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Computed Tomography Image Reconstruction for Disease Prediction: A Systematic Review

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ABSTRACT

A common medical imaging method that produces clear images of the internal body structures is computed tomography (CT). Recent advancements in CT technology have enabled the development of sophisticated image reconstruction techniques that can enhance image quality and aid in disease diagnosis and prediction. In this systematic review, we summarize the present state of research on CT image reconstruction for disease prediction. We searched PubMed, Embase, and Scopus databases for studies published between 2010 and 2022 that used CT image reconstruction for disease prediction. After screening and eligibility assessment, we included 48 studies in the review. The studies were categorized into four groups based on the disease area of focus: cardiovascular disease, respiratory disease, cancer, and neurological disease. The study demonstrated the effectiveness of CT image reconstruction for disease prediction in various disease areas.

KEYWORDS

Computed tomography; Artificial intelligence; Machine learning.

1. INTRODUCTION

Mathematical process is used for image reconstruction in computed tomography. Image is generated with the help of X-ray projection data obtained at number of different angles on all side of the patient in mathematical process. Reconstruction of images has major effects, which affect radiation dose. For a given radiation dose, it is preferable to reconstruct images with the least amount of noise possible without compromising image accuracy and spatial resolution. Since the same quality of images can be restored at a reduced dose, reconstruction that enhances image quality can be converted into radiation dose. There are two subcategories of tomography namely single positron emission computed tomography (SPECT), and positron emission tomography (PET). There are two main categories of tomography image reconstruction method.

1 Analytical tomography image reconstruction (AI)

2 Iterative tomography image reconstruction (IR)

The number of analytical reconstruction methods exit in practice. All the most popular analytical reconstruction techniques involve filtered back projection (FBP). The paper by Flohr, et al. [1] provides an explanation of the analytical computed tomography image reconstruction techniques utilized in computed tomography scanners.

Scanning methods and image reconstruction have a special influence on picture quality and radiation dose in ECG-gated cardiac computerized tomography. In an article by Flohr, et al. [2], the scanning and reconstruction methods used in cardiac CT are described.

Images are rebuilt using the iterative optimization of objective functions, which typically include edge preserve directive terms and data dependability terms [3].

Iterations of frontward projection and rearward projection between image and projection space are concerned for optimization process in IR. With the advancements in computing technology, iterative reconstruction has emerged as a highly regarded option in routine computer tomography practice due to its many advantages over cautious FBP approaches.

The gridding approach with the proper density compensation parameters [4] is quick and efficient for well sampled non-cartesian data. The expected image reconstruction technique for k-space data with full Cartesian sampling has been the inverse FFT method, which has been of great use to the MR community. When only under sampled data is present or when non-fourier physical effects like field inhomogeneity are significant, iterative algorithms based on suitable models can upgrade picture quality at the expense of algorithms subjected to enlarged computation. The gridding/FFT method for image reconstruction is suboptimal.

Any signal processing technique used to create pictures from measuring instruments like MRI scanners must take the apt physics into account. The physics of MRI have been adequately documented in a survey in the IEEE signal processing journal [5] and

A book [6] developed from the viewpoint of signal processing. Here, Jeffery A. Fressler provides an unusual summary of the physics that makes it easier to describe some of the "non-Fourier" characteristics of MRI .

2. PREVIOUS WORK (2010-2022)

In July-2010, Jeffrey A. Fessler [7] has done a reviewed work for MRI with iterative techniques using model-based reconstruction. He has suggested that there is a broad family problem depending upon what physical effects incorporated in the signal model in image reconstruction using MRI technique. He examined numerous examples of every physical effect, and the system model he used only included samples from object Fourier transforms. Model-based approaches rely on estimations of a wide range of model parameters, which leads to growing issues when those parameters are hampered by either independent scanning for calibration or estimating the image and those parameters simultaneously.

MariyaLyra and AgapiPloussi have reviewed a paper on filtering in single proton emission computed tomography (SPECT) image reconstruction in 2011[8]. They have suggested that image filtering techniques affect the quality of image so that they are very important to tomography image reconstruction. Any procedure employed on an image's pixels is referred to as image filtering. Image filtering, which also covers smoothing, edge enrichment, and resolution recovery, is a mathematical technique for hiding pictures in noise. In order to preserve spatial resolution and contrast in tomography pictures, Filer quickly eliminates statistical noise. This work has addressed several filters.

In 2012, W. D. Foltz and D. A. Jaffray [9] worked on the principle of resonance imaging. For those applying magnetic resonance imaging in the biomedical field, they advised a learning manual on the subject. They have given biological users of MRI some insight into the fundamentals, reducing an often-excessive language barrier.

To accurately analyze the brain images and to diagnose the diseases and issues, we require brain image reconstruction operation methods. The reconstruction process in [10] is extremely practical and relevant in handling magnetoencephalography [MEG], electroencephalography [EEG], magnetic resonance imaging [MRI], computed tomography [CT], and positron emission tomography [PET]. The fundamental goal of the reconstruction procedure is to properly analyze the brain pictures to detect and assess sickness and disorders. There are three fundamental methods of rebuilding. They are iterative reconstruction, filtered back projection, and random transform. In the work [10], many picture reconstruction algorithms are described.

Due to the rapid system and hardware development over the past 30 years, X-ray CT technologies have been complemented by equally exciting breakthroughs in image reconstruction approaches. The algorithms are developed in three core areas including model-based iterative reconstruction, application-oriented reconstruction, and analytical reconstruction in [11]. It is required to focus only on a few key regions of tomography reconstruction due to limited span. It may not be enough to simply stimulate development in order to fulfil unique clinical needs. Since the occurrence of irregular and rapid vascular motion, cardiac coronary artery imaging continues to provide substantial problems to CT despite the unique scanner hardware enhancement. Because of rapidity of some of the coronary artifacts, motion induced artifacts even become visible in low heart-rates patient. Recent improved algorithms can solve this problem [11]. The motion-correction technique uses pictures that were rebuilt from slightly varied cardiac phases to characterize the vascular motion and uses these motion vectors to adjust for imaging artefacts.

The paper [12] describes an overview of several super-resolution methods. In this study, several approaches that have been used in each domain were reviewed, and the features of these approaches are discovered. We looked at super-resolution techniques in the frequency, spatial, and wavelet domains.

Medical imagining is an inter-disciplinary field that includes physics, biology, mathematics, and computational science. An overview of the MRI image reconstruction technique is provided in the paper [13]. The computational aspects of medical picture reconstruction are reviewed in this study. The medical technique of magnetic resonance imaging is one that is frequently employed.

MRI scanner collects k-space data for image reconstruction. The numerous approaches include the homodyne algorithm, the zero-filling method, dictionary learning, and the projections on to convex set (POCS) method. These techniques rebuild an image using K-space data. This study discusses all the K-space data characteristics and the MRI data acquisition methodology. The various algorithms used for the reconstruction of images are also explained in detail. Functional MRI and diffusion MRI have been also discussed which are modern magnetic resonance techniques. In this study, the idea of contemporary approaches like the sphere-shaped support vector machine and recent methods like Expectation Maximization, Sensitive Encoding, level set method, and Alternating minimization is also reviewed. It has been found that many of these strategies reduce scanning time and enhance gradient encoding. With the high degree of phase fluctuation in partial k-space, traditional techniques produce an undesired blurring effect. Due to iterative processes, contemporary reconstruction methods like Dictionary learning function well even with a large phase difference.

Zero filled method Algorithm is an unimportant method. It works well with the availability of full k-space. It gives unnecessary blurring with partial k-space. The phase correction techniques of conjugate symmetry, homodyne algorithm, and projection on to convex set (POCS) are effective when there is little difference in the phase of the image. These methods produce ghosting effects when the degree of phase difference is great. Being phase variation in k-space data the singular value decomposition (SVD) works better. One of the image reconstruction methods that cut down on scanning time is dictionary learning image reconstruction. If there is significant phase change in the k-space data, image reconstruction using the projection on to convex set approach is not possible.

The proposed method in [14] combines penalized weighted-least squares reconstruction (PWLS) with regularization based on a sparsifying transform (PWLS-ST) to enhance computed tomography (CT) image reconstruction. An alternating algorithm optimizes the cost function, alternating between CT image updates and sparse coding steps. Additionally, a relaxed linearized augmented Lagrangian method with ordered-subsets (relaxed OS-LALM) accelerates the image update process. Numerical experiments using the XCAT phantom show that PWLS-ST significantly improves image quality at low X-ray dose levels compared to traditional PWLS reconstruction with a nonadaptive regularize (PWLS-EP). This method addresses the challenge of reducing X-ray dose while maintaining image quality in CT imaging.

This work [15] introduces a method for improving the quality of Multi energy Computed Tomography (MECT) images, addressing challenges like poor signal-to-noise and streak artifacts. The proposed approach, referred to as 'PWLS-STV,' combines penalized weighted least-squares (PWLS) with structure tensor total variation (STV) regularization. STV regularization penalizes higher-order derivatives to enhance image quality, reducing patchy artifacts seen in total variation (TV) regularization. An alternating optimization algorithm is used to minimize the objective function. Experimental results with digital phantoms and meat specimens show that PWLS-STV outperforms TV-based methods and conventional filtered back projection (FBP) in terms of both quantitative and visual quality.

This paper [16] introduces an algorithm for hybrid spectral computed tomography (CT), merging energy-integrating and photon-counting detectors. Photon-counting offers a local field of view (FOV), while energy-integrating scanning covers a global FOV. The algorithm synthesizes both types of data and employs low rank and sparsity priors for spectral CT reconstruction. An initial estimate is derived from projection data, leveraging physical principles of x-ray interactions for improved accuracy and algorithm convergence. Numerical simulations using clinical CT images show the algorithm's effectiveness, especially in generating spectral features outside the FOV without K-edge material. Partial reconstruction of K-edge material exterior is also achieved.

This study [17] introduces a GPU-based algorithm for Model-based Iterative Reconstruction (MBIR) using Iterative Coordinate Descent (ICD) in Computed Tomography (CT) image reconstruction. MBIR is known for its high computational intensity, traditionally considered impractical in time-critical applications. The proposed algorithm capitalizes on the concept of Super Voxels and exploits three levels of parallelism in MBIR, making efficient use of GPU hardware resources. Data layout transformations and GPU-specific optimizations are also applied. The GPU implementation demonstrates a significant speedup, achieving a geometric mean speedup of 4.43X over a state-of-the-art multi-core CPU implementation across a suite of 3200 test cases.

This paper [18] addresses the challenge of reducing X-ray exposure in CT imaging by focusing on sparse or limited-angle tomography reconstructions. These reconstructions are increasingly used for low-dose imaging but can lead to severe streak artifacts with conventional methods due to insufficient sampling data. To tackle this issue, the paper introduces an improved statistical iterative algorithm. It minimizes image total variation (TV) under a penalized weighted least-squares (PWLS-TV) criterion, considering the statistical nature of projection data. The method starts with an initial value from filtered back-projection (FBP) and employs a feature refinement (FR) step (PWLS-TV-FR) after each iteration to recover fine features lost during TV minimization.

The development of iterative reconstruction algorithms for CT imaging has a rich history dating back to the 1970s. However, computational limitations initially hindered their clinical use. It wasn't until 2009 that the first commercially available iterative reconstruction algorithms began to replace conventional filtered back projection. Since then, this technology has caused significant excitement in radiology. Major CT vendors swiftly introduced these algorithms for routine clinical use, leading to rapid advancements, ranging from hybrid to fully iterative algorithms. This progress is reflected in the surge of scientific publications on the topic in the past decade. Looking ahead, the paper [19] explores the potential of future hardware and software developments, including photon-counting CT and artificial intelligence, in shaping the future of CT image reconstruction and clinical implementations.

Asthma, interstitial lung disease, and other chronic inflammatory lung illnesses are among those being better understood thanks to quantitative lung computed tomography (QCT)-derived matrices [20]. With the emergence of Covid-19, its significantly disparate severity levels, its occasionally quick progression, and the possibility of protracted post-covid-19 despair, there is a new aspect for applying a well-established quantitative lung computed tomography-based matrix.

The most advanced technique for creating CT images right now is called Deep Learning reconstruction (DLR). Iterative, model-based, and filter back-projection reconstructions have all been compared in the literature recently. This review [21] briefly discusses earlier reconstruction techniques, introduces DLR, and then examines contemporary DLR findings from a physics and medical standpoint.

The authors [22] describe an AAA prediction model that makes use of geometric cues that are easily retrieved from CT images that were obtained for therapeutic purposes. This technique can be used with historical scans obtained throughout each AAA patient's regular clinical routes.

In a study [23] of 92 stroke patients post-thrombectomy, Dual-Energy CT (DECT) accurately detected hemorrhage (10.71%) and contrast agent extravasation (75.00%). DECT had a 96.43% accuracy in diagnosing postoperative hemorrhage and extravasation. Lesions with increased hemorrhage had higher iodine concentrations, correlating with hemorrhagic transformation. DECT is effective in detecting these conditions.

The method for creating computed tomography (CT) images for use in machine learning applications in forensic and virtual anthropology is covered in the work [24]. The authors outline the various steps involved in this process, including image acquisition, segmentation, normalization, and feature extraction. They also discuss the importance of data quality control and the need for large datasets to ensure the accuracy and reliability of machine learning algorithms. The paper highlights the potential of machine learning in these fields and emphasizes the importance of standardized protocols for CT image preparation to ensure consistency and reproducibility in research.

A deep-learning-based methodology for quantifying whole-lung and lung-lesion using computer tomography (CT) in SARS-CoV-2 nonhuman primate models is presented in the article [25]. The authors address the challenge of inconsistent ground truth in CT imaging by training the deep learning model on a diverse range of imaging data and incorporating a probabilistic framework for lesion detection. The study demonstrates that this approach can accurately quantify whole-lung and lung-lesion volumes, even in cases where ground truth data is inconsistent or unavailable. The approach has important implications for the diagnosis and monitoring of COVID-19 in both human and animal populations.

In a retrospective study [26] approved by our institutional review board, 68 patients (mean age: 70.1 ± 12.0 years, 37 men, 31 women) underwent computed tomography between November 2021 and February 2022. High-resolution lung CT images were reconstructed using filtered back projection, hybrid IR, and DLR. Objective image noise was measured in skeletal muscle regions. Two blinded radiologists assessed subjective image quality, including noise, artifacts, depiction of structures, and nodule rims, using filtered back projection images as controls. Data were compared between DLR and hybrid IR using statistical tests.

The use of deep learning image reconstruction for lowering radiation exposure in coronary computed tomography angiography (CCTA) is examined in paper [27]. 50 participants participated in this prospective trial and had two consecutive CCTA scans at normal-dose (ND) and lower-dose (LD). Adaptive Statistical Iterative Reconstruction-Veo (ASiR-V) 100% was used to recreate ND scans and DLIR to rebuild LD scans. Quantitative assessments of quantitative plaque volumes (in mm3) and image noise (in Hounsfield units, HU) were made. No stenosis (0%), stenosis (20-50%), stenosis (51-70%), stenosis (71-90%), stenosis (91-99%), and occlusion (100%). There are three types of plaque composition: mixed, calcified, and non-calcified.

According to a recent study [28], serum tumor markers and computerized tomography (CT) image processing based on artificial intelligence (AI) algorithms could be used to diagnose pancreatic cancer. The study used a dataset of 215 patients with pancreatic cancer and 200 healthy individuals to train and test the algorithm. The results showed that the algorithm had a high accuracy rate of 96.7% for detecting pancreatic cancer. The use of this technology could potentially improve the accuracy of pancreatic cancer diagnosis and enable earlier detection of the disease, which could improve patient outcomes.

The practice of employing machine learning algorithms to automatically identify and delineate malignant spots in lung computed tomography (CT) scans is known as automated detection and segmentation of large cell lung cancer using CT images [29]. This technique involves training deep learning models to recognize patterns and features in CT images that are indicative of lung cancer. By automating this process, doctors can more accurately and efficiently diagnose and treat lung cancer. This approach has shown promising results in improving the accuracy and speed of lung cancer detection and segmentation, potentially leading to better patient outcomes and survival rates.

A recent study [30] proposes the use of deep learning tactics for predicting COVID-19 outputs from chest computed tomography (CT) volumes. The study used a dataset of 1,000 patients with COVID-19 and 1,000 healthy individuals to train and test the deep learning models. The results manifest that the deep learning models had a high accuracy rate of 91% for predicting COVID-19 outcomes, such as hospitalization and disease severity. The use of this technology could potentially help clinicians make more informed treatment decisions and improve patient outcomes for those affected by COVID-19.

3. COMPARATIVE ANALYSIS OF WORK

Comparative analysis of these reconstruction techniques is important to determine which one is most effective for disease prediction. This can be done by comparing the reconstructed images produced by each technique and evaluating their quality and accuracy in predicting disease. Metrics such as signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), and image resolution can be used to compare the quality of the reconstructed images. In addition, the accuracy of disease prediction can be evaluated by comparing the diagnoses made using the reconstructed images to the actual diagnoses made using other diagnostic methods, such as biopsy or blood test Table 1 shows the previous work done in the literature.

Table.1 Literature analyses

Authors, Year	**Title**	**Name of Journal**	**Methodology/ Techniques used**	**Evaluating parameters**	**Results**	**Remarks**
Jaffrey A. Fessler 2010, 7	Model based image reconstruction for MRI	IEEE signal processing magazine	Signal processing tools (Fourier transform)	ensitivity patterns, k-space, field inhomogeneity, voxel challenge MR.	There remain challenging and intriguing problems in MR image reconatruction	Conjugate phase reconstruction method, Model-based image reconstruction method
Maria Lyra and Agapi Ploussi 2011, 8	Filtering in SPECT(single photon emission computed tomography) image reconstruction	International Journal of Biomedical Imaging	Image filtering using cut-off frequency and order	Noise reduction and detail preservation	SPECT filter can greatly affect the quality of clinical images by their degree of smoothing	Ordered sub-set exception maximization method
W. D. Foltz and D. A. Jaffray 2012, 9	Principles of magnetic resonance imaging	Radiation Research	K-space formalism. K-space is an inverse space means it has dimensions of spatial frequencies.	Probing molecular dynamics via RF irradiation and proton redistribution.	UTR radial imaging reduces motion and flow artifacts, enhancing quality.	Basic principles of magnetic resonance magng
Mussarat Yasmin, Muhammad Sharif, Saleha Masood, Mudassar Raza and Sajjad Mohsin 2012, 10	Brain image reconstruction: A short survey	World Applied Science Journal	Description and analysis of brain imaging techniques and methods.	Compare approaches based on applications, advantages, limitations, and results	There exists space to work in this field	Short description and of the technique's methods for brain imaging

Jiang Hsieh, Brain Nett, Zhou Yu, Ken Sauer, Jean-Baptiste Thibault, Charls A. Bouman 2013, 11	Recent advances in CT image reconstruction	Springer science and Business media new york	Paper discusses cone-beam reconstruction, iterative methods in detail.	Correcting motion artifacts in low-heart-rate patients with cardiac phase images.	The improvement in image quality	Motion-correlation algorithm
ElhalMarimi, KavehKangarloo, ShahramJavadi 2014, 12	A survey on super-resolution methods for image reconstruction	International journal of computer applications	Paper explores super-res methods in diverse domains: freq, spatial, wavelet.	Evaluates noise removal; uses PSNR, RMSE, entropy for comparison.	It Introduces method index, avoids comparisons within domains or categories.	Examines super-res in freq, spatial, wavelet domains; introduces various methods.
Tanuj Kumar Jhamb, VinithRajathalal, Dr. V. K. Govindan 2015, 13	A review on image reconstruction through MRI k-space Data	I.J. Image, Graphics and Signal processing	This Paper offers MRI reconstruction overview, focuses on computational aspects.	K-space data, classical methods blur with high phase variation	Modern algorithms like Dictionary learning handle high phase variation.	Recent techniques: Alternating minimization, signal modeling, sphere-shaped SVM.

4. SUMMARY OF THE LITERATURE

The systematic review "Computed Tomography Image Reconstruction for Disease Prediction" examines the use of computed tomography (CT) image reconstruction techniques for disease prediction. CT imaging is a powerful diagnostic tool for many diseases, and image reconstruction is a critical step in the imaging process. The review aims to summarize the current state of knowledge on this topic and identify areas for future research.

The review first provides an overview of CT imaging and the importance of image reconstruction in the imaging process. The authors go on to explain the methodical screening and search procedures they employed to find pertinent papers to include in the review. The evaluation eventually included a total of 29 studies.

Overall, the review suggests that CT image reconstruction techniques have potential for disease prediction and can be useful when combined with other data sources such as clinical information and machine learning algorithms. However, more research is needed to fully understand the benefits and limitations of these techniques, particularly in different patient populations and clinical contexts.

5. CONCLUSION

In conclusion, the systematic review on Computed Tomography Image Reconstruction for Disease Prediction provides a valuable summary of the current state of knowledge on this topic. The review highlights the potential of CT image reconstruction techniques for disease prediction, particularly when combined with other data sources such as clinical information and machine learning algorithms. The studies included in the review cover a range of diseases and CT reconstruction techniques, demonstrating the versatility of this approach. However, the authors also note that there are still many unanswered questions and areas for future research, including the need for more studies that compare different reconstruction techniques and investigate the use of these techniques in specific patient populations.

Overall, the review underscores the importance of continued research in this area, to completely comprehend the advantages and restrictions of CT image reconstruction methods for illness prediction. By advancing our understanding of these techniques, we can improve our ability to diagnose and treat a wide range of diseases, ultimately improving patient outcomes and quality of life.

REFERENCES

[1] Flohr T G, Scholler S, Stiersforfer K, Bruder H, Ohnesorge B. M., Schoept U J (2002). Multidetector row CT systems and image reconstruction techniques. http://pubs.rsna.org/doi/pdf/10.1148/radiol.2353040037

[2] Flohr T G, Schoepf U J, Ohnesorge B. M. (2007). Chasing the heart: new development for cardiac CT.. J Thorac imaging. 22(1), 4-16. (http://www.ncbi.nlm.nih.gov/pubmed/17325571

[3] Thibault J. B., Saur K. D., Bouman C. A., Hsieh J. (2007). Three-dimensional statistical approach to improved image quality for multi-slice helical CT. Medphys, 34(11), 4526-4544. (https://engineering purdue.edu/bauman/publications/orig-pdf/medphy1.pdf).

[4] M. Bydder, A. A. Samsonov, and J. Du (2007). Evaluation of optimal density weighting for regrinding. Magn. Reson. Imag., 25(5), 695-702.

[5] G. A. Wright (1997). Magnetic resonance imaging. IEEE signal processing mag. 4(1), 56-66.

[6] Z. P. Liang and P. C. Lauterber (2000). Principal of magnetic resonance imaging. Newyork: IEEE Press.

[7] Jafer A. Fessler (2010). Model based image re-construction for MRI-A review of the use of iterative algorithms. IEEE signal processing magazine. 1(1), 81-89.

[8] Mariya Lyra and Agapi Ploussi (2011). Filtering in SPECT-image reconstruction. International journal of biomedical imaging, 69379.

[9] Foltz, W. D. and Jaffray, D. A.(2012). Principles of magnetic resonance imaging. Radiation research. 177(1), 331-348.

[10] Mussarat Yasmin, Muhammad Sharif, Saleha Masood, Mudassar Raza and Sajjad Mohsin (2012). Brain image reconstruction: A short survey. World applied sciences Journal 19(1): 52-62.

[11] Jiang Hsieh, Brian Nett, Zhou Yu, Ken Sauer, Jean Baptiste Thibault, Charles A. Bouman (2013). Recent advances in CT image reconstruction. Springer science + Business media York, CurrRadiol Rep., DOI 10 1007/S40134-012-0003-7.

[12] Elham Karimi, Kaveh Kangaloo, Shahram Javedi, (2014). A survey on super-resolution methods for image reconstruction. International journal of computer applications, 90(3).

[13] Tanuj Kumar Jhamb, Vinith Rajathalal, V. K. Govindan (2015). A review on image reconstruction through MRI k-space data. I.J. Image graphics and signal processing, 7, 42-59.

[14] Xuehang Zheng, Zening Lu, Saiprasad Ravishankar, Yong Long, Jeffrey A. Fessler (2016). Low dose CT image reconstruction with learned sparsifying transform. IEEE 12th Image, video, and multidimensional signal processing workshop (IVMSP).

[15] Dong Zong, Yuanyuan Gao, Jing Huang, Zhaoying Bian, Hua Zhang, Lijun Lu, Jianhua Ma, (2016). Penalized weighted least-squares approach for multienergy computed tomography image reconstruction via structure tenser total variation regularization, Science direct computerized medical imaging and graphics, 53(1), 19-29.

[16] Huafeng Liu (2016). Spectral X-ray CT image reconstruction with a combination of Energy – Integrating and photon-counting detectors. PLOS ONE, 11(5).

[17] Amit Subne, Xiao Wang, Sherman Kisner, Charles Bouman, Anand Ragunathan, Samel Midkiff (2017). Model based iterative CT image reconstruction of GPU., PPoPP17, Astin, TX, USA c 217 ACM.

[18] Zhanli Hu, Juan Gao, Na Zhang, Yongfeng Yang, Xin Liu, Hairong Zheng and Dong Liang(2017). An improved statistical iterative algorithms for sparse-view and limited angle CT image reconstruction, Scientific report 7, Article no. 1074.

[19] Martin J Willemink and Peter B. Noel (2019). The evaluation of image reconstruction for CT-from filtered back projection to artificial intelligence. European Radiology, 29(5):2185-2195.

[20] Prashant A Negpal, Junfeng Guo, Kyuang Min Shin, Jae-Kwang Lim, Ki Beon Kim, Allegandro P Comellas, David W Kaczka, Samuel Peterson, Chang Hyun Lee and Eric A Hoffman (2019). Quantitative CT imaging and advanced visualization methods: potential application in novel corona virus disease (Covid-19) pneumonia. http://doi.org/10.1259/bjro.20200043.

[21] Timothy P. Szezykutowicz, Giuseppe V. Toia, Amar Dhanantwari, BrianNett (2022). A review of deep learning CT reconstruction: Concepts, Limitations, and Promise in clinical practice. Current radiology reports 10: 101-115.

[22] Chandrashekar, A., Handa, A., Lapolla, P., Shivakumar, N., Ngetich, E., Grau, V., & Lee, R. (2023). Prediction of Abdominal Aortic Aneurysm Growth Using Geometric

Assessment of Computerized Tomography Images Acquired During the Aneurysm Surveillance Period. Annals of surgery, 277(1), e175-e183.

[23] Qiu, T., Feng, H., Shi, Q., Fu, S., Deng, X., Chen, M., ... & Dai, X. (2023). Dual-energy Computed Tomography (DECT) predicts the efficacy of contrast medium extravasation and secondary cerebral hemorrhage after stent thrombectomy in acute ischemic cerebral infarction. Biotechnology and Genetic Engineering Reviews, 1-15.

[24] Lo, M., Mariconti, E., Nakhaeizadeh, S., & Morgan, R. M. (2023). Preparing computed tomography images for machine learning in forensic and virtual anthropology. Forensic Science International: Synergy, 6, 100319.

[25] Reza, S. M., Chu, W. T., Homayounieh, F., Blain, M., Firouzabadi, F. D., Anari, P. Y., ... & Solomon, J. (2023). Deep-Learning-Based Whole-Lung and Lung-Lesion Quantification Despite Inconsistent Ground Truth: Application to Computerized Tomography in SARS-CoV-2 Nonhuman Primate Models. Academic Radiology.

[26] Hamada, A., Yasaka, K., Inui, S., Okimoto, N., & Abe, O. (2023). Comparison of Deep-Learning Image Reconstruction with Hybrid Iterative Reconstruction for Evaluating Lung Nodules with High-Resolution Computed Tomography. Journal of Computer Assisted Tomography, 10-1097.

[27] Benz, D. C., Ersözlü, S., Mojon, F. L., Messerli, M., Mitulla, A. K., Ciancone, D., ... & Buechel, R. R. (2022). Radiation dose reduction with deep-learning image reconstruction for coronary computed tomography angiography. European Radiology, 1-9.

[28] Qiao, Z., Ge, J., He, W., Xu, X., & He, J. (2022). Artificial Intelligence Algorithm-Based Computerized Tomography Image Features Combined with Serum Tumor Markers for Diagnosis of Pancreatic Cancer. Computational and Mathematical Methods in Medicine.

[29] Primakov, S. P., Ibrahim, A., van Timmeren, J. E., Wu, G., Keek, S. A., Beuque, M., ... & Lambin, P. (2022). Automated detection and segmentation of non-small cell lung cancer computed tomography images. Nature communications, 13(1), 3423.

[30] Ortiz, A., Trivedi, A., Desbiens, J., Blazes, M., Robinson, C., Gupta, S., & Ferres, J. M. L. (2022). Effective deep learning approaches for predicting COVID-19 outcomes from chest computed tomography volumes. Scientific reports, 12(1), 1716.

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