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Review

A survey on deep learning in medical image reconstruction

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ABSTRACT

Medical image reconstruction aims to acquire high-quality medical images for clinical usage at minimal cost and risk to the patients. Deep learning and its applications in medical imaging, especially in image reconstruction have received considerable attention in the literature in recent years. This study reviews records obtained electronically through the leading scientific databases (Magnetic Resonance Imaging journal, Google Scholar, Scopus, Science Direct, Elsevier, and from other journal publications) searched using three sets of keywords: (1) Deep learning, image reconstruction, medical imaging; (2) Medical imaging, Deep learning, Image reconstruction; (3) Open science, Open imaging data, Open software. The articles reviewed revealed that deep learning-based reconstruction methods improve the quality of reconstructed images qualitatively and quantitatively. However, deep learning techniques are generally computationally expensive, require large amounts of training datasets, lack decent theory to explain why the algorithms work, and have issues of generalization and robustness. The challenge of lack of enough training datasets is currently being addressed by using transfer learning techniques.

1. Introduction

Medical imaging modalities like computed tomography (CT), magnetic resonance imaging (MRI), X-ray, and ultrasound have been used in medicine to image body extremities, organs, and other tissues. However, images acquired from these imaging modalities may suffer from low signal-to-noise-ratio (SNR) and low contrast-to-noise ratio (CNR) along with image artifacts [1]. Image reconstruction techniques have been developed to overcome these challenges and to improve the quality of images for better visual interpretation, understanding, and analysis. Deep learning (DL) techniques have been used successfully in medical imaging, among others for radionics, computer-aided detection and diagnosis, and medical image analysis [2–3]. Deep learning, also called representation learning [4], has attracted much attention in the recent past for medical image analysis [5]. Deep learning is far superior when compared to the traditional machine learning methods because it can learn features from raw input data during training. It has multiple hidden layers that enable it to learn abstractions based on inputs [6]. The recent developments in efficient computational infrastructures such as graphical processing units (GPUs) and cloud computing systems have accelerated the use and applications of deep learning in various fields [3] including medical image reconstruction.

Image reconstruction is the formation of an image from measurements. The process of image reconstruction involves a sensor encoding, i.e., the representation of an object in the sensor domain which is then converted into an image by inversion of the encoding function. Image reconstruction is a challenging task because the analytic knowledge of the exact inverse transform may not exist a priori, especially in the presence of sensor non-idealities and noise [7]. "Conventional approaches for image reconstruction are imperfect because knowledge of the exact inverse transform is not always possible. They also require the use of approximations by chains of highly tuned signal-processing modules, which can be error-prone, especially for realistic, noisy data" [7]. Deep learning techniques will revolutionize the process of image reconstruction [8]. Moreover, deep-learning-based techniques improve the speed, accuracy, and robustness of medical image reconstruction.

The main goal of this study is to review the current applications of deep learning in medical imaging, in particular for medical image reconstruction. We focused on open science medical imaging research, the currently available open imaging data sets for deep learning, and also on the open-source software packages that are available for medical image processing. A lot of research has been done that explains in detail the deep learning techniques and their applications; however, there is a scarcity of research publications that provide a review of the ap-

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plications of deep learning in medical image reconstruction. The study [9] gives an extensive review of deep learning in medical image reconstruction but the paper focuses more on the mathematical models of several deep learning algorithms in medical image reconstruction. In contrast, the focus of this paper is on the reviews of the applications of different deep-learning algorithms and architectures in medical image reconstruction.

The rest of the article is organized as follows. In section 2, the methodology used during literature selection is explained. Section 3 gives an overview of deep-learning applications in medical imaging. Section 4 gives open source tools and datasets for deep learning research. Section 5 discusses our findings, and also makes concluding remarks.

2. Methodology

This study employs a preferred reporting items for systematic reviews and meta-analyses (PRISMA)flow diagram and protocol [6], for the identification of the relevant research articles that are discussed in this paper. The four main phases involved include: (1) identification phase, this phase involves acquiring articles from various sources; (2) the screening process, during this phase, article duplicates were excluded and also inadequate articles were removed; (3) eligibility phase, we analyzed the articles to determine their eligibility for further review and ineligible articles were excluded; (4) the final phase also called the included phase, articles that are included in this study were analyzed during this phase.

3. Overview of deep learning

Deep learning techniques have their roots in artificial neural networks (ANNs) [4]. Deep learning became popular in 2012 when a DL-based technique won an overwhelming victory in the computer vision competition [2]. More so, deep-learning techniques improved their performances since 2010 and by 2015, they had exceeded human accuracy during large-scale visual recognition challenges [3]. Deep learning learns image data directly while traditional techniques require human intervention for feature extraction [2,4]. A more general overview of deep learning can be found in the studies [2-4, 6,10-12].

3.1. Deep learning applications in medical imaging

Medical images have been used in disease diagnosis and therapy since their discovery. Image processing techniques have been used to improve the quality of the images through tasks such as contrast enhancement and also in image analysis to aid in the interpretation of the images by clinicians. Automatic and semi-automatic methods of image analysis relieve the human operators from tedious tasks of image interpretation thereby saving time, improving accuracy, and increasing the reliability of the interpretation task needed to carry out a medical procedure by the clinicians [13]. Deep learning has been currently used with success for medical image analysis tasks such as classification, segmentation, and registration [14]. More information on the application of deep learning in medical imaging can be found in [3,10,15-18].

3.2. Image reconstruction techniques in medical imaging

The study [8] shows that the field of medical image reconstruction has experienced three phases of development as discussed in Table 1 below.

3.3. Medical image reconstruction using deep learning

Existing literature on deep-learning applications in medical image reconstruction is scarce. Researchers believe that since machine learning has been successfully applied for image processing tasks like segmentation, classification, edge detection, and super-resolution, it can be useful for medical image reconstruction as well. The major objective of our study is to review the existing literature on medical image reconstruction. Related studies on medical imaging can be found in [8, 9, 19–22]. In the following section, we review the deep-learning applications in image reconstruction for MRI, CT, positron emission tomography (PET), and ultrasound imaging.

3.3.1. Deep learning in MRI

Deep learning techniques particularly convolutional neural networks (CNNs) have been used in medical imaging modalities including MRI. The image reconstruction in MRI is done using data obtained in the frequency domain, also called the k-space. All the information required to reconstruct an image is contained in k-space data and it also gives a comprehensive way of understanding and classification of the method of reconstruction and imaging properties [23]. The signals with low frequencies are arranged in the center of the k-space and these low frequencies signals contain contrast information. The signals with high frequencies in the k-space data are spaced outside the center, and these high-frequencies signals contain information about spatial resolution or sharpness. Currently, image reconstruction is undergoing a paradigm shift. Traditional transform-based or optimization-based methods have dominated image reconstruction. Of recent, data-driven machine learning methods, in particular deep learning, have demonstrated a significant potential for image reconstruction over traditional methods. Deep learning techniques such as CNNs have been used for image reconstruction in MRI. Many deep learning frameworks like AUTOMAP [7] have been proposed and experimental results have demonstrated high-quality image reconstructions over traditional and compressed sensing-based reconstruction methods. The issue of large amounts of training data required has been solved by reducing the number of trainable parameters [24–25]. However, several limitations have also been identified such as the existing techniques being computationally expensive [7], some frameworks do not apply to parallel imaging [29], and theoretical analysis is still needed to explain why the algorithms work [24]. The summary of some of the articles reviewed is shown in Table 2 below.

3.3.2. Deep learning in CT

Image reconstruction in CT is done using projection data. Filtered back projection (FBP) algorithms produce high-quality images when the projection data are sufficiently complete. However, some applications like the reduction of the scan time, decrease of the X-ray radiation which may expose patients to other health risks, scanning of some long objects with limited angular range, may result in incomplete projection data and therefore FBP algorithms may not be appropriate. Also, iterative methods like total variation (TV)-based methods produce good quality reconstructions from incomplete projection data but some artifacts appear on the edges of the reconstructed image when the projection data are acquired from the limited-angle CT, in addition to staircase effects or blocky artifacts that may appear in the reconstructed image. Currently, deep learning approaches have been used to address those challenges [56]. Deep learning frameworks for image reconstruction in CT include DEAR [57], PYRO-NN [58], LEARN [59], Improved GoogLeNet [60], among others. Also, several other studies report accurate image reconstructions when compared to the existing traditional approaches [61]. These deep learning approaches have been used in two-dimensional (2D) and three-dimensional (3D) reconstructions, effective in reducing noise, enhancing the spatial resolution, and perform faster on graphical processing units (GPUs). The summary of some of the articles reviewed is given in Table 3 below.

3.3.3. Deep learning in PET

Positron emission tomography (PET) is used in research, clinical and industrial applications. It is also used in cancer care for more precise diagnosis and staging, which is correlated with early treatment and

Table 1 Techniques used in medical image reconstruction

Phase	Techniques used	Strength	Limitations
First phase	Analytical methods e.g. the inverse Fourier transform and the filtered back-projection method (FBP)	They are efficient	Requires proper sampling
Second phase	Iterative methods e.g. combination of wavelets and total variation	The statistical and physical properties of the imaging device are considered	Discrepancies between the model and physical factors e.g. inhomogeneous magnetic fields
Third phase	Data-driven and learning-based methods e.g. deep learning and dictionary learning methods	Images can be reconstructed from poor quality data using learned signal models	They are not computationally efficient and require large sets of training data

Table 2 Overview of papers using deep learning techniques for image reconstruction in MRI

References	Brief overviews
[7]	A deep learning framework for MR image reconstruction called AUTOMAP. It is accurate when compared to conventional methods. However, it is computationally intensive.
[24]	An approach to restoring high-resolution MR images from under-sampled k-space data. It performs better than the existing compressed sensing algorithms.
[25]	An approach for faster MRI reconstructions by reducing k-space data with sub-Nyquist sampling strategies. Theoretical analysis is still needed to explain why the algorithm works and it also has high complexity.
[26]	A reconstruction method using severely undersampled dynamic cardiac MRI data. It is 2x faster than compressed sensing-based methods. However, it does not apply to parallel imaging.
[27]	An approach using transfer learning for MR image reconstruction. Results demonstrated the applicability of transfer learning in MRI reconstruction to supplement scarce training data.
[28]	A DNN model for image reconstruction from subsampled MRI scans. It can also be used for image denoising and super-resolution. However, not all image properties are explicitly exploited.
[29]	A deep learning model for reconstructing perceived stimuli from brain responses in fMRI. It is also suitable for the development of new neuroprosthetic devices.
[30]	Several DL methods for MR image reconstruction were discussed. Accurate reconstructions were obtained.
[31]	An end-to-end framework for super-resolution MR reconstruction. Good quality images are reconstructed from noisy, low-resolution clinical MRI scans.
[32]	A CNN architecture for high-quality cardiac MR image reconstruction from highly undersampled k-space data.
[33]	The proposed method outperforms current MR reconstruction methods in terms of reconstruction accuracy and speed.
[34]	A model for extracting nonlinear features from visual images, and also robust in capturing correlations among voxel activities of fMRI recordings. However, there is still a need to incorporate RNN in the current framework can help to explore the reconstruction of dynamic vision.
[35]	An end-to-end reconstruction model for fMRI. Its drawback is the information in the decoded features is not all the visual information that can be decoded from the brain.
[36]	A model that combines the mathematics of variational models with DL. The model outperforms the standard reconstruction algorithms. Different choices of error metrics still need to be investigated.
[37]	An approach for denoising and data consistency enforcement during image reconstructions. It does not require a lot of training data due to a reduction in trainable parameters.
[38]	A method for MR image reconstruction using DNN. Assigning lower weights to noisy the noisy training images in the weighted loss function improved the image quality of the reconstruction.
[39]	A model for image reconstruction in parallel MRI. The study further revealed the existence of many open problems and high-impact applications of deep learning in the medical imaging community.
[40]	An approach for MR image reconstruction using deep cascaded CNN. The results show improved quality of reconstructed images when compared to other deep networks of similar complexity.
[41]	Two categories of deep learning-based approaches were analyzed i.e. those that are based on unrolled algorithms and those that are not. Also, several signal processing tasks where DL can be applied was discussed especially in fast MRI image reconstruction.
[42]	Several deep learning frameworks for image reconstruction in MRI were proposed. Results revealed improved reconstructions when compared to the existing methods.
[43]	Bayesian deep learning (DL) technique to model the uncertainty associated with DL-based reconstructions. The proposed method achieved competitive results and outperformed the baseline method.
[44]	Deep learning frameworks for image reconstruction in MRI, CT, and imaging other modalities were proposed. Results showed improved reconstructions when compared to the existing methods.
[45]	Deep learning frameworks for image reconstruction in MRI, CT, and imaging other modalities were proposed. Results showed improved reconstructions when compared to the existing methods.
[46]	A model for image reconstruction using deep neural networks. The model addressed the computational complexity of compressed sensing-based methods.
[47]	A framework for MR image reconstruction from undersampled k-space data. The framework is also robust to noise.
[48]	A deep learning framework 2D MRI reconstruction from undersampled data. Good quality reconstructions were obtained at the 11-fold undersampling preserving anatomical structure.
[49]	A model is known as DAGAN for image reconstruction in MRI. Superior reconstructions with preserved image details when compared to other existing DL approaches.
[50]	A deep learning model for fMRI image reconstruction from the activities of the human brain. Hierarchical neural representations were effectively combined to reconstruct perceptual and subjective images.
[51]	A CNN model for high-quality MR image reconstruction from undersampled k-space data. In terms of restoring tissue structures and removing aliasing artifacts, the model performed better than the existing conventional methods.
[52]	A deep learning model for fast and accurate CS-MRI reconstruction. There is still a need to understand the architecture of the proposed method.
[53]	A deep learning framework for the CS-MRI inversion problem. Results show that the proposed model achieves consistently improves a variety of CS-MRI inversion techniques.
[54]	A hybrid CNN model for compressed sensing reconstruction of MR images. Visual assessments of the images reconstructed are similar to the fully sampled reconstruction reference.
[55]	A method for fast MRI reconstruction. High-quality MR images were used as the training datasets. Results reveal efficient and accurate reconstructions.

MRI: magnetic resonance imaging; MR: magnetic resonance; CNN: convolutional neural network; fMRI: functional magnetic resonance imaging; CT: computerized tomography; CS-MRI: compressed sensing magnetic resonance imaging; DNN: deep neural network; 2D: two-dimensional.

Table 3 Overview of papers using deep learning techniques for image reconstruction in CT

References	Brief overviews
[56]	An image reconstruction framework based on U-net. It is superior to noise and angle artifacts while preserving the image structures but it is computationally expensive and requires large training datasets.
[57]	A framework called DEAR for 3D CT image reconstruction from few-view data. However, more experiments to optimize and validate the DEAR-3D network are required.
[58]	A framework based on Tensorflow for iterative reconstructions with data from real CT systems. The limitation is that it requires graphical processing units (GPUs).
[59]	A framework called LEARN for CT reconstruction. It improves both image quality and computational efficiency. There is still a need to optimize the framework for clinical applications.
[60]	An Improved GoogLeNet for removing streak artifacts in sparse-view CT reconstruction. The method is effective in reducing the artifacts and preserving the quality of the reconstructed image.
[62]	A deep learning framework for high-quality reconstructions in CT. The framework can differentiate and remove noise from the input signal.
[63]	An algorithm for image reconstruction in CT scans. High-quality results were obtained when compared to iterative methods. However, the algorithm needs to be validated with a bigger population.
[64]	A CNN framework for streak removal from CT images during reconstruction. The framework requires more training to distinguish between artifacts and features.
[65]	A model based on CNN for the CT reconstruction process. High-quality reconstructions were obtained. However, more training data is required for more accurate and reliable performance.
[66]	A model for improving image quality in CT. However, the model needs to be tested on polyenergetic low-intensity data since monoenergetic was used.
[67]	A DNN framework for image reconstruction in sparse-view CT. The framework performed better than the existing methods in terms of image quality. More work on the application of this framework in fan-beam CT, cone-beam CT, and helical multiple fan-beam CT.
[68]	A framework called DIRE, based on 3D residual convolutional network architecture. More clinical datasets are still required for an in-depth assessment.
[69]	A model based on Wasserstein generative adversarial networks for the 2D CT slice image reconstruction method from a limited number of projection images. The model needs to be validated by expert radiologists.
[70]	A CNN-based method for image reconstruction in sparse view computed tomography. Results reveal improved visual quality results and also preserves image structures as well as diagnostic details.
[71]	A deep learning method for image reconstruction in CT. Results show better performance compared to hybrid iterative reconstruction methods. However, it needs to be validated with different clinical trials.
[72]	A method for sparse-data CT reconstructions. Results reveal quality performance in terms of artifact reduction, feature preservation, and computational speed. The method needs to be optimized for clinical applications.
[73]	A method for a few-view CT reconstruction with a lightweight structure. It directly learns an end-to-end mapping between a few- and full-view image optimization.
[74]	A model that integrates deep learning with the Model-Based Iterative Reconstruction method. The model improved image quality reconstructions at a minimal computational cost.
[75]	A framework for image reconstruction using incomplete data in CT was proposed. Improvement of the model with advanced methods was recommended.
[76]	A deep CNN model for mapping low-dose CT images towards their corresponding normal-dose counterparts in a patch-by-patch fashion. Results reveal an improved performance in terms of image quality and reconstruction speed over iterative and patch-based methods.
[77]	The model is a relaxed version of projected gradient descent (PGD). Results reveal an improved performance over the existing methods.
[78]	A deep learning model is known as SIPID that combines sinogram interpolation with image denoising. The model can be adapted to other types of CT reconstruction approaches.
[79]	A deep learning model for high-quality image reconstructions from sinogram data. It is effective in reducing noise, enhancing spatial resolution, and fast without loss of quality.
[80]	A deep learning method suitable for solving ill-posed inverse problems in parallel beam X-ray computed tomography. The model outperformed total variation-regularized iterative methods.
[81]	A deep learning model for high-quality three-dimensional (3D) reconstructions under sparse sampling conditions. The SSIM values of sparsely sampled CT reconstruction were 0.85 or higher.
[82]	A deep-learning method for image reconstruction in CT. Results reveal improved image quality with reduced image noise when compared to other state-of-the-art techniques.
[83]	A deep learning model for computed tomography (CT) data processing in sinogram-space while bypassing the image reconstruction step. The model made it easy to analyze and interpret sinograms that are virtually impossible for human experts.

3D: three-dimensional; CT: computed tomography; CNN: convolutional neural network; DNN: deep neural network; PGD: projected gradient descent

better patient outcomes. Tomographic PET projection data, also called sonograms, cannot be interpreted by a human observer, but must first be reconstructed into images. The most common reconstruction methods in PET include analytical filtered back-projection (FBP) and iterative maximum-likelihood methods [84]. However, these methods suffer from data inconsistencies, data mismatches, and data over-fitting which results in artifacts like noise and streaks in the reconstructed images. These drawbacks have been addressed by using machine learning-based methods, in particular deep learning techniques. Experimental results with deep learning methods reveal lower noise, reduced ringing, and partial volume effects, as well as sharper edges and improved resolution [84-89]. The summary of some of the articles reviewed is shown in Table 4 below.

3.3.4. *Deep learning in ultrasound imaging systems*

Currently, there is a high demand for high-quality reconstructions from a limited number of radio-frequency measurements in ultrasound imaging systems. Due to the presence of side lobe artifacts from the radio frequency sub-sampling, the standard beamformer produces blurry images with less content which are unsuitable for clinical use [90]. Compressed sensing methods have been used to address those challenges but they require either computationally expensive algorithms or changes in hardware and also the quality of the reconstructed images is limited. Deep learning methods have demonstrated high-quality image reconstructions in ultrasound imaging. Some studies [90-94] showed the succees in applying deep learning in medical image reconstructions; these studies reported significant improvements in reconstruction quality when compared to the existing state-of-art methods(Table 5).

3.3.5. *Deep learning frameworks for image reconstruction in other imaging modalities*

Deep learning methods have been used for image reconstruction in other imaging modalities like in fluorescence microscopy [95], photoacoustic tomography (PAT) [96], optical microscopy [97], diffuse optical tomography (DOT), electromagnetic tomography (EMT) [98], monocular colonoscopy [99], holographic image reconstruction [100],

Table 4 Overview of papers using deep learning techniques for image reconstruction in PET

References	Brief overviews
[84]	An encoder-decoder-based framework for image reconstruction in PET. The limitation is that synthetic data was used instead of real patient data.
[85]	A method for dynamic PET image reconstruction. U-Nets were combined in parallel for deep images prior. Results reveal the excellent performance of the method when compared to the conventional methods.
[86]	A framework based on auto-encoder for dynamic PET imaging. There is still a need to validate the method with PET images from different tissues.
[87]	A model based on CNN for improved PET reconstructions. However, better network training approaches need to be explored as well as further evaluations using more clinical datasets.
[88]	A framework for iterative PET reconstruction using denoising CNN a local linear fitting function to address the disparity of noise levels. It outperforms total variation based on conventional methods.
[89]	A model for the post-reconstruction step for reducing reconstruction artifacts. Results reveal lower noise, reduced ringing, and partial volume effects, as well as sharper edges and improved resolution.

PET: positron emission tomography; CNN: convolutional neural network

Table 5 Overview of papers using deep learning techniques for image reconstruction in ultrasound

References	Brief overviews
[90]	An approach for accelerated B-mode ultrasound imaging. There was a significant increase in PSNR, CNR, and SSIM when compared to other existing methods.
[91]	A deep learning-based tool known as WaveFlow. Data obtained from wire and cyst phantoms were used to evaluate the tool. The tool can run on both GPU and CPU.
[92]	A DNN method to address the challenge of poor image quality in ultrasound. The DNN model had the best CNR. The limitation was that DNN training needs to be refined.
[93]	A model for image reconstruction ultrasound imaging. The model improves the vector flow estimations in more challenging environments where the analyzed displacement spans a large dynamic range.
[94]	A generative adversarial network (GAN) framework for ultrasound image reconstruction. The proposed framework reconstructed ultrasound images with improved quality.

GPU: graphics processing unit; CPU: central processing unit; DNN: deep neural network; GAN: generative adversarial network

Table 6 Overview of papers using deep learning techniques for image reconstruction in other modalities

References	Brief Overviews
[97]	The study provided an overview of DNNs in optical microscopy. Results revealed that DNNs improve the quality of image reconstruction in optical microscopy.
[98]	A method for solving imaging problems in electromagnetic tomography (EMT). The preliminary results verify its feasibility.
[99]	A framework for depth estimation from monocular colonoscopy images. There is a need to validate the framework using better validation schemes and clinical studies.
[106]	A model that combines transfer learning and DL for super-resolution reconstruction in medical imaging. Better results were obtained when compared to other conventional methods.
[107]	An image reconstruction model using diffuse optical tomography (DOT) projection data. There is a need to validate the model clinical scenarios.

DNNs: deep neural networks; EMT: electromagnetic tomography; DL: deep learning; DOT: diffuse optical tomography

stochastic microstructure reconstruction [101], reconstruction of neural volumes [102], neutron tomography [103], coherent imaging systems [104], tomographic 3D reconstruction of a single-molecule structure [105], and the integration of deep and transfer learning in imaging [106]. Table 6 shows deep learning frameworks for image reconstruction in other medical imaging modalities.

3.4. Current challenges of deep learning in image reconstruction

The application of deep learning techniques in medical image reconstruction is growing and high-quality results have been reported in the literature. Better quality images are obtained while using deep learning than when compared to analytical, iterative, and compressed sensing methods. However, various issues have been hindering its progress. These include: the issue of generalization and robustness, the theoretical analysis of how deep learning methods achieve results is still required, they are computationally expensive, and require a lot of training data when compared to the compressed sensing algorithms and other existing methods [17, 108]. The issues of large training data and computational expensiveness are being addressed by using transfer learning and special computing devices like graphical processing units (GPUs) respectively. In the following section, we discuss the issues of generalizability, stability, and training data in detail.

3.4.1. Generalizability

Generalization means how good a model is at learning from a given data and applying the learned model elsewhere. Generalizability is a concern when applying a deep learning model trained on one dataset to other datasets. Training a universal model that works anywhere, anytime, for anybody is unrealistic. Generalizability may be a significant problem when applying a trained deep learning model to datasets from another vendor's scanners [109]. The study further revealed that transfer learning may help to address the issue by fine-tuning the trained source model to the target domain dataset. Also, the study [110] proposed numerical generalization guarantees for deep learning, and also the theoretical insights on how and why can generalize well. The study of investigating how norm-based control, sharpness, and robustness drives generalization in deep networks revealed that some combination of expected sharpness and norms seem to capture much of the generalization behavior of deep networks. However, the study revealed that the relationship between optimization and generalization needs to be investigated [111].

3.4.2. Stability

The two pillars of image reconstruction algorithms are accuracy and stability. While deep learning algorithms have demonstrated accurate reconstructions, the stability pillar is still absent in the current deep learning-based algorithms for image reconstruction. Three crucial instability issues of the use of deep learning methods in image reconstruction include: (1) instabilities concerning certain tiny perturbations, (2) instabilities concerning small structural changes (e.g. a brain image with or without a small tumor), and (3) instabilities concerning changes in the number of samples [112]. The significance of stability and accurate methods of image reconstruction in medical imaging cannot be under-

Table 7 Deep learning tools

References	Deep learning tools	Descriptions
[120]	Tensorflow	This is one of the most used deep learning tools. It is based on Python and it was developed by Google Brain Team. It is continuously updated and maintained frequently for additional functionality.
[121]	MXNet	This is a flexible and efficient deep learning library that provides an API for python developers. MXNet enables developers to exploit the full capabilities of cloud computing and CPUs.
[122]	Theano	This is a deep learning python library that lets users define, optimize, and evaluate mathematical expressions that are essential in deep learning implementations.
[123]	Caffe	This is a deep learning framework that was developed by Berkeley AI Research (BAIR) and is being maintained by community contributors. It was developed by Yang Qing Jia as a project during his Ph.D. at UC Berkeley.
[124]	DeepLearning4j	This is an open-source deep learning distributed library. It is designed to be used in business environments on distributed CPUs and GPUs. It can import neural network models via Keras from Caffe, Torch, Theano, and Tensorflow.
[125]	Torch	This is a deep learning framework with wide support for machine learning algorithms that puts GPUs first. It is fast and efficient due to its GPU support.
[126]	Keras	This is a deep learning library for Theano and Tensorflow. It is written in Python. It supports recurrent neural networks and convolutional neural networks or combinations of the two.
[127]	Microsoft Cognitive Toolkit	This is an open-source easy to use deep learning toolkit. It was previously known as CNTK. It is also described as a unifying deep learning toolkit that describes neural networks as a series of computational steps via a directed graph.
[128]	Neural Designer	This is a data mining package that utilizes neural networks in its operations. It was developed by Artelnics based in Spain.

estimated since they are traditionally considered a necessity to secure stable and reliable methods used for instance in disease diagnosis.

3.4.3. Quality and amount of training datasets

Deep learning methods are highly dependent on the quality and the amount of training dataset [113]. A large amount of training data leads to overfitting and bias. Also, there could be legal and ethical issues in the use of clinical imaging data in commercial applications since the performance accuracy are dependent on the quality of the training data [17,114]. The challenge of large amounts of training data required to train deep learning methods is currently one of the barriers to the success of deep learning in medical imaging, but it is being addressed by using transfer learning. It has been reported that the quality of training data in the field of deep learning, especially in image reconstruction, plays a significant role in the final result [56,113]. More so, the success of deep learning models mainly depends on the presence of large datasets with high-quality labels [9].

4. Open source tools and datasets for deep learning research

There are many open-source tools and datasets for deep learning. These open-source materials are available for researchers to use and duplicate results. All this has been possible due to the open-science movement that advocates for the sharing of resources, data, methodologies, and open peer reviews. For example, different research groups across the world are developing sustainable imaging modalities such as MRI systems by sharing methodologies and designs [115]. Embracing open science and innovations by these research groups may result in a reduction of development times, reduction of investment, and operational costs. Also, open science allows free availability of research data and results, and also advocates for the removal of barriers that hinder research developments [116]. Neuroscience researchers state that freely sharing technologies, including data and software packages, will speed the development of affordable medical imaging systems [115]. Also, the Open Data movement advocates the sharing of data openly and freely [115]. People have joined the movement by donating their corps to science, e.g. “a former inmate who gave his life to science, upon his death, CT and MRI scans were done on the whole of his body and also color cryosections (photographs) were generated by cutting the frozen body into thin slices” [117]. Furthermore, different organizations and individuals have joined the open-source community and there are various infrastructures to share open-source software and codes such as GitHub, GitLab, and iPython notebooks, among others. In the following section, we discuss deep-learning tools and datasets that can be freely utilized by researchers during image reconstruction research.

4.1. Deep learning tools

There are many open-source deep learning software tools for deep-learning research. These open-source software tools enable the development of cost-effective applications and also reproducible study results [3]. This section reviews the most commonly used open access deep-learning software tools for deep-learning research. More deep-learning software tools can be found in [118–119]. Table 7 shows the deep learning tools we identified during this study.

4.2. Open source datasets

Currently, deep learning researchers are having challenges with enough data for the training of deep learning systems. However, there are some imaging data sources [129] that researchers in the field can utilize during their experiments. Table 8 shows the open-source datasets we identified during this study.

4.3. Open source deep learning codes for medical image reconstruction

This study identified open-source deep-learning codes implemented to solve the ill-posed problem of medical image reconstruction from different research groups as shown in Table 9 below. From the findings, it was noted that much of the implementations are done in Python, followed by Matlab programming languages.

5. Conclusion

During this study we reviewed the current literature on the application of deep learning in medical image reconstruction. PRISMA flow diagram and protocol were used for the identification of relevant articles that we discussed in this paper. It was noted that deep learning became popular in 2012 when deep learning-based technique won an overwhelming victory in the computer vision competition. It was also revealed that deep learning automatically learns features from the training datasets, unlike traditional machine learning algorithms that require human intervention. Our study shows that deep learning techniques have been successfully applied for image reconstruction. They can help to accelerate data acquisition thereby decreasing the imaging time. Results in MRI, CT, PET, and ultrasound imaging systems revealed improvement in image quality and efficient noise removal when compared to analytical, iterative, and compressed sensing-based methods. Deep learning has also been successfully applied to other medical image processing tasks like classification, segmentation, and registration. However, the reviewed literature also shows that that deep learning techniques are computationally expensive, require large amounts of training datasets,

Table 8 Open source datasets

References	Datasets	Descriptions
[130]	UK Biobank dataset	The dataset contains medical image data available for use by the public and researchers.
[131]	Give A-Scan	This contains images and clinical data for lung patients and those at risk for the disease.
[132]	OpenNeuro dataset	This contains neuroimaging data obtained with various imaging modalities and protocols.
[133]	ADNI dataset	This contains image data for Alzheimer's disease neuroimaging initiative.
[134]	ABIDE dataset	This contains imaging data with Autism Spectrum Disorder and their controls.
[135]	TCIA dataset	This contains cancer imaging data and it hosts a large archive of medical images
[136]	FastMRI dataset	It contains 1,500 fully sampled knee MRIs obtained on 3 and 1.5 Tesla magnets and DICOM images from 10,000 clinical knees MRIs also obtained at 3 or 1.5 Tesla.
[137]	Cancer dataset	Contains lots of links to datasets most especially for cancer-related data
[138]	Imaging dataset	Contains lots of links to imaging datasets from a variety of sources
[139]	CT medical images	The dataset contains CT images from the cancer imaging archive
[140]	Medical imaging	This contains links to various medical imaging datasets
[141]	Medical imaging repository	Open-Access medical image repositories from NIH database, national biomedical imaging archive, OASIS, UCI Machine Learning Repository, Japanese Society of Radiological Technology (JSRT) Database, and others
[142]	Medical imaging	CT, MRI, PET, and other image data different imaging modalities
[143]	Digitized images	It contains a collection of digitized images. The database is maintained to support research in image processing, image analysis, and machine vision.
[144]	Machine learning datasets	Contains several links to machine learning datasets

Table 9 Open-source deep learning codes for medical image reconstruction

References	Imaging modalities	Descriptions	Implementations
[145]	CT	Image reconstruction codes in computed tomography	Matlab
[146]	MRI	The code for various experiments analyzing various regularization parameter for K-space based parallel MR image reconstruction	Matlab
[147]	MRI	GRAPPA is a popular parallel imaging reconstruction algorithm. The codes implement GRAPPA-like algorithms.	Python
[148]	Other	Reconstruction of three-dimensional porous media using generative adversarial neural networks.	Python
[149]	MRI	Deep cascade of CNNs and convolutional recurrent neural networks for MR image reconstruction	Python
[150]	Other	Image reconstruction method to represent detailed images purely from the binary sparse edge and flat color domain.	Python
[151]	MRI	Codes for deep learning, image processing, dictionary learning and compressed sensing	Python
[152]	MRI	An open-source implementation of the deep learning platform for undersampled MRI reconstruction	Python
[153]	MRI	Several open-source AI tools and codes for fast MRI	Various implementations
[154]	CT	PYRO-NN, a state-of-the-art reconstruction algorithm to neural networks integrated into Tensorflow.	Python
[155]	MRI	Links to several deep learning implementations for image reconstruction	Python
[156]	MRI	A deep learning implementation for undersampled MRI reconstruction	Python
[157]	MRI	A TensorFlow implementation for MRI reconstruction	Python
[158]	MRI	Links to several deep learning implementations for image reconstruction	Various implementations
[159]	CT	Links to several deep learning implementations for image reconstruction	C++
[160]	Several modalities	Links to several deep learning implementations for image reconstruction	Various implementations

that theoretical analysis explaining why the algorithms work is still required (the black-box nature of deep learning) [15], and also that the issues of generalization and robustness of deep learning techniques need to be addressed. Also, the reliability of deep-learning systems is a concern in case they are used independently from the supervision of a radiologist, therefore there is a question of whom to blame in case the misinformation or an error that leads to patient harm [14]. Next to a comprehensive review of literature on deep-learning techniques for image reconstruction, the study identified open-source tools, codes, and datasets that, we believe, may be utilized by deep learning researchers, especially the novice. Therefore, this paper may be used as a reference point, since it has identified the majority of these resources.

Conflict of interest statement

The authors declare that they have no conflicts of interest.

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Author contributions

Emmanuel Ahishakiye: Methodology, Writing - original draft. Martin Bastiaan Van Gijzen: Methodology, Writing - review & editing. Julius Tumwiine: Writing - review & editing. Ruth Wario: Writing - review & editing. Johnes Obungoloch: Methodology, Writing - review & editing.

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References

[1] Singh S, Bansal RK, Bansal S. Medical image enhancement using histogram processing techniques followed by median filter. IJIPA 2012;3(1):1–9.
[2] Suzuki K. Overview of deep learning in medical imaging. Radiol Phys Technol 2017;10(3):257–73. doi:10.1007/s12194-017-0406-5.
[3] Kim J, Hong J, Park H. Prospects of deep learning for medical imaging. Precis Futur Med 2018;2:37–52. doi:10.23838/pfm.2018.00030.
[4] Pouyanfar S, Sadiq S, Yan Y, et al. A survey on deep learning: algorithms, techniques, and applications. ACM Comput Surv 2018;51(5):1–36. doi:10.1145/3234150.

[5] Fuyong Xing, Yuanpu Xie, Hai Su, et al. Deep learning in microscopy image analysis: a survey. IEEE Trans Neural Netw Learn Syst 2018;29(10):4550–68. doi:10.1109/TNNLS.2017.2766168.
[6] Bakator M, Radosav D. Deep learning and medical diagnosis: a review of literature. Multimod Technol Interact 2018;2(3). doi:10.3390/mti2030047.
[7] Zhu B, Liu JZ, Cauley SF, et al. Image reconstruction by domain-transform manifold learning. Nature 2018;555(7697):487–92. doi:10.1038/nature25988.
[8] Wang G, Ye JC, Mueller K, et al. Image reconstruction is a new frontier of machine learning. IEEE Trans Med Imaging 2018;37(6):1289–96. doi:10.1109/TMI.2018.2833635.
[9] Zhang HM, Dong B. A review on deep learning in medical image reconstruction. Journal of the Operations Research Society of China 2020;8(4). doi:10.1007/s40305-019-00287-4.
[10] Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60–88. doi:10.1016/j.media.2017.07.005.
[11] Kamilaris A, Prenafeta-Boldu FX. Deep learning in agriculture: a survey. Comput Electron Agric 2018;147:70–90. doi:10.1016/j.compag.2018.02.016.
[12] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436–44. doi:10.1038/nature14539.
[13] Toennies KD. Advances in Computer Vision and Pattern Recognition: Guide to Medical Image Analysis-Methods and Algorithms. New York: Springer-Verlag London Limited; 2012:2012. doi:10.1007/978-1-4471-2751-2.
[14] Lee JG, Jun S, Cho YW, et al. Deep learning in medical imaging: general overview. Korean J Radiol 2017;18(4):570–84. doi:10.3348/kjr.2017.18.4.570.
[15] Wang Ge. A perspective on deep imaging. IEEE Access 2017;4:8914–24. doi:10.1109/ACCESS.2016.2624938.
[16] Lundervold AS, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Z Med Phys 2019;29(2):102–27. doi:10.1016/j.zemedi.2018.11.002.
[17] Kim M, Yun J, Cho Y, et al. Deep Learning in Medical Imaging. Neurospine 2019;16(4):657–68. doi:10.14245/ns.1938396.198.
[18] Strack Rita. Imaging: AI transforms image reconstruction. Nat Methods 2018;15(5) 309-309. doi:10.1038/nmeth.4678.
[19] Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017, 42:60-88. doi: 10.1016/j.media.2017.07.005.
[20] Kha B, Fk C. Machine learning for image reconstruction. Handbook of Medical Image Computing and Computer Assisted Intervention 2020:25–64. doi:10.1016/B978-0-12-816176-0.00007-7.
[21] Liang D, Cheng J, Ke Z, et al. Deep MRI Reconstruction: Unrolled Optimization Algorithms Meet Neural Networks; 2019.
[22] Ghodrati V, Shao J, Bydder M, et al. MR image reconstruction using deep learning: evaluation of network structure and loss functions. Quant Imaging Med Surg 2019;9(9):1516–27. doi:10.21037/qims.2019.08.10.
[23] Aibinu AM, Salami M, Shafie AA, et al. MRI reconstruction using discrete Fourier transform: a tutorial. Proc World Acad Sci Eng Technol 2011:209.
[24] Hyun CM, Kim HP, Lee SM, et al. Deep learning for undersampled MRI reconstruction. Phys Med Biol 2018;63(13):135007. doi:10.1088/1361-6560/aac71a.
[25] Aggarwal HK, Mani MP, Jacob M . Model Based Image Reconstruction using Deep Learned Priors (MODL). Proc IEEE Int Symp Biomed Imaging 2018:671–4. doi:10.1109/isbi.2018.8363663.
[26] Schwartz GE, Fair PL, Salt P, et al. Facial muscle patterning to affective imagery in depressed and nondepressed subjects. Science 1976;192(4238):489–91. doi:10.1126/science.1257786.
[27] Dar SUH, Özbey M, Çatlı AB, et al. A transfer-learning approach for accelerated MRI using deep neural networks. Magn Reson Med 2020;84(2):663–85. doi:10.1002/mrm.28148.
[28] Cheng JY, F Chen, Alley MT, et al. Highly scalable image reconstruction using deep neural networks with bandpass filtering. 2018.
[29] Gucluturk Y, et al. Reconstructing perceived faces from brain activations with deep adversarial neural decoding In NIPS 2017: 31st Conference on Neural Information Processing Systems; 2017. doi:105555/32949963295179.
[30] Ramzi Z, Ciuciu P, Starck JL. Benchmarking MRI reconstruction neural networks on large public datasets. Appl Sci 2020;10(5):1816. doi:10.3390/app10051816.
[31] Chun J, Zhang H, Gach HM, et al. MRI super-resolution reconstruction for MRI-guided adaptive radiotherapy using cascaded deep learning: In the presence of limited training data and unknown translation model. Med Phys 2019;46(9):4148–64. doi:10.1002/mp.13717.
[32] Qin C, Schlemper J, Caballero J, et al. Convolutional recurrent neural networks for dynamic MR image reconstruction. IEEE Trans Med Imaging 2019;38(1):280–90. doi:10.1109/TMI.2018.2863670.
[33] Du C, Du C, He H. Sharing deep generative representation for perceived image reconstruction from human brain activity. IEEE; 2017. doi:101109/IJCNN20177965968.
[34] Shen G, Dwivedi K, Majima K, et al. End-to-end deep image reconstruction from human brain activity. Front Comput Neurosci 2019;13:21. doi:10.3389/fncom.2019.00021.
[35] Hammernik K, Klatzer T, Kobler E, et al. Learning a variational network for reconstruction of accelerated MRI data. Magn Reson Med 2018;79(6):3055–71. doi:10.1002/mrm.26977.
[36] Han Y, Yoo J, Kim HH, et al. Deep learning with domain adaptation for accelerated projection-reconstruction MR. Magn Reson Med 2018;80(3):1189–205. doi:10.1002/mrm.27106.
[37] Jeelani H, Martin J, Vasquez F, et al. Image quality affects deep learning reconstruction of MRI 2018 IEEE 15th International Symposium on Biomedical Imaging. ISBI; 2018. doi:101109/ISBI20188363592.
[38] Knoll F, Hammernik K, Zhang C, et al. Deep-learning methods for parallel magnetic resonance imaging reconstruction: a survey of the current approaches, trends, and issues. IEEE Signal Process Mag 2020;37(1):128–40. doi:10.1109/MSP.2019.2950640.
[39] Kocanaogullari D, Eksioglu EM. Deep learning for MRI reconstruction using a novel projection based cascaded network. 2019 IEEE 29th International Workshop on Machine Learning for Signal Processing (MLSP. IEEE; 2019. doi:101109/MLSP20198918715.
[40] Liang D, Cheng J, Ke Z, et al. Deep magnetic resonance image reconstruction: inverse problems meet neural networks. IEEE Signal Process Mag 2020;37(1):141–51. doi:10.1109/MSP.2019.2950557.
[41] Oh C, Kim D, Chung JY, et al. ETER-net: End to End MR Image Reconstruction Using Recurrent Neural Network. Cham: Springer; 2018. doi:101007/978-3-030-00129-2_2.
[42] Estienne Théo, Vakalopoulou Maria, Christodoulidis Stergios, et al. U-ReSNet: Ultimate Coupling of Registration and Segmentation with Deep Nets. MICCAI; 2019. doi:101007/978-3-030-32248-9.
[43] Knoll F, Goos G. Machine learning for medical image reconstruction. Second International Workshop, MLMIR 2019 Held in Conjunction with MICCAI Shenzhen, China; 2019. doi:101007/978-3-030-33843-5.
[44] Vishnevskiy V, Walheim J, Kozerke S. Deep variational network for rapid 4D flow MRI reconstruction. Nat Mach Intell 2020(2):228–35. doi:10.1038/s42256-020-0165-6.
[45] Pawar Kamlesh, Zhaolin Chen, Shah Jon, et al. A deep learning framework for transforming image reconstruction into pixel classification. IEEE Access 2019:177690–702 7. doi:10.1109/ACCESS.2019.2959037.
[46] Schlemper J, Caballero J, Hajnal JV, et al. A Deep Cascade of Convolutional Neural Networks for Dynamic MR Image Reconstruction. IEEE Trans Med Imaging 2018;37(2):491–503. doi:10.1109/TMI.2017.2760978.
[47] Yang G, Yu S, Dong H, et al. DAGAN: deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction. IEEE Trans Med Imaging 2018;37(6):1310–21. doi:10.1109/TMI.2017.2785879.
[48] Shen G, Horikawa T, Majima K, et al. Deep image reconstruction from human brain activity. PLoS Comput Biol 2019;15(1):e1006633. doi:10.1371/journal.pcbi.1006633.
[49] Eo T, Jun Y, Kim T, et al. KIKI-net: cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images. Magn Reson Med 2018;80(5):2188–201. doi:10.1002/mrm.27201.
[50] Quan TM, Nguyen-Duc T, Jeong WK. Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss. IEEE Trans Med Imaging 2018;37(6):1488–97. doi:10.1109/TMI.2018.2820120.
[51] Sun L, Wu Y, Fan Z, et al. A deep error correction network for compressed sensing MRI. BMC Biomed Eng 2020;2:4. doi:10.1186/s42490-020-0037-5.
[52] Souza R, Lebel RM, Frayne R. A Hybrid, Dual Domain. Cascade of Convolutional Neural Networks for Magnetic Resonance Image Reconstruction; 2019.
[53] Sun L, Fan Z, Yue H, et al. Compressed Sensing MRI Using a Recursive Dilated Network. 2018.
[54] Wang S, Su Z, Ying L, et al. Accelerating Magnetic Resonance Imaging via Deep Learning. Proc IEEE Int Symp Biomed Imaging 2016:514–17. doi:10.1109/ISBI.2016.7493320.
[55] Wu Y, Ma Y, Liu J, et al. Self-attention convolutional neural network for improved MR image reconstruction. Inf Sci (N Y) 2019;490:317–28. doi:10.1016/j.ins.2019.03.080.
[56] Wang J, Liang J, Cheng J, et al. Deep learning based image reconstruction algorithm for limited-angle translational computed tomography. PLoS One 2020;15(1) e0226963. doi:10.1371/journal.pone.0226963.
[57] Xie H, Shan H, Wang G. Deep Encoder-Decoder Adversarial Reconstruction(DEAR) network for 3D CT from few-view data. Bioengineering (Basel). 2019, 6(4):111. doi: 10.3390/bioengineering6040111.
[58] Syben C, Michen M, Stimpel B, et al. Technical Note: PYRO-NN: Python reconstruction operators in neural networks. Med Phys 2019;46(11):5110–15. doi:10.1002/mp.13753.
[59] Chen H, Zhang Y, Chen Y, et al. LEARN: Learned Experts' Assessment-Based Reconstruction Network for Sparse-Data CT. IEEE Trans Med Imaging 2018;37(6):1333–47. doi:10.1109/TMI.2018.2805692.
[60] Xie S, Zheng X, Chen Y, et al. Artifact removal using Improved GoogLeNet for sparse-view CT reconstruction. Sci Rep 2018;8(1):6700. doi:10.1038/s41598-018-25153-w.
[61] Topal E, Löffler M, Zschech E. Deep Learning-based Inaccuracy Compensation in Reconstruction of High Resolution XCT Data. Sci Rep 2020;10(1):7682. doi:10.1038/s41598-020-64733-7.
[62] Boedeker K. AiCE deep learning reconstruction : bringing the power of ultra-high resolution CT to routine imaging. 2019.
[63] Akagi M, Nakamura Y, Higaki T, et al. Deep learning reconstruction improves image quality of abdominal ultra-high-resolution CT. Eur Radiol 2019;29(11):6163–71. doi:10.1007/s00330-019-06170-3.
[64] Gjesteby L, et al. Deep neural network for ct metal artifact reduction with a perceptual loss function. The fifth international conference on image formation in X-ray computed tomography.
[65] Gjesteby L, Yang Q, Yan X, et al. Deep learning methods to guide CT image reconstruction and reduce metal artifacts Medical Imaging 2017: Physics of Medical Imaging. International Society for Optics and Photonics; 2017. doi:101117/122254091.
[66] Gupta H, Jin KH, Nguyen HQ, et al. CNN-based projected gradient descent for consistent CT image reconstruction. IEEE Trans Med Imaging 2018;37(6):1440–53. doi:10.1109/TMI.2018.2832656.

[67] Hoyeon L, Jongha L, Hyeongseok K, et al. Deep-neural-network based sinogram synthesis for sparse-view CT image reconstruction. IEEE Transactions on Radiation & Plasma Medical Sciences; 2018. 1-1. doi:10.1109/trpms.2018.2867611.
[68] Liu J, Zhang Y, Zhao Q, et al. Deep iterative reconstruction estimation (DIRE): approximate iterative reconstruction estimation for low dose CT imaging. Phys Med Biol 2019;64(13):135007. doi:10.1088/1361-6560/ab18db.
[69] Thaler F, Hammernik K, Payer C, et al. Sparse-View CT Reconstruction Using Wasserstein GANs. Spain: First International Workshop, MLMIR 2018 Granada; 2018. doi:101007/978-3-030-00129-2_9.
[70] Knoll F, Maier A, Rueckert D. A U-nets cascade for sparse view computed. Tomography 2018:91–9. doi:10.1007/978-3-030-00129-2_11.
[71] Nakamura Y, Higaki T, Tatsugami F, et al. Deep Learning–based CT Image Reconstruction: Initial Evaluation Targeting Hypovascular Hepatic Metastases. 2019. doi: 10.1148/ryai.2019180011.
[72] Chen H, Zhang Y, Chen Y, et al. LEARN: learned experts' assessment-based reconstruction network for sparse-data CT. IEEE Trans Med Imaging 2018;37(6):1333–47. doi:10.1109/TMI.2018.2805692.
[73] Ji Z, Chen Z, Li Z, et al. Few-View CT reconstruction method based on deep learning. 2016 IEEE Nuclear Science Symposium Medical Imaging Conference and Room-Temperature Semiconductor Detector Workshop (NSS/MIC/RTSD). IEEE; 2016. doi:101109/NSSMIC20168069593.
[74] Ziabari A, Ye D H, Srivastava S, et al. 2.5D deep learning for CT image reconstruction using a multi-GPU implementation 2018 52nd Asilomar Conference on Signals, Systems, and Computers. IEEE; 2019. doi:101109/ACSSC20188645364.
[75] Dong J, Fu J, He Z. A deep learning reconstruction framework for X-ray computed tomography with incomplete data. PLoS One 2019;14(11) e0224426. doi:10.1371/journal.pone.0224426.
[76] Chen H, Zhang Y, Zhang W, et al. Low-dose CT via convolutional neural network. Biomed Opt Express 2017;8(2):679–94. doi:10.1364/boe.8.000679.
[77] Gupta H, Jin KH, Nguyen HQ, et al. CNN-based projected gradient descent for consistent CT Image reconstruction. IEEE Trans Med Imaging 2018;37(6):1440–53. doi:10.1109/TMI.2018.2832656.
[78] Yuan H, Jia J, Zhu Z . SIPID: a deep learning framework for sinogram interpolation and image denoising in low-dose CT reconstruction. 2018:1521-1524. doi: 10.1109/ISBI.2018.8363862.
[79] Ye DH, Buzzard GT, Ruby M, et al. Deep back projection for sparse-view CT reconstruction 2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP); 2018. doi:101109/GlobalSIP20188646669.
[80] Qin C, Schlemper J, Caballero J, et al. Convolutional recurrent neural networks for dynamic MR image reconstruction. IEEE Trans Med Imaging 2019;38(1):280–90. doi:10.1109/TMI.2018.2863670.
[81] Lee D, Choi S, Kim HJ. High quality imaging from sparsely sampled computed tomography data with deep learning and wavelet transform in various domains. Med Phys 2019;46(1):104–15. doi:10.1002/mp.13258.
[82] Higaki T, Nakamura Y, Zhou J, et al. Deep Learning reconstruction at CT: phantom study of the image characteristics. Acad Radiol 2020;27(1):82–7. doi:10.1016/j.acra.2019.09.008.
[83] Ravishankar S, Cameron AL, Blocker C, et al. Deep dictionary-transform learning for image reconstruction 2018 IEEE 15th International Symposium on Biomedical Imaging Washington, DC, USA; 2018. doi:101109/ISBI20188363788.
[84] Häggström I, Schmidtlein CR, Campanella G, et al. DeepPET: a deep encoder-decoder network for directly solving the PET image reconstruction inverse problem. Med Image Anal 2019;54:253–62. doi:10.1016/j.media.2019.03.013.
[85] Yokota T, Kawai K, Sakata M, et al. Dynamic PET image reconstruction using nonnegative matrix factorization incorporated with deep image prior 2019 IEEE/CVF International Conference on Computer Vision (ICCV). IEEE; 2020. doi:101109/ICCV201900322.
[86] Cui J, Liu X, Wang Y, et al. Deep reconstruction model for dynamic PET images. PLoS One 2017;12(9) e0184667. doi:10.1371/journal.pone.0184667.
[87] Gong Kuang, Guan Jiahui, Kim Kyungsang, et al. Iterative PET image reconstruction using convolutional neural network representation. IEEE Trans Med Imaging 2019;38(3):675–85. doi:10.1109/TMI.2018.2869871.
[88] Kim K, Wu D, Gong K, et al. Penalized PET reconstruction using deep learning prior and local linear fitting. IEEE Trans Med Imaging 2018;37(6):1478–87. doi:10.1109/TMI.2018.2832613.
[89] Costa-Luis C, Reader AJ. Deep Learning for Suppression of Resolution-Recovery Artefacts in MLEM PET Image Reconstruction. IEEE; 2018. doi:101109/NSSMIC20178532624.
[90] Yoon YH, Khan S, Huh J, et al. Efficient B-mode ultrasound image reconstruction from sub-sampled RF data using deep learning. IEEE Trans Med Imaging 2019;38(2):325–36. doi:10.1109/TMI.2018.2864821.
[91] Jarosik P, Byra M, Lewandowski M. WaveFlow - Towards Integration of Ultrasound Processing with Deep Learning. IEEE; 2018. doi:101109/ULTSYM20188579825.
[92] Byram B, Dei K, Luchies A. In: IEEE 2017 51st Asilomar Conference on Signals, Systems, and Computers - Pacific Grove;2017:1012–15. doi:10.1109/ACSSC.2017.8335501.
[93] Perdios D, Vonlanthen M, Martinez F, et al. Deep learning-based ultrasound image reconstruction method: a time coherence study. IEEE Int Ultrason Symp IUS 2019. doi:10.1109/ULTSYM.2019.8925595.
[94] Wang R, Fang Z, Gu J, et al. High-resolution image reconstruction for portable ultrasound imaging devices. EURASIP J Adv Signal Process 2019;2019(1). doi:10.1186/s13634-019-0649-x.
[95] Belthangady C, Royer LA. Applications, promises, and pitfalls of deep learning for fluorescence image reconstruction. Nat Methods 2019;16(12):1215–25. doi:10.1038/s41592-019-0458-z.
[96] Guan S, Khan AA, Sikdar S, et al. Limited-view and sparse photoacoustic tomography for neuroimaging with deep learning. Sci Rep 2020;10(1):8510. doi:10.1038/s41598-020-65235-2.
[97] Haan B, Rivenson Y, Wu Y, et al. Deep-learning-based image reconstruction and enhancement in optical microscopy. In: Proceedings of the IEEE; 2019:1–21. doi:10.1109/JPROC.2019.2949575.
[98] Xiao J, Liu Z, Zhao P, et al. Deep learning image reconstruction simulation for electromagnetic tomography. IEEE Sens J 2018;18(8):3290–8. doi:10.1109/JSEN.2018.2809485.
[99] Mahmood F, Durr NJ. Topographical reconstructions from monocular optical colonoscopy images via deep learning. 2018 IEEE 15th International Symposium on Biomedical Imaging. IEEE; 2018. doi:101109/ISBI20188363558.
[100] Rivenson Y, Zhang Y, Günaydın H, et al. Phase recovery and holographic image reconstruction using deep learning in neural networks. Light Sci Appl 2018;7:17141. doi:10.1038/lsa.2017.141.
[101] Li X, Zhang Y, Zhao H, et al. A transfer learning approach for microstructure reconstruction and structure-property predictions. Sci Rep 2018;8(1):13461. doi:10.1038/s41598-018-31571-7.
[102] Shahbazi A, Kinnison J, Vescovi R, et al. Flexible learning-free segmentation and reconstruction of neural volumes. Sci Rep 2018;8(1):14247. doi:10.1038/s41598-018-32628-3.
[103] Micieli D, Minniti T, Evans LM, et al. Accelerating Neutron Tomography experiments through Artificial Neural Network based reconstruction. Sci Rep 2019;9(1):2450. doi:10.1038/s41598-019-38903-1.
[104] Liu T, de Haan K, Rivenson Y, et al. Deep learning-based super-resolution in coherent imaging systems. Sci Rep 2019;9(1):3926. doi:10.1038/s41598-019-40554-1.
[105] Zhai X, Lei D, Zhang M, et al. LoTToR: an algorithm for missing-wedge correction of the low-tilt tomographic 3D reconstruction of a single-molecule structure. Sci Rep 2020;10(1):10489. doi:10.1038/s41598-020-66793-1.
[106] Zhang Y, An M . Deep learning- and transfer learning-based super resolution reconstruction from single medical image. J Healthc Eng 2017:5859727. doi:10.1155/2017/5859727.
[107] Yedder HB, Bentaieb A, Shokoufi M, et al. Deep Learning Based Image Reconstruction for Diffuse Optical Tomography. Cham: Springer; 2018. doi:101007/978-3-030-00129-2_13.
[108] Vasudevan H, Michalas A, Shekokar N, et al. Algorithms for intelligent systems: advanced computing technologies and applications. In: Proceedings of 2nd International Conference on Advanced Computing Technologies and Applications-ICACTA; 2020.
[109] Liang X, Nguyen D, Jiang S. Generalizability issues with deep learning models in medicine and their potential solutions: illustrated with Cone-Beam Computed Tomography (CBCT) to Computed Tomography (CT) image conversion. 2020. doi: 10.1088/2632-2153/abb214.
[110] Kawaguchi K, Kaelbling LP, Bengio Y . Generalization in deep learning. 2017.
[111] Neyshabur B, Bhojanapalli S, McAllester D, et al. Exploring generalization in deep learning. Adv Neural Inf Process Syst 2017. doi:10.5555/3295222.3295344.
[112] Antun V, Renna F, Poon C, et al. On instabilities of deep learning in image reconstruction and the potential costs of AI. Proc Natl Acad Sci USA. 2020;117(48):30088–95. doi:10.1073/pnas.1907377117.
[113] Dey N, Ashour AS, Borra S. Deep Learning for Medical Image Processing: Overview. Challenges and the Future Classification in BioApps;2018:323–50. Chapter 12. doi:10.1007/978-3-319-65981-7_12.
[114] Kaissis GA, Makowski MR, Rückert D, et al. Secure, privacy-preserving and federated machine learning in medical imaging. Nat Mach Intell 2020. doi:10.1038/s42256-020-0186-1.
[115] "Open Source Magnetic Resonance Imaging: From the Community to the Community." [Online]. Available from: http://www.opensourceimaging.org/. [Accessed February 11, 2019].
[116] Mcabee ST, Grubbs JB, Zickar MJ. Open science is robust science. Industr Org Psychol 2018;11(1):54–61. doi:10.1017/iop.2017.85.
[117] Jomier J. Open science – towards reproducible research. Inf Serv Use 2017;37(3):361–7. doi:10.3233/ISU-170846.
[118] Wikipedia. Comparison of deep-learning software. Available from: https://en.wikipedia.org/wiki/Comparison_of_deep-learning_software. [Accessed March 23, 2019].
[119] Deep Learning Software. Available from: https://www.capterra.com/deep-learning-software. [Accessed March 23, 2019].
[120] An end-to-end open source machine learning platform. Available from: https://www.tensorflow.org. [Accessed March 22, 2019].
[121] Apache MXNet (Incubating): a flexible and efficient library for deep learning. Available from: https://mxnet.apache.org. [Accessed March 20, 2019].
[122] Theano (software). Available from: http://deeplearning.net/software/theano. [Accessed March 20, 2019].
[123] Caffe. Available from: http://caffe.berkeleyvision.org. [Accessed March 20, 2019].
[124] Deep Learning for Java. Available from: https://deeplearning4j.org. [Accessed March 22, 2019].
[125] Torch. Available: http://torch.ch. [Accessed March 20, 2019].
[126] Keras: The Python Deep Learning library. Available from: https://keras.io. [Accessed March 21,2019].
[127] Microsoft Cognitive Toolkit. Available from: https://www.microsoft.com/en-us/cognitive-toolkit. [Accessed March 21,2019].
[128] Neural Designer. Available from: https://www.neuraldesigner.com. [Accessed March 22,2019].
[129] List of neuroscience databases. Available from: https://en.wikipedia.org/wiki/List_of_neuroscience_databases. [Accessed March 11,2019].
[130] UK Biobank. Available from: https://www.ukbiobank.ac.uk. [Accessed February 15, 2019].

[131] Give A Scan. Available from: http://giveascan.org. [Accessed February 15,2019].
[132] OpenNeuro. Available from: https://openneuro.org. [Accessed February 14, 2019].
[133] The Alzheimer's Disease Neuroimaging Initiative. Available from: http://adni.loni.usc.edu. [Accessed February 14, 2019].
[134] Autism Brain Imaging Data Exchange. Available from: http://fcon_1000.projects.nitrc.org/indi/abide. [Accessed February 15, 2019].
[135] TCIA Collections. Available from: https://www.cancerimagingarchive.net. [Accessed February 15, 2015].
[136] Welcome to the fastMRI Dataset. Available from: https://fastmri.med.nyu.edu.
[137] Dataset Directory. Available from: https://www.acrdsi.org/DSI-Services/Dataset-Directory. [Accessed May 23, 2020].
[138] Moore CM, Murphy A. Imaging data sets (artificial intelligence). Available from: https://radiopaedia.org/articles/imaging-data-sets-artificial-intelligence?lang=us. [Accessed May 23, 2020].
[139] Mader KS. CT images from cancer imaging archive with contrast and patient age. Available from: https://www.kaggle.com/kmader/siim-medical-images. [Accessed May 23, 2020].
[140] Medical-imaging-datasets. Available from: https://github.com/sfikas/medical-imaging-datasets. [Accessed May 23, 2020].
[141] Open-Access Medical Image Repositories. Available from: http://www.aylward.org/notes/open-access-medical-image-repositories. [Accessed May 23, 2020].
[142] List of Open Access Medical Imaging Datasets. Available from: https://www.radrounds.com/profiles/blogs/list-of-open-access-medical-imaging-datasets. [Accessed May 23, 2020].
[143] The USC-SIPI Image Database. Available from: http://sipi.usc.edu/database. [Accessed May 23, 2020].
[144] Machine learning datasets. Available from: https://www.datasetlist.com. [Accessed May23, 2020].
[145] Computed Tomography Image Reconstruction Project using MATLAB. Available from: https://github.com/SanketD92/CT-Image-Reconstruction. [Accessed May 25, 2020].
[146] Analyzing various regularization parameter for k-space based parallel MR image reconstruction. Available from: https://github.com/saradindusengupta/Regularization_parametre_in_reconstruction_of_cparallel-MR-image. [Accessed May 25, 2020].
[147] Python implementations of GRAPPA-like algorithms. Available from: https://github.com/mckib2/pygrappa. [Accessed May 25, 2020].
[148] Reconstruction of three-dimensional porous media using generative adversarial neural networks. Available from: https://github.com/LukasMosser/PorousMediaGan. [Accessed May 25, 2020].
[149] Deep Cascade of Convolutional Neural Networks for MR Image Reconstruction: Implementation & Demo. Available from: https://github.com/js3611/Deep-MRI-Reconstruction. [Accessed May 25, 2020].
[150] PI-REC: Progressive Image Reconstruction Network With Edge and Color Domain. Available from: https://github.com/youyuge34/PI-REC. [Accessed May 25, 2020].
[151] Codes for Deep learning, image processing, Dictionary learning, and compressed sensing. Available from: http://www.escience.cn/people/liuqiegen/index.html;jsessionid=EF35915AF727AD78591A00484B56E2F6-n1. [Accessed May 25, 2020].
[152] An open-source implementation of the deep learning platform for undersampled MRI reconstruction. Available from: https://github.com/Corey-Zumar/MRI-Reconstruction. [Accessed May 25, 2020].
[153] New fastMRI open-source AI research tools from Facebook and NYU School of Medicine. Available from: https://engineering.fb.com/ai-research/fastmri/. [Accessed May 25, 2020].
[154] Python Reconstruction Operators in Neural Networks. High-level python API for PYRO-NN-Layers. Available from: https://github.com/csyben/PYRO-NN. [Accessed May 25, 2020].
[155] Powerful Deep Learning. Available from: http://leotam.github.io/general/2017/12/25/DLtools.html. [Accessed May 25, 2020].
[156] Deep learning for undersampled MRI reconstruction. Available from: https://github.com/hpkim0512/Deep_MRI_Unet. [Accessed May 25, 2020].
[157] Variational Network for Magnetic Resonance Image (MRI) Reconstruction. Available from: https://github.com/VLOGroup/mri-variationalnetwork. [Accessed May 25, 2020].
[158] Software. Available from: http://research.engineering.uiowa.edu/cbig/content/software. [Accessed May 25, 2020].
[159] Software. Available from: https://biotech.rpi.edu/centers/bic/resources/software. [Accessed May 25, 2020].
[160] Papers with code. Available from: https://github.com/zziz/pwc. [Accessed May 25, 2020].