to FBP and have become the standard methods of CT image reconstruction. The initial image estimation obtained by the measurement data is forward projected to the artificial raw data, and iterative correction is performed through comparison. When the predefined stopping criterion is met, the entire iterative process stops. There are two main categories of iterative reconstruction algorithms: hybrid IR methods and model-based IR (MBIR) methods. The hybrid IR method is also called the statistical IR method, which involves the statistical adjustments of the sinogram domain and the image domain. Model-based IR methods use process modeling to achieve iterative filtering in the sinogram domain and the image domain. The model-based IR method requires higher computing power and more reconstruction time than the hybrid IR method, but it is better than the hybrid infrared method in denoising and de-artefacting. However, the slow reconstruction speed and low computational efficiency limit the clinical application of IR imaging.

Compressed sensing (CS) is a widely used tool for representing compressible signals at a rate lower than the Nyquist rate. This method has been used in various radar and CT tests. However, due to the need to repeat forward-projection and back-projection during the iterative update process, this method is computationally expensive. In addition, these optimization algorithms are not generalisable and must be solved on a problem-by-problem basis. The advantages of the CS system are that the image is reconstructed by achieving data consistency conditions in each iteration, and the regulariser is manually tuned using known image features. The shortcomings of this framework are the long image restoration time and the complicated evaluation of the quality of reconstructed images, due to the location-dependent spatial resolution, contrast resolution and noise texture. Using regular lifting factors such as total variation, CS reconstructed images can be smoothed and patchy.

Recently, researchers have been trying to use AI technology especially deep learning to improve the image quality reconstructed in CT. The application of artificial intelligence in image reconstruction has become a trend that attracts more and more attention based on the promising contribution of these technologies. This review will introduce an overview of the use of deep learning approaches in low-dose CT image reconstruction together with their benefits, limitations, and opportunities for improvement.

Methods

The study of deep learning methods for low-dose CT image reconstruction was conducted according to the methodology of Kitchenham and Charter [1] and was divided into three stages: (i) planning the review, finding related works and determining the need for the review, and research question; (ii) conducting the review, choosing data sources, and extracting data and synthesis, and (iii) results, finding out what deep learning methods are being used, how are they being used, what are the advantages and disadvantages of deep learning methods, and what are the effects of deep learning use on low-dose CT image reconstruction.

Planning the review

Related works and needs for the review

To the best of our knowledge, the literature that surveys and compares available deep learning approaches for low-dose CT image reconstruction is quite restricted. To begin, a total of six reviews in this field were chosen [2–7] using a systematic search as described in “Data sources”, to gain a general understanding of the topic. The goal of this review was to evaluate and characterize deep learning approaches in a broad context. Deep learning approaches have the potential to improve both the efficiency and accuracy of low-dose CT image reconstruction. To fill a vacuum in the available literature, we conducted a thorough search of electronic bibliographic databases from January 2016 to February 2021 for low-dose/sparse-view CT image reconstruction using deep learning algorithms.

Review questions

The research questions are as follows: (i) identify and critically appraise what deep learning methods are being used in low-dose CT reconstruction and their targeted outcomes; (ii) evaluate the advantages and disadvantages of using deep learning methods in CT reconstruction based on the literature; and (iii) evaluate the effects on CT image and diagnosis because of deep learning use.
Conducting the review

Data sources

Springer, Science Direct, arXiv, PubMed, ACM, IEEE, and Scopus were used to conduct a systematic search of the literature. The searches were exclusively conducted in English. Only deep learning for CT reconstruction was selected; however, some other types of medical imaging such as PET or MRI were added to provide general context. The following key terms were searched in the title, abstract or keywords of the published papers: “low-dose CT”, “CT reconstruction”, “deep learning”, “neural network”, “sparse-view CT” and “few-view CT”. Other key terms were utilized to narrow and focus the search, and unrelated papers were eliminated. We looked for studies published between January 1, 2016, and February 1, 2022. Before eliminating irrelevant papers, a total of 255 papers were discovered at this stage.

Based on the purpose of our systematic review, the following seven exclusion criteria were applied to papers: (i) studies that do not use deep learning methods in low-dose CT reconstruction; (ii) studies that use inferior methods; (iii) studies that provide insufficient method information; (iv) studies of deep learning methods that focus on diagnosis or segmentation of CT images—our focus was on image reconstruction; and (v) papers that are only available in the form of abstracts or PowerPoint presentations due to insufficient funding. A total of 191 papers were finally selected in this stage.

Extracting data and synthesis

To ensure the quality of the selected research, one reviewer abstracted each article that satisfied the inclusion criteria and completed a questionnaire for each manuscript. Each question was aimed to extract information on potential flaws in the study’s quality. The evaluation questions were as follows: (i) Was the deep learning method well described (network structure, parameters, training process)? (ii) Was the dataset well described (i.e., source of data, number of images)? (iii) Did the authors provide open-source code for replication? (iv) Was the result well described? Answers that suggested quality problems were assessed to see if they were significant enough to diminish confidence in the results.

Results

The included studies were analysed to answer our three research questions. The first research question “to identify and critically appraise what deep learning methods are being used in low-dose CT reconstruction and their targeted outcomes” is covered in “Deep learning methods for image reconstruction in low-dose CT”. There, we present an analysis of the available deep learning methods for low-dose CT image reconstruction considering their target outcomes, action domains, network structures, results, computational costs and dataset(s), among others. Table 1 is an analysis of medical cases using FDA-approved CT reconstruction systems. Table 2 summarises the deep learning models and supporting results of the studies and help answer our research questions. Table 3 introduces different unrolling dynamics methods. Table 4 contains a summary of reviewed studies. Figure 1 introduces the process of deep learning methods applied in different domains. The second research question “to evaluate, based on the literature, the advantages and disadvantages of using deep learning methods in CT reconstruction” is covered in “Advantages and disadvantages of using deep learning methods”. The third research question “to evaluate the effects on CT image and diagnosis as a consequence of deep learning use” is covered in “Effects of using deep learning methods”.

Deep learning methods for image reconstruction in low-dose CT

Mainstream approaches in deep learning-based methods

By reviewing studies, we found that deep learning-based methods have several most common models such as CNNs (especially ResNet, 36 studies), U-Net (18 studies) and generative adversarial network (GAN, 18 studies).

The dominant neural network framework applied in imaging problems is the convolutional neural network (CNN). CNN consists of various kinds of layers and activation functions, there are three groups of layers: convolution layer, pooling layer, and fully connected layer. In CNN, convolutional layers, batch normalization, residual connection and ReLu activation function are the most prevalent components. The residual neural network (ResNet) gained popularity because of its skipping connections which bypasses one layer or more, thus the neural network’s training procedure becomes less complex while avoiding additional parameters that need to be tuned. With the use of ResNet, prior information from earlier layers can be simply transferred to later layers without extra computation.

The architecture of U-Net [8] comprises two components: an encoder and a decoder. The encoding path is usually a common convolutional network topology including convolutional layers, batch norm, pooling layers and ReLu activation function so that input images can be downsampled to feature maps. The symmetrical decoding path has similar architecture except the pooling layers are changed to deconvolutional layers to upsample feature maps back to reconstructed images. Residual connections on various layers link the two components together so that properties from
encoding layers can be simply transferred to decoding layers without extra computational complexity.

A generative adversarial network (GAN) comprises two networks: a generator network (G) and a discriminator network (D). The goal of G network is to produce fake images which are as real as possible to fool D network, while the goal of D network is to distinguish whether the input image is a real one or a fake one and not be fooled. GAN trains G network and D network at the same time until the two networks attain the Nash equilibrium. However, due to the dynamic procedure of GAN, this kind of network is very sensitive and hard to train.

In terms of practical application, the US Food and Drug Administration (FDA) has approved two deep learning-based CT image reconstruction systems. The first system is Canon Medical Systems’ Advanced intelligent ClearIQ Engine (AiCE). AiCE is trained with MBIR to distinguish signals from noise using deep convolutional neural networks (DCNN). The second system is GE Healthcare’s TrueFidelity (DLIR). TrueFidelity uses deep neural networks (DNN) to process high noise sinogram data and comparing the resulting image to the same image with high quality. Table 1 contains an analysis of some studies using AiCE and TrueFidelity (DLIR), which shows that results from AiCE and DLIR are always better than conventional methods such as hybrid IR and MBIR.

**Applications in different domains**

To solve the low-quality imaging problem, there are many algorithms used trying to improve the low-dose CT image reconstruction process. Those algorithms can generally be divided into four categories: (1) image processing, (2) sinogram domain interpolation, (3) mixed domain and (4) data-image direct transformation. Figure 1 introduces the process of DL methods in various domains. Table 2 contains the analysis of some studies in different domains with a comparison of their results.

In the first pathway, starting from the measured data, we first obtain the FBP image, and then use a neural network to suppress the artifacts produced by the FBP. Most of the deep learning methods focus on the image domain [2, 13–57] because this method is the most straightforward and mature. For example, [14] proposed the concept of residual encoder CNN (RED-CNN), which combined deconvolutional network, autoencoder and shortcut connection to realize LDCT imaging. [20] proposed a near-end front-rear splitting (PFBS) frame expansion method based on data-driven image regularization based on a deep neural network. A new and improved GoogLeNet was proposed to reduce the sparse view CT reconstruction artifacts in [51, 52]. [36] built a deep learning framework including convolutional neural network (CNN) blocks, residual learning, and exponential linear units (ELUs). In particular, the image quality was improved by the
Table 1: Analysis of medical cases using FDA-approved CT reconstruction systems

| References         | Reconstruction methods | Sample size | Results                                                                 |
|-------------------|------------------------|-------------|-------------------------------------------------------------------------|
| Benz et al. [9]   | ASiR-V 70% SD + HD    | 43          | Noise was lower in DLIR-H and higher in ASiR-V HD; Image quality higher for DLIR-M and DLIR-H (highest) compared to ASiR-V |
|                   | DLIR-M + DLIR-H       |             |                                                                         |
| GE healthcare     |                        |             |                                                                         |

| Canon medical systems | Hybrid-IR (AIDR3D) MBIR (FIRST) DLR (AiCE) | 46          | DLR has lowest image noise and highest CNR; DLR has highest image quality, while MBIR has lowest |

| Akagi et al. [10]  | Hybrid-IR (AIDR3D) MBIR (FIRST) DLR (AiCE) | 58          | DLR has lowest noise and highest CNR than hybrid IR; DLR has higher liver lesions scores |

| Nakamura et al. [11] | Hybrid-IR (AIDR3D) DLR (AiCE) | 30          | DLR has lowest image noise and highest CNR; DLR has best overall visual image quality |

| Narita et al. [12] | Hybrid-IR (AIDR3D) MBIR DLR (AiCE) |             |                                                                         |

Combination of the structural similarity loss index (SSIM) and the final objective function.

- Advantages: Direct image processing is the most straightforward solution in CT image reconstruction problems because there are already massive numbers of applicable models and technologies in this area. Deep learning-based methods can better learn and detect patterns automatically than conventional methods even without prior information, while conventional methods such as IR still have problems of high computational cost and presence of artifacts.

- Disadvantages: The outcomes of traditional methods such as FBP and IR have a significant impact on image domain DL methods since outcome images are initial images to be inputted to DL methods. Thus, it is difficult to retrieve the information lost from raw data or first step reconstruction.

The second approach is sinogram domain data inpainting, which preprocesses a neural network in a few-view sinogram domain and synthesizes it into a complete view sinogram [58–76]. Applying analytical image reconstruction algorithms such as filtered back projection (FBP) directly to sparse view data will result in poor image quality and serious fringe artifacts. People try to fill in the data which are missed to input the complete data into the image reconstruction process. Data synthesis with interpolation in the raw data domain is a simple example. Sinogram domain learning method tries to use a neural network to learn sensor domain interpolation and denoising. For example, [72] proposed a method to restore the angular resolution in the raw data domain according to the deep residual convolutional neural network (CNN), which can accurately estimate the projection of the unmeasured view. [76] proposed a projection domain denoising method based on a convolutional neural network (CNN) together with a filter loss function. In comparison to the denoising method in the image domain, the estimate of the noise level in the projection can be obtained with the measured value of every detector box. [73] used a network called Pix2Pix to complete the sparsely sampled sinogram, which was a conditional GAN structure.

- Advantages: Signal loss can be lowered and errors in sinogram can be adjusted in the first place, allowing the reconstruction procedure to start with a rather low-noise condition. As a result, methods in sinogram domain have higher robustness when dealing with errors.

- Disadvantages: However, if deep learning methods are restricted in sinogram domain, the shortcomings of conventional methods can still significantly affect the results of reconstruction in post-processing.

The third approach is to connect the first approach with the second approach [77–98]. In this type of method, the image quality is improved by introducing data consistency items when training the neural network. [83] proposed an improved dual-domain U-net (MDD-U-net), which used the combination of losses of sinogram domain together with image domain. [87] proposed an algorithm that combined a deep convolutional neural network (CNN) together with the wavelet transform coefficients of low-dose CT images, the
| References             | Reconstruction models          | Results (PSNR) | Comparisons and comments                                                                 |
|-----------------------|-------------------------------|----------------|------------------------------------------------------------------------------------------|
| **Image DOMAIN**      |                               |                |                                                                                          |
| Chen et al. [14]      | RED-CNN                       | 44.1024        | Baseline method                                                                         |
|                      |                               |                | Outperforms FBP and TV                                                                   |
|                      |                               |                | Outperforms FBP and ADS-POCS, efficiency lower than FBP but much higher than ADS-POCS   |
|                      |                               |                | Better than CNN3 and RED-CNN                                                            |
| Ding et al. [20]      | PFBS-AIR                      | 50.1927        |                                                                                          |
| Xie et al. [52]       | GoogLeNet                     | 49.67          |                                                                                          |
| Ma et al. [36]        | Deep CNN + Res + ELUs         | 43.0612        |                                                                                          |
| **Sinogram domain**  |                               |                |                                                                                          |
| Dong et al. [61]      | U-Net                         | 43.69          | The learning accuracy and efficiency is limited by the characteristics of U-net          |
| Lee et al. [69]       | U-Net                         | 48.68          | Outperforms FBP and POCS-TV, long training time                                          |
| Liu et al. [73]       | Pix2Pix (GAN)                 | Higher than interpolation | Good generalization ability over different patient sizes                                 |
| Feng et al. [83]      | Hybrid domain                 | 33.5127        | Better than BM3D                                                                          |
| Kang et al. [87]      | Wavelet CNN                   | Around 36      | Better than MBIR but over smoothing, low efficiency                                       |
| Kang et al. [86]      | WaveResNet                    | 38.70          | High convergence but low generalizability but low generalizability                       |
| Zheng et al. [97]     | CNN + U-Net                   | SSIM 93.30%    | Robust to different noise levels and datasets. Need fine-tuned if system changes         |
| **Direct transformation** |                             |                |                                                                                          |
| Zhu et al. [115]      | AUTOMAP                       | Best visual effect and t-SNE 31.9676 ± 6.0831 | Good results but low efficiency                                                         |
| Xie et al. [111]      | DEER                          | 50.9           | Low computational complexity, can be applied to other imaging modalities                 |
| Kida et al. [102]     | DCNN (U-Net)                  | 50.9           | Fast computation time; elimination of small intestines                                    |
| Kandarpa et al. [101] | DUG: double U-Net             | 50.9           | Less parameters needed, instantaneous reconstruction                                      |

**Table 2** Analysis of DL-based LDCT reconstruction methods in different domains
directional component of artifacts were extracted by directional wavelet transform, based on intra-band and inter-band correlation. [86] proposed a denoising algorithm which was frame-based using a wavelet residual network, this method utilized the deep learning’s expression ability with the performance guarantee of frame-based denoising algorithm. Apart from the wavelet method, [97] proposed a function optimization method with deep learning technology for this low-dose reconstruction problem, which combined the Radon inverse operator and unentangles every piece.

- **Advantages**: Hybrid domain applications can process both raw projections and post images using DL methods, thus reconstructed images can achieve higher quality compared to one-domain methods. It can recover images with smaller differences to the ground truth using two DL methods in distinct areas.
- **Disadvantages**: Dual-domain applications require much larger datasets since it has two training procedures, which certainly increases the computation complexity and training time.

The fourth approach is recently developed, through the intelligent CT network [99–116] to achieve image domain transformation. For example, in AUTOMAP, this data-image transformation method can directly convert measured data into reconstructed images [115]. However, the fully connected layers used in AUTOMAP made it not easy to be achieved in practice due to high dimensionality. [111] proposed a deep efficient end-to-end reconstruction (DEER) network for the reconstruction of breast CT images with few views. The reconstruction can be achieved by a neural network with only $O(N)$ parameters, in which $N$ was the number of images to be reconstructed. $O$ was side length. [102] was inspired by the idea of expanding the near-end gradient-based optimization algorithm to limited iterations, then instead of the near-end term, a trainable deep artificial neural network was used. It proposed an end-to-end solution that can be directly reconstructed from low-dose measurements to full-dose tomography image. [101] proposed a direct reconstruction framework specifically using deep learning architecture, which was built of three parts: denoising part, reconstruction part and super-resolution (SR) part. In the reconstruction part, a new dual U-Net generator (DUG) was used, to learn the conversion of symbolic images to images.

- **Advantages**: Direct transformation is the most advanced kind of method because it can automatically obtain information about features and complex patterns using numerous numbers of layers in deep neural networks.
- **Disadvantages**: The entire sinogram data as input to the network demands massive memory space and can cause a tremendous computational burden. The execution of high-dimensional measurements can be very challenging because of the high processing cost.

### Applications in different dimensions

In practice, radiologists can obtain pathological information with more accuracy and reliability by circulating adjacent slices. The three-dimensional reconstruction of the tumor by magnetic resonance (MR) or computer tomography (CT) scans shows key information that cannot be obtained in 2D images. Computed tomography works by taking hundreds or thousands of 2D digital projections around a 360-degree rotation of an object. Some specific algorithms are then can be used to reconstruct the 2D projections into a 3D CT volume, which can be viewed and sliced part at any angle. Whereas the resolution of CT and MR images in the z-direction is rather low, compared to the resolution in the x-direction and y-direction, so the quality of the three-dimensional reconstructed images is lower. Therefore, optimising the network and extending it from 2 to 3D or even 4D is a good opportunity for improvement, so that more structural details can be recovered by denoising models. 4DCT records multiple images over time. It allows playback of scans as a video so that internal movement can be tracked. In this case, 3D [32, 34, 49, 89, 97, 98, 117–123] and even 4D [59, 120, 124–126] applications have been proposed. For example, in [120], the end-to-end DeepOrganNet framework was based on the three-variable tensor product deformation technology. Smooth deformation fields were obtained from multiple templates, then lung models in 3D or 4D of various geometric shapes can be reconstructed efficiently and effectively. Using information-rich latent descriptors extracted from the input 2D image, [117] proposed to use of convolutional auto-encoders (CAEs) to solve this defect and developed an interslice interpolation (CARISI) framework based on convolutional auto-encoders.

### Applications in semi-supervised/unsupervised manner

Most of the deep learning methods used in image reconstruction belong to supervised learning. Supervised learning means that the neural network performs low-dose CT reconstruction by learning the mapping between noisy images and noise-free (or high-dose) labelled images. However, it is very difficult or even impossible to obtain noise-free labelled images. On the issue of low-dose CT, experiments that require two exposures using both low and high doses are rarely approved by the Institutional Review Board (IRB) because they greatly increase the radiation risk to the patient. Therefore, in the AAPM challenge, low-dose images are produced by inputting artificial noise to the full-dose projection...
Applications in unrolling dynamics

Unrolling dynamics approach is to unroll traditional reconstruction methods into deep learning frameworks so that both benefits from conventional iterative approaches and deep learning technologies can be combined. [80] used CNN for the unrolled iterative scheme in which a learned alternative minimization method acted as a forward operator in a deep neural network. [50] unrolled the proximal gradient descent algorithm for iterative image reconstruction to finite iterations where CNN was used instead of cost function, which significantly reduced memory required and training time. AirNet [77] combined analytic reconstruction (AR) and iterative reconstruction (IR) using modified proximal forward–backward splitting (PFBS). By unrolling PFBS into IR, AirNet included all the benefits from AR, IR and DNN. Metaln-Net [96] proposed a novel unrolling dynamics model which needed much less parameters to train because it only learned an initializer for the conjugate gradient (CG) algorithm without image priors and hyperparameter settings. The performance, efficiency and generalizability of Metaln-Net are superior.

The combination of DL models and conventional models provides better interpretability than DL models alone. Training with a small dataset can also be feasible because of the reduced amount of parameters needed in unrolling dynamics method. Referring to [96], various unrolling dynamics models have their own structures of image reconstruction subproblem and image denoising subproblem with or without learnable parameters. Table 3 introduces some different categories of different unrolling dynamics methods based on their designs of corresponding subproblems.

| References | Image reconstruction subproblem | Image denoising subproblem | Image prior |
|------------|---------------------------------|----------------------------|-------------|
| DUBLIND [141], ADMM-Net [142] | Least square problem (with parameters learned) | Soft-threshold (with parameters learned) | Learned |
| DnCNN [143], ADMM-CSNet [144] | Least square problem (with parameters learned) | CNN (with parameters learned) | Learned |
| AirNet [77], Computationally Efficient NN [50], PFBS-AIR [20] | Gradient descent (with parameters learned) | CNN (with parameters learned) | Learned |
| Metaln-Net [96] | Conjugate gradient (with parameters learned) | Soft-threshold | Handcrafted |
| PD-Net [145], FSR-Net [80] | CNN (with parameters learned) | CNN (with parameters learned) | Learned |

Other applications

In recent years, generative adversarial networks (GAN) have been extensively developed in the field of low-dose CT reconstruction [71, 73, 109, 118, 123, 127, 132, 134, 146–155]. In contrast to convolutional neural networks (CNNs) in patches, [147] proposed denoising networks which are FCN-based using images in full size for training, and because they reused the underlying feature maps, the computational efficiency was very high. In the training phase, the denoising network was included with a CNN-based classifier to ensure that the generated high-quality image is similar to the input image. The classifier combined the CT noise model to evaluate the...
consistency of the FBP reconstructed image and the denoising network image. Then, the entire network became a type of generative adversarial network (GAN) with this complementary structure. Another current trend applied more complex loss functions so that observed smoothing artifacts can be overcome [18, 54, 71, 95, 100, 109, 123, 129, 130, 134, 146, 150, 151, 154, 156–159]. Especially in [159], the loss function utilized in comparison has two pixel-level losses (mean square error and mean absolute error), the perceptual loss was based on the Visual Geometry Group network (VGG loss), and the one generated by Wasserstein for training gradient penalty adversarial network (WGAN-GP) adversarial loss, and their weighted sum. The evaluation results based on tSNR, NPS and MTF showed that CNN based on VGG loss was more effective in natural denoising of low-dose images than CNN without VGG loss. WGAN-GP loss can improve the noise-reducing effect of CNN based on VGG loss.

What is more, [160] proposed a sparse reconstruction framework (aNETT) for solving inverse problems. [161] proposed quadratic neurons in which the inner product in current artificial neurons was replaced with a quadratic operation on inputs, thereby enhancing the capability of an individual neuron. Then it used quadratic neurons to construct an encoder-decoder structure, referred to as the quadratic autoencoder, and apply it for low-dose CT denoising. [162] proposed an approach that employed deep reinforcement learning to train a system that can automatically adjust parameters in a human-like manner during optimisation. Other than medical application, [163] explored the use of deep learning techniques for the reconstruction of baggage CT data and compared these techniques to constrained reconstruction methods (Table 4).

**Advantages and disadvantages of using deep learning methods**

According to reviews, several advantages of deep learning-based image reconstruction are closely related to the shortcomings of conventional reconstruction methods [2–7].

(a) The reconstruction results of conventional methods are always restricted to lack of prior information, while prior knowledge is not necessary for DL-based techniques, they are more robust and generalizable. However, additional prior information can help deep learning-based methods achieve better results.

(b) Compared to conventional methods, deep learning-based methods have the capability to deal with a massive amount of data and learn complex patterns.

(c) Deep learning-based approaches are capable of real-time reconstruction so that the diagnosis time can be reduced due to its higher efficiency.

Despite the fact that the DLR algorithm appears to be quite effective at enhancing image quality, there are still some limitations or concerns to be addressed [2–7].

(a) Unlike the clear theoretical understanding of traditional technologies, the deep learning algorithm’s decision-making mechanism is a black box. The intricacy of neural networks is enormous, particularly in the realm of CT image reconstruction. Even if the DL image reconstruction method produces the right image, its rationale could be flawed.

(b) Traditional approaches might be simpler to implement, while DL methods require a complex design of the network and are challenging to train. Choices of parameters (and hyperparameters) are crucial in both ways and demand a significant amount of computation.

(c) The results of deep learning-based methods can be significantly affected by a little change in parameters. The robustness, together with convergence remain unanswered in DL approaches.

(d) The training process of deep learning-based methods could be a much lengthier time than traditional approaches, a small modification may result in a restart of training.

It’s not easy to solve the problem of unreliability. To be adopted with confidence, deep learning methods need to be lawful, ethical and robust [164]. Data used for training must be correctly priced, and transactions with AI firms must be consolidated. Companies must clearly specify their policies on anonymization and consent, and patients must fully understand how their data will be used. To make data capable of artificial intelligence, it must first be cleansed, purified, digitized, and centralized before being fed into algorithms. Finally, data should indicate properties on behalf of demographics. Before applying deep learning algorithms, they must be approved by a health authority to be adequately supervised. Protocols for error duties supervised and unsupervised AI roles and equitable workforce distribution (between AI and radiologists) should be established, with agreements updated at predetermined intervals. If any errors occur, a thorough error analysis should be performed, and the results should be communicated to firms. This ethical training and integration can lead to deep learning technology that is dependable and trustworthy in the application of medical imaging.

**Effects of using deep learning methods**

According to several comparisons and phantom studies [107, 165–179], DL-based image reconstruction is superior to other conventional reconstruction techniques for image quality and lesion detection.
Table 4 An overall summary of reviewed studies

| Groups                  | Introduction                                                                 | Works                                                                 | Number of works |
|-------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------|-----------------|
| Image domain            | Use neural networks to optimise reconstructed image                          | [2, 13–57]                                                           | 45              |
| Sinogram domain         | Use neural networks to interpolate sinogram                                  | [58–76]                                                              | 19              |
| Hybrid domain           | Neural networks applied in both sinogram and image domains                  | [77–98]                                                              | 22              |
| Direct transformation   | Directly transform raw data into images                                      | [99–116]                                                             | 18              |
| 3D/4D                   | Gain spatial and temporal information in CT images                           | [32, 34, 49, 89, 97, 98, 117–123], [59, 120, 124–126]                  | 18              |
| Semi-supervised/unsupervised | Neural networks training without reference or with small reference pairs | [39, 66, 74, 127–140]                                               | 17              |
| Unrolling dynamics      | Unroll traditional reconstruction methods into deep learning frameworks      | [20, 50, 77, 80, 96, 141, 145]                                       | 7               |
| GAN                     | Generative adversarial networks-based methods                               | [71, 73, 109, 118, 123, 127, 132, 134, 146–155]                       | 18              |
| Loss functions          | Use more sophisticated loss functions in Neural networks                    | [18, 54, 71, 95, 100, 109, 123, 129, 130, 134, 146, 150, 151, 154, 156–159] | 18              |
| Others                  | Other applications                                                          | [160–163]                                                             | 4               |
[180] proposed a Discriminative feature representation (DFR) approach with good adaptability to various CT systems because it can be directly applied to DICOM image without the need for raw measurement data. DFR outperformed iterative TV reconstruction in visual and quantitative results which showed its good robustness and performance. A 3D feature constrained reconstruction method (3D-FCR) based on 3D feature dictionary was proposed in [181]. By assessing its performance with 3D-TV method on simulated and clinical experiments, PSNR of 3D-FCR gained 40.82 while 3D-TV was 36.59. The DIRE network [34] was trained to learn the mapping from low-dose analytically reconstructed images to normal-dose IR reconstructed images. Compared with FBP, RED-CNN and ResNet, DIRE achieved the best PSNR and SSIM indexes while FBP had the worst. [182] proved the feasibility of the proposed material-decomposition-based deep learning model using two independent data groups while both groups showed significant improvement compared to standard dual-energy CT imaging. DP-ResNet [183] combined the traditional FBP reconstruction method with network processing in both sinogram domain (SD-net) and image domain (ID-net). Comparing to FBP, TV, S-DFR and RED-CNN, the proposed DP-ResNet provided better image quality than the other four approaches and still be quite efficient in practical applications.

[179] compared the image and diagnostic qualities of a DEep Learning Trained Algorithm (DElTA) for half-dose contrast-enhanced liver computed tomography (CT) with those of a commercial hybrid iterative reconstruction (HIR) method used for standard-dose CT (SDCT). The results showed that the noise of LDCTDL was significantly lower than that of SDCTHIR and LDCTHIR. The SNR and CNR of LDCTDL were significantly higher than those of the other two groups, LDCT with DELTA had approximately 49% dose reduction compared to SDCT with HIR while maintaining image quality on contrast-enhanced liver CT. [169] compared the image noise characteristics, spatial resolution, and task-based detectability on deep learning reconstruction (DLR) images and those images reconstructed with other state-of-art techniques. On images reconstructed with DLR, the noise was lower than on images subjected to other reconstructions, especially at low radiation dose settings. The image noise was lower on DLR images, and high-contrast spatial resolution and task-based detectability were better than on those images reconstructed with other state-of-art techniques.

Conclusions and future work

It will undoubtedly confront more and more problems when deep learning is applied more extensively in the field of low-dose CT image reconstruction.

As we have mentioned earlier, DL methods are capable of processing a huge amount of data and extract complex patterns from it. On the other hand, a small sample size can be a severe issue in the field of low-dose CT reconstruction, performance of network training and results of DL methods in such case become unreliable and even worse than conventional analytical methods. The following machine learning algorithms (not limited to these methods) have the potential to solve this problem: (1) unsupervised learning: can address the fine labeling problem; (2) transfer learning: applying current machine learning models or knowledge of related modalities and diseases to new tasks; (3) one-shot learning; (4) self-supervised learning; and (5) gradual learning.

In supervised learning-based technologies, normal dose projection data which still contains unavoidable missing raw measurements and error signals is considered to be the ground truth data, resulting in the reduction of reconstructed image quality. What is more, data labeling of CT images is also a challenge that greatly limits the wide and in-depth application of deep learning, it is very challenging to acquire labelled data pairs in clinical practice considering the radiation risk exposed to patients. In reviewed supervised studies, their used clinical data for training is usually from several public datasets such as NBIA/NCIA dataset [184], AAPM-Mayo dataset, piglet dataset [185], etc. To obtain paired low-dose measurements, earlier studies tend to add artificial noises such as Gaussian noise to normal-dose projection data to generate the simulated paired dataset. The quality of the training dataset directly affects the performance and efficiency of DL reconstruction methods. As a result, the proposal of new and reliable unsupervised learning-based DL methods is empirical in the future development of low-dose CT reconstruction.

Current DL frameworks are usually too generic and not finely tuned for specific situations. The topology and structure of deep learning networks can be improved by resolving those different key problems in corresponding applications. In another point of view, the generalizability of DL methods has a crucial impact on their adaptability and usefulness in practical use. Thus, it is vital to propose novel deep learning-based methods that can be applied to different datasets, noise
levels, various scanners and vendors, and different organs and parts of the body while remaining reliable in all cases in the future. Furthermore, generalizability can be improved by making use of feature similarity in data obtained across different modalities, which can also reduce the amount of radiation needed for patients. Hence, inter-modality image reconstruction technologies, such as MR/CT, and CT/PET have become a rising topic and further study in this field is needed.

In addition, interpretability is critical in the use of CT image analysis. Improving the interpretability of deep neural networks in diverse tasks of CT image analysis has always been a difficult problem. It is also vital to understand how to construct human–machine collaboration medical therapy. The lightweight deep neural network is simple to deploy to portable medical equipment, allowing portable equipment to perform more powerful functions, which is also an area worth investigating.

The final goal of reconstructing the noise-free images is to obtain the most accurate diagnosis and prediction. Other than reconstructing high quality images from limited raw measurements, LDCT technology can also be applied to some clinical tasks. Because of its efficiency and convenience of use, LDCT-based cancer screening is now widely used. [186] proposed a multi-dimensional nodule detection network (MD-NDNet) for the increase of pulmonary nodule detection accuracy, since nodule detection plays an important role in early-stage lung cancer screening. There are two steps in automatic nodule detection: the detection of possible nodules and the reduction of false-positive identification. Low-dose measurements may cause raise in the number of false-positive candidates thus lead to less accurate diagnosis results. Through experiments with LUNA16 data, MD-NDNet obtained a CPM score of 0.9008 which showed accurate and reliable results. Another task is the segmentation of various body structures, such as bones, and spine. The detected labelling of segmented, say composition of bones, may be able to offer somewhat accurate reference of other human organs, enabling furthermore analysis. [187] presented a completely automatic system for segmenting and identifying specific bones framework based on LDCT chest images and achieved highly accurate results. The denoising deep-learning-based algorithms in LDCT methods can also be used in other subtle imaging applications. For example, a deep CNN based on residual learning (DeSpecNet) [188] was proposed to reduce speckle in retinal optical coherence tomography images. When applied to OCT pictures, the suggested technique resulted in significant improvements in both visual quality and quantitative indicators. In terms of more applications in clinical trials, [189] presented an evaluation model for input image based on a composition of a fuzzy system combined with a neural network and reached 92.56% accuracy of prediction. Adaptive Independent Subspace Analysis (AISA) method [190] was capable to discover meaningful electroencephalogram activity in the MRI scan of brains while a novel correlation learning mechanism (CLM) method was proposed in [191] for evaluation of CT brain scans. Apart from that, it is considered to skip the image reconstruction step and obtain classification or prediction of diagnosis and treatment directly from raw measurements. Furthermore, concentrating on task-specific performance guarantees that every computation work is dedicated to task-specific training but not the unneeded intermediary phase of image reconstruction [4].

In conclusion, deep learning has produced outstanding results in a variety of CT imaging jobs, but a further in-depth study in such as unsupervised-manner methods and 3D/4D reconstruction applications is required to enable the widespread application of intelligent diagnosis and treatment solutions based on CT imaging.

**Declarations**

**Conflict of interest** The authors declare that there is no conflict of interest.

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