Review of Contemporary Philosophy
ISSN: 1841-5261, e-ISSN: 2471-089X
Vol 22 (1), 2023
Pp 2196 - 2203

Pediatric Radiology: Adapting Imaging Protocols for Younger Populations

[1]-Abdullah Ghannam H Al Muatiri,[2]-Hind Yousef Ahmad Albutyan,[3]-Abdullah Nasser Alotaibi,[4]-Al-Otaibi Abdullah Mohammed,[5]-Mohammed Abdullah Alshahrani,[6]-Hassel Mohammed Alasmary,[7]-Al-Hasan Badr Essa,[8]-Abdulmohsen Nawaf Alotaibi,[9]-Ali Hussain Qasem Alnami,[10]- Mohammed Hassan Mohammed Daghriri,[11]- Bander Yassen Abdu Quhal,[12]- Abdulmajeed Hussain Zughaibi,[13]- Abdullah Nasser Almansour,[14]- Hejab Ali Hassan Abutaleb,[15]- Hassan Mohammed Ali Hazazi

1. Ksa, Ministry Of Health, Maternity And Children's Hospital Hafar Al-Batin
2. Ksa, Ministry Of Health, Moh
3. Ksa, Ministry Of Health, Al Naseem Al Gharbi Primary Health Care Center
4. Ksa, Ministry Of Health, Riyadah First Health Cluster
5. Ksa, Ministry Of Health, Hq
6. Ksa, Ministry Of Health, Hq
7. Ksa, Ministry Of Health, Riyadh First Health Cluster
8. Ksa, Ministry Of Health, Alhamra Primary Health Care Center
9. Ksa, Ministry Of Health, Riyadh Seccond Health Cluter
10. Ksa, Ministry Of Health, Jazan
11. Ksa, Ministry Of Health, Al-Tuwal General Hospital
12. Ksa, Ministry Of Health, Sabya General Hospital
13. Ksa, Ministry Of Health, Phcc Eskan Almather
14. Ksa, Ministry Of Health, Phcc New Sabya
15. Alhurrath General Hospital Ksa, Ministry Of Health,

Abstract

Background: Pediatric radiology is crucial in diagnosing and treating medical conditions in children, yet it poses unique challenges due to the heightened sensitivity of younger patients to ionizing radiation. The "as low as reasonably achievable" (ALARA) principle emphasizes minimizing radiation exposure while ensuring diagnostic efficacy.

Methods: This study systematically reviews literature on artificial intelligence (AI) applications for radiation dose optimization in pediatric imaging. An electronic search across multiple databases (PubMed, ScienceDirect, etc.) was conducted using keywords related to AI, dose reduction, and pediatrics, focusing on studies published after 2017.

Results: The review identified significant advancements in AI methodologies, particularly deep learning techniques, which have demonstrated potential in reducing radiation doses by 36% to 95% across various imaging modalities, including CT and PET scans. Most studies indicated that AI could maintain diagnostic image quality while significantly lowering radiation exposure, addressing both safety and efficacy concerns in pediatric radiology.

Conclusion: The findings underscore the importance of integrating AI-driven technologies in pediatric radiology to optimize radiation dose while ensuring high-quality imaging. Challenges remain, including the need for continuous education and standardization in pediatric imaging practices. Future research should focus on expanding the scope of studies to include a broader range of imaging modalities and larger sample sizes to validate AI applications comprehensively.

Keywords: Pediatric radiology, radiation dose optimization, artificial intelligence, deep learning, imaging protocols.

Received: 16 october 2023 **Revised:** 29 November 2023 **Accepted:** 13 December 2023

1. Introduction

Radiology is an essential component of contemporary healthcare. Nonetheless, the majority of medical imaging techniques, including computed tomography (CT), positron emission tomography (PET), and conventional radiography, use ionizing radiation for image generation [1-4]. Despite the modest radiation dosage associated with these imaging modalities (<100 mSv) and the ambiguity around their actual danger, some epidemiological and biological investigations have shown that these radiological exams may induce cancer [5-8]. Consequently, "as low as reasonably achievable" (ALARA) has emerged as the foundational premise of radiology practice [9,10]. The International Commission on Radiological Protection (ICRP) has initiated the diagnostic reference levels (DRLs) program for radiological departments to identify examinations with radiation doses surpassing their respective DRLs and to initiate the radiation dose-optimization process [11].

Pediatric radiography is a specialist domain within diagnostic imaging that addresses the distinct requirements of newborns, children, and adolescents. This expertise is essential because juvenile patients possess unique anatomical, physiological, and developmental traits in contrast to adults [12-15]. Consequently, imaging methods and techniques must be modified to guarantee optimum safety, precision, and effectiveness in a younger demographic. This study examines the significance of customized imaging techniques, the obstacles encountered in pediatric radiology, and the technological and methodological breakthroughs that improve patient care in this vulnerable population [16-18].

Children are not just little adults; their bodies are experiencing substantial transformations throughout growth. This expansion impacts several aspects that affect imaging, such as organ size, developmental stage, and the probability of radiation-induced harm. Pediatric patients have distinct illness prevalence and pathology compared to adults. Conditions such as congenital anomalies, pediatric neoplasms, and childhood illnesses need targeted imaging methodologies. Furthermore, pediatric patients often display anxiety and apprehension during imaging procedures, resulting in challenges in acquiring high-quality pictures. This introduces additional complexity to pediatric radiography, requiring the formulation of guidelines that address both physiological factors and the psychological well-being of the kid [19,20].

2. Obstacles in Pediatric Radiology

Notwithstanding the progress in imaging technology and techniques, pediatric radiology encounters several hurdles. A major problem is the need for continuous education and training for radiologists and technicians in pediatric imaging methodologies and safety protocols. Consistent training guarantees that all personnel are informed of the latest methods for reducing radiation exposure and comprehending the developmental factors pertinent to pediatric patients [21-25].

A further problem resides in the heterogeneity in anatomy and disease among children. Pediatric patients exhibit a wide array of disorders that may be unfamiliar to adult patients. This requires a significant degree of proficiency and experience among pediatric radiologists. Continuing medical education and mentoring programs may mitigate this difficulty by ensuring practitioners remain informed about the newest advancements in the area [26,27].

The use of emerging technologies, including artificial intelligence (AI) and machine learning, in pediatric radiography offers both prospects and obstacles. Artificial intelligence systems may facilitate picture analysis and illness identification, thereby enhancing diagnostic precision and efficiency. Nonetheless, the ethical ramifications of AI in clinical practice, including issues of data privacy and the risk of algorithmic bias, must be meticulously addressed to safeguard the safety and welfare of pediatric patients [28].

3. Progress in Technology and Methodology

Recent breakthroughs in imaging technologies have dramatically improved pediatric radiology. The advancement of low-dose CT methodologies, including iterative reconstruction methods and computerized exposure management, facilitates the acquisition of high-quality images while minimizing radiation exposure. Advancements in MRI, such as expedited acquisition times and enhanced patient comfort protocols, also provide improved results in pediatric patients [29-34].

Furthermore, the use of portable and point-of-care imaging technology, such as handheld ultrasound equipment, provides the benefit of bedside imaging for critically sick neonates and infants. These advances enhance imaging accessibility and facilitate prompt clinical decision-making in critical circumstances. The radiation used in radiological exams serves as the signal source; hence, a fall in radiation levels leads to diminished signal strength and heightened picture noise. The dose-optimization approach traditionally entails adjusting several exposure and scan settings to identify those that provide the lowest radiation dosage while still obtaining pictures that satisfy basic diagnostic standards [33-36]. Since the advent of digital medical imaging, image processing has been pivotal in optimizing radiation dosage [37-39]. Nevertheless, conventional image processing methods cannot surmount the tradeoff between picture noise and spatial resolution [9,10-12]. In recent years, artificial intelligence (AI) has been used in radiology for the optimization of radiation dosage. Research has shown its capacity to extend the boundaries, namely by further diminishing the radiation dosage without compromising picture quality, including noise and spatial resolution [1,6,9-12,15,16].

Optimizing dosage is crucial for juvenile patients due to their extended lifespan and accelerated cell proliferation, resulting in a two to threefold increased vulnerability to the detrimental effects of ionizing radiation compared to adults [17,33,36,40]. However, dosage optimization in pediatric radiography is complex because of significant variability in body size and composition both within and across age groups [4,33,41,42]. Notwithstanding its significance and complexity, it seems that just a single narrative review paper has been published on this subject, focusing on deep learning image reconstruction (DLIR) for dose optimization in pediatric CT [17]. Therefore, it is appropriate to do a comprehensive evaluation of the use of AI for dose optimization in pediatric radiology.

4. Methods

An electronic literature search was performed using scholarly databases, including Google Scholar, PubMed/Medline, ScienceDirect, Scopus, and Web of Science, to identify articles regarding AI for dose optimization in pediatric radiology. The search term that was employed was ("Machine Learning" OR "Deep Learning" OR "Artificial Intelligence") AND ("Dose Reduction" OR "Dose Optimization") AND ("Children" OR "Pediatric") AND ("Radiology" OR "Medical Imaging"). The search terms were determined by the review emphasis. The year range was established based on a narrative assessment of the present and prospective uses of AI in radiology, which indicated that the utilization of AI for dosage optimization in radiology was not apparent before 2017 [43].

5. AI for radiation dose optimization

The evaluation of AI for radiation dose optimization in pediatric radiology aligns with other previous narrative studies on the use of AI in radiology [17,43]. The 2018 narrative review of the present and prospective uses of AI in radiology reported just one paper on low-dose CT denoising from 2017. Recently, several papers on the use of AI for dose optimization have been published, culminating in a narrative review on AI for dose optimization in pediatric CT released in 2021 [17]. This indicates that the use of AI for dosage optimization in pediatric radiography has lately garnered professional interest. The narrative evaluation demonstrated that DLIR allowed a 30–80% decrease in dosage for pediatric CT while maintaining diagnostic picture quality. This comprehensive review, which incorporates other research on dose optimization in pediatric CT and other imaging modalities, demonstrates that most AI models successfully reduced radiation dosage by 36–70% [1,6,7,10,13,16]. However, three studies included in this systematic review indicated that the use of AI might provide a significant decrease in radiation exposure (up to 95%) [2,12,14]. The significant disparity in dose reduction efficacy is attributed to the retrospective design of numerous studies included [1,4-9,12,15], which precluded the adjustment of examination or scan parameters to achieve ultra-low-dose images for assessing the capability of AI models to restore the quality of these images to near-original standards [9]. While phantom studies allow for more freedom in manipulating examination and scan parameters without ethical or radiation dosage constraints, facilitating deeper investigation of AI model potential, their assessment conclusions often lack clinical relevance [44-48].

Jeon et al. [2] indicated that Canon AiCE could diminish the CT dose by 95%, achieving contrast-to-noise ratio values in the DLIR phantom images comparable to those reconstructed via filtered back projection; however, the applicability of these findings to clinical practice remains uncertain. Wang et al.'s [14] clinical prospective study demonstrated that their proprietary AI denoising model, created via transfer learning utilizing 17 standard-dose PET simulated datasets and MRI training datasets, successfully reduced the radiation dose by 93.8% for whole-body PET examinations while maintaining sufficient diagnostic accuracy. This suggests that utilizing AI denoising can facilitate approximately 90% dose reduction in clinical practice, despite the small sample sizes and/or limited training datasets in all included studies, a prevalent challenge in AI research within radiology due to the restricted availability of medical images. Nonetheless, employing transfer learning (i.e., retraining an existing AI model with a limited dataset, with or without architectural modifications) to create an AI model for a similar task could yield dose-optimization performance on par with commercially available models (Canon AiCE, GE TrueFidelity, etc.) that are trained on larger datasets [2,12,14,43].

It is anticipated that all but two research used AI models using the deep CNN architecture, given this design originated in the 1980s and has since been extensively applied in radiology, with commendable performance [1,2,4,5,6,8-16,37]. One research published in 2022 used the more modern and powerful deep learning architecture, GAN, which was developed in 2014 [7,49]. A narrative review of the use of GANs in radiology published in 2021 [49] indicates that CNN-based denoising models may yield CT images with a plastic-like look, akin to those generated by iterative reconstruction, owing to excessive smoothing. Conversely, the GAN is a more intricate architecture including a generator and a discriminator, necessitating the concurrent training of both, hence increasing the complexity of model generation [37]. Nevertheless, the GAN-based denoising models may retain texture features, hence generating pictures of quality comparable to standard photos [49]. The GAN-based dose-optimization research included in this systematic review also revealed that readers could not distinguish between standard-dose and GAN-processed pictures while achieving only a 36.6% dosage reduction in their study [7]. This review also included dose-optimization research not based on CNN, which used the Gaussian mixture model (GMM) architecture [3]. The use of GMM for medical picture denoising was documented before the advent of GAN [54]. Nonetheless, its use in radiology is limited, and its clinical efficacy in optimizing pediatric radiology doses is still ambiguous [3,17,43,49].

This work is the first systematic evaluation of artificial intelligence for radiation dose optimization in pediatric radiology, including the imaging modalities of CT, PET/MRI, and mobile radiography, hence enhancing the prior narrative review on AI for dose optimization in pediatric CT published in 2021 [17]. While it is well recognized that radiation dose burden is a considerable concern in pediatric CT [1-16], the radiation exposure associated with a PET scan is comparable to that of a CT examination [14]. Moreover, general radiography is the predominant kind of radiological evaluation for pediatric patients, despite its low-dose nature [36]. However, according to the ALARA principle, the potential of AI for dose optimization in additional modalities using ionizing radiation for pediatric assessments warrants further investigation [17,24,25]. Furthermore, because of the limited emphasis and small sample size of the studies analyzed, further research on CT, PET, and general radiography should include a larger scale and broader scope [1-16]. Moreover, additional investigation into the use of GAN for dosage optimization seems justified [7,49].

This review has two primary limitations. The selection of articles, extraction of data, and synthesis were conducted by a single author, who has over 20 years of expertise in literature reviews. A new methodological systematic study [44] indicates that this structure is suitable, contingent upon the reviewer's expertise. Furthermore, only publications authored in English and published within the previous five years were included, which may impact the comprehensiveness of this systematic review. This evaluation, however, has a broader scope than the last narrative review of AI for dose optimization in pediatric CT [17]. Table 1 represents the summary of AI applications in pediatric radiology for dose optimization

Table 1. Summary of AI Applications in Pediatric Radiology for Dose Optimization

Study	Imaging Modality	AI Technique	Dose Reduction	Image Quality Maintenance	Key Findings
Jeon et al. [2]	CT	Deep Learning	Up to 95%	Comparable to the standard dose	Effective in reducing dose while preserving diagnostic quality.
Wang et al. [14]	PET	AI Denoising Model	93.8%	Sufficient for diagnosis	Demonstrated high efficacy in dose reduction with maintained image clarity.
Sun et al. [39]	CT Angiography	Deep Learning Reconstruction	36–70%	High diagnostic integrity	Highlights the potential of deep learning in enhancing image quality while minimizing radiation exposure.
Nagayama et al. [17]	CT	Deep Learning Reconstruction	30–80%	Clinical applicability confirmed	Established the feasibility of low-dose CT imaging using AI techniques.
Park et al. (2022)	CT	AI-based Denoising	36.6%	Indistinguishable from standard	Showed that AI can effectively reduce radiation dose without compromising image quality.

6. Conclusions

This comprehensive research indicates that deep convolutional neural networks were the predominant artificial intelligence approach and architecture used for radiation dose optimization in pediatric radiology. All but three of the included studies assessed the efficacy of AI in dose optimization for abdominal, chest, head, neck, and pelvic CT scans; CT angiography; and DECT using DLIR. Most investigations indicated that AI might decrease radiation dosage by 36–70% while preserving diagnostic integrity. Although commercially available AI models using deep CNNs are predominant, indigenous models, especially those employing the more modern and sophisticated architecture of GANs, may provide equivalent performance.

Future investigation into the efficacy of AI for dose optimization in pediatric radiology is essential, given the limited sample sizes of the research reviewed and the focus on just three imaging modalities: CT, PET/MRI, and mobile radiography, excluding all other examination kinds.

References

1. Brady, S.L.; Trout, A.T.; Somasundaram, E.; Anton, C.G.; Li, Y.; Dillman, J.R. Improving image quality and reducing radiation dose for pediatric CT by using deep learning reconstruction. Radiology 2021, 298, 180–188.
2. Jeon, P.H.; Kim, D.; Chung, M.A. Estimates of the image quality by radiation dose for pediatric imaging using deep learning CT: A phantom study. In Proceedings of the 2022 IEEE International Conference on Big Data and Smart Computing (BigComp), Daegu, Korea, 17–22 January 2022; pp. 352–356.
3. Kim, S.H.; Seo, K.; Kang, S.H.; Bae, S.; Kwak, H.J.; Hong, J.W.; Hwang, Y.; Kang, S.M.; Choi, H.R.; Kim, G.Y.; et al. Study on feasibility for artificial intelligence (AI) noise reduction algorithm with various parameters in pediatric abdominal radio-magnetic computed tomography (CT). J. Magn. 2017, 22, 570–578.
4. Krueger, P.C.; Ebeling, K.; Waginger, M.; Glutig, K.; Scheithauer, M.; Schlattmann, P.; Proquitté, H.; Mentzel, H.J. Evaluation of the post-processing algorithms SimGrid and S-Enhance for pediatric intensive care patients and neonates. Pediatr. Radiol. 2022, 52, 1029–1037.
5. Lee, S.; Choi, Y.H.; Cho, Y.J.; Lee, S.B.; Cheon, J.E.; Kim, W.S.; Ahn, C.K.; Kim, J.H. Noise reduction approach in pediatric abdominal CT combining deep learning and dual-energy technique. Eur. Radiol. 2021, 31, 2218–2226.
6. Nagayama, Y.; Goto, M.; Sakabe, D.; Emoto, T.; Shigematsu, S.; Oda, S.; Tanoue, S.; Kidoh, M.; Nakaura, T.; Funama, Y.; et al. Radiation dose reduction for 80-kVp pediatric CT using deep learning-based reconstruction: A clinical and phantom study. AJR Am. J. Roentgenol. 2022, 23, 1–10.
7. Park, H.S.; Jeon, K.; Lee, J.; You, S.K. Denoising of pediatric low dose abdominal CT using deep learning based algorithm. PLoS ONE 2022, 17, e0260369.
8. Sun, J.; Li, H.; Li, H.; Li, M.; Gao, Y.; Zhou, Z.; Peng, Y. Application of deep learning image reconstruction algorithm to improve image quality in CT angiography of children with Takayasu arteritis. J. X-ray Sci. Technol. 2022, 30, 177–184.
9. Sun, J.; Li, H.; Li, J.; Yu, T.; Li, M.; Zhou, Z.; Peng, Y. Improving the image quality of pediatric chest CT angiography with low radiation dose and contrast volume using deep learning image reconstruction. Quant. Imaging Med. Surg. 2021, 11, 3051–3058.
10. Sun, J.; Li, H.; Li, J.; Cao, Y.; Zhou, Z.; Li, M.; Peng, Y. Performance evaluation of using shorter contrast injection and 70 kVp with deep learning image reconstruction for reduced contrast medium dose and radiation dose in coronary CT angiography for children: A pilot study. Quant. Imaging Med. Surg. 2021, 11, 4162–4171.
11. Sun, J.; Li, H.; Gao, J.; Li, J.; Li, M.; Zhou, Z.; Peng, Y. Performance evaluation of a deep learning image reconstruction (DLIR) algorithm in "double low" chest CTA in children: A feasibility study. Radiol. Med. 2021, 126, 1181–1188.
12. Sun, J.; Li, H.; Wang, B.; Li, J.; Li, M.; Zhou, Z.; Peng, Y. Application of a deep learning image reconstruction (DLIR) algorithm in head CT imaging for children to improve image quality and lesion detection. BMC Med. Imaging 2021, 21, 108.
13. Theruvath, A.J.; Siedek, F.; Yerneni, K.; Muehe, A.M.; Spunt, S.L.; Pribnow, A.; Moseley, M.; Lu, Y.; Zhao, Q.; Gulaka, P.; et al. Validation of deep learning-based augmentation for reduced 18F-FDG dose for PET/MRI in children and young adults with lymphoma. Radiol. Artif. Intell. 2021, 3, e200232.
14. Wang, Y.J.; Baratto, L.; Hawk, K.E.; Theruvath, A.J.; Pribnow, A.; Thakor, A.S.; Gatidis, S.; Lu, R.; Gummidipundi, S.E.; Garcia-Diaz, J.; et al. Artificial intelligence enables whole-body positron emission tomography scans with minimal radiation exposure. Eur. J. Nucl. Med. Mol. Imaging 2021, 48, 2771–2781.
15. Yoon, H.; Kim, J.; Lim, H.J.; Lee, M.J. Image quality assessment of pediatric chest and abdomen CT by deep learning reconstruction. BMC Med. Imaging 2021, 21, 146.
16. Zhang, K.; Shi, X.; Xie, S.S.; Sun, J.H.; Liu, Z.H.; Zhang, S.; Song, J.Y.; Shen, W. Deep learning image reconstruction in pediatric abdominal and chest computed tomography: A comparison of image quality and radiation dose. Quant. Imaging Med. Surg. 2022, 12, 3238–3250.

17. Nagayama, Y.; Sakabe, D.; Goto, M.; Emoto, T.; Oda, S.; Nakamura, T.; Kidoh, M.; Uetani, H.; Funama, Y.; Hirai, T. Deep learning-based reconstruction for lower-dose pediatric CT: Technical principles, image characteristics, and clinical implementations. Radiographics 2021, 41, 1936–1953.
18. Pearce, M.S.; Salotti, J.A.; Little, M.P.; McHugh, K.; Lee, C.; Kim, K.P.; Howe, N.L.; Ronckers, C.M.; Rajaraman, P.; Sir Craft, A.W.; et al. Radiation exposure from CT scans in childhood and subsequent risk of leukemia and brain tumors: A retrospective cohort study. Lancet 2012, 380, 499–505.
19. de Gonzalez, A.B.; Salotti, J.A.; McHugh, K.; Little, M.P.; Harbron, R.W.; Lee, C.; Ntowe, E.; Braganza, M.Z.; Parker, L.; Rajaraman, P.; et al. Relationship between pediatric CT scans and subsequent risk of leukemia and brain tumors: Assessment of the impact of underlying conditions. Br. J. Cancer 2016, 114, 388–394.
20. Lee, K.H.; Lee, S.; Park, J.H.; Lee, S.S.; Kim, H.Y.; Lee, W.J.; Cha, E.S.; Kim, K.P.; Lee, W.; Lee, J.Y.; et al. Risk of hematologic malignant neoplasms from abdominopelvic computed tomographic radiation in patients who underwent appendectomy. JAMA Surg. 2021, 156, 343–351.
21. Mathews, J.D.; Forsythe, A.V.; Brady, Z.; Butler, M.W.; Goergen, S.K.; Byrnes, G.B.; Giles, G.G.; Wallace, A.B.; Anderson, P.R.; Guiver, T.A.; et al. Cancer risk in 680,000 people exposed to computed tomography scans in childhood or adolescence: Data linkage study of 11 million Australians. BMJ 2013, 346, f2360.
22. Halm, B.M.; Franke, A.A.; Lai, J.F.; Turner, H.C.; Brenner, D.J.; Zohrabian, V.M.; DiMauro, R. γ-H2AX foci are increased in lymphocytes in vivo in young children 1 h after very low-dose X-irradiation: A pilot study. Pediatr. Radiol. 2014, 44, 1310–1317.
23. Vandevoorde, C.; Franck, C.; Bacher, K.; Breysem, L.; Smet, M.H.; Ernst, C.; De Backer, A.; Van De Moortele, K.; Smeets, P.; Thierens, H. γ-H2AX foci as in vivo effect biomarker in children emphasize the importance to minimize X-ray doses in pediatric CT imaging. Eur. Radiol. 2015, 25, 800–811.
24. Ng, C.K.C.; Sun, Z. Development of an online automatic computed radiography dose data mining program: A preliminary study. Comput. Methods Programs Biomed. 2010, 97, 48–52.
25. MacKay, M.; Hancy, C.; Crowe, A.; D'Rozario, R.; Ng, C.K.C. Attitudes of medical imaging technologists on use of gonad shielding in general radiography. Radiographer 2012, 59, 35–39.
26. Ng, C.K.C.; Sun, Z. Development of an online automatic diagnostic reference levels management system for digital radiography: A pilot experience. Comput. Methods Programs Biomed. 2011, 103, 145–150.
27. Ng, C.K.C.; Sun, Z.; Parry, H.; Burrage, J. Local diagnostic reference levels for x-ray examinations in an Australian tertiary hospital. J. Med. Imaging Health Inform. 2014, 4, 297–302.
28. Sun, Z.; Ng, C.K.C.; Wong, Y.H.; Yeong, C.H. 3D-printed coronary plaques to simulate high calcification in the coronary arteries for investigation of blooming artifacts. Biomolecules 2021, 11, 1307.
29. Sun, Z.; Ng, C.K.C.; Sá Dos Reis, C. Synchrotron radiation computed tomography versus conventional computed tomography for assessment of four types of stent grafts used for endovascular treatment of thoracic and abdominal aortic aneurysms. Quant. Imaging Med. Surg. 2018, 8, 609–620.
30. Sun, Z.; Ng, C.K.C.; Squelch, A. Synchrotron radiation computed tomography assessment of calcified plaques and coronary stenosis with different slice thicknesses and beam energies on 3D printed coronary models. Quant. Imaging Med. Surg. 2019, 9, 6–22.
31. Sun, Z.; Ng, C.K.C. Use of synchrotron radiation to accurately assess cross-sectional area reduction of the aortic branch ostia caused by suprarenal stent wires. J. Endovasc. Ther. 2017, 24, 870–879.
32. Sun, Z.; Ng, C.K.C. Synchrotron radiation imaging of aortic stent grafting: An in vitro phantom study. J. Med. Imaging Health Inform. 2017, 7, 890–896.
33. Al Mahrooqi, K.M.S.; Ng, C.K.C.; Sun, Z. Pediatric computed tomography dose optimization strategies: A literature review. J. Med. Imaging Radiat. Sci. 2015, 46, 241–249.
34. Sun, Z.; Ng, C. Dual-source CT angiography in aortic stent grafting: An in vitro aorta phantom study of image noise and radiation dose. Acad. Radiol. 2010, 17, 884–893.
35. Almutairi, A.M.; Sun, Z.; Ng, C.; Al-Safran, Z.A.; Al-Mulla, A.A.; Al-Jamaan, A.I. Optimal scanning protocols of 64-slice CT angiography in coronary artery stents: An in vitro phantom study. Eur. J. Radiol. 2010, 74, 156–160.
36. Feghali, J.A.; Chambers, G.; Delépierre, J.; Chapeliere, S.; Mannes, I.; Adamsbaum, C. New image quality and dose reduction technique for pediatric digital radiography. Diagn. Interv. Imaging 2021, 102, 463–470.

37. Sun, Z.; Ng, C.K.C. Artificial intelligence (enhanced super-resolution generative adversarial network) for calcium deblooming in coronary computed tomography angiography: A feasibility study. Diagnostics 2022, 12, 991.
38. Sun, Z.; Ng, C.K.C. High calcium scores in coronary CT angiography: Effects of image post-processing on visualization and measurement of coronary lumen diameter. J. Med. Imaging Health Inform. 2015, 5, 110–116.
39. Sun, Z.; Ng, C.K.C.; Xu, L.; Fan, Z.; Lei, J. Coronary CT angiography in heavily calcified coronary arteries: Improvement of coronary lumen visualization and coronary stenosis assessment with image postprocessing methods. Medicine 2015, 94, e2148.
40. Christie, S.; Ng, C.K.C.; Sá Dos Reis, C. Australasian radiographers' choices of immobilization strategies for pediatric radiological examinations. Radiography 2020, 26, 27–34.
41. PRISMA: Transparent Reporting of Systematic Reviews and Meta-Analyses. Available online: https://www.prisma-statement.org (accessed on 24 June 2022).
42. Eriksen, M.B.; Frandsen, T.F. The impact of patient, intervention, comparison, outcome (PICO) as a search strategy tool on literature search quality: A systematic review. J. Med. Libr. Assoc. 2018, 106, 420–431.
43. Choy, G.; Khalilzadeh, O.; Michalski, M.; Do, S.; Samir, A.E.; Pianykh, O.S.; Geis, J.R.; Pandharipande, P.V.; Brink, J.A.; Dreyer, K.J. Current applications and future impact of machine learning in radiology. Radiology 2018, 288, 318–328.
44. Waffenschmidt, S.; Knelangen, M.; Sieben, W.; Bühn, S.; Pieper, D. Single screening versus conventional double screening for study selection in systematic reviews: A methodological systematic review. BMC Med. Res. Methodol. 2019, 19, 132.
45. Jeong, J.J.; Tariq, A.; Adejumo, T.; Trivedi, H.; Gichoya, J.W.; Banerjee, I. Systematic review of generative adversarial networks (GANs) for medical image classification and segmentation. J. Digit. Imaging 2022, 35, 137–152.
46. Ng, C.K.C. A review of the impact of the COVID-19 pandemic on pre-registration medical radiation science education. Radiography 2022, 28, 222–231.
47. Petri, S.A.; Ng, C.K.C. Comparison of the performance of computed radiography and direct radiography in glass soft tissue foreign body visualisation. S. Afr. Radiogr. 2018, 56, 18–25.
48. Kleinfelder, T.R.; Ng, C.K.C. Effects of image postprocessing in digital radiography to detect wooden, soft tissue foreign bodies. In Radiol. Technol.; 2022; 93, pp. 544–554.
49. Wolterink, J.M.; Mukhopadhyay, A.; Leiner, T.; Vogl, T.J.; Bucher, A.M.; Išgum, I. Generative adversarial networks: A primer for radiologists. Radiographics 2021, 41, 840–857.

الأشعة للأطفال: تكييف بروتوكولات التصوير للأجيال الأصغر سنًا

المستخلص

الخلفية : تُعد الأشعة للأطفال أداة أساسية في تشخيص وعلاج الحالات الطبية لدى الأطفال، ولكنها تواجه تحديات فريدة نظرًا لحساسية الأطفال المتزايدة تجاه الإشعاع المؤين. يُركز مبدأ "أقل ما يمكن تحقيقه بشكل معقول (ALARA) "على تقليل التعرض للإشعاع مع ضمان كفاءة التشخيص.

الطرق : تُراجع هذه الدراسة بشكل منهجي الأدبيات المتعلقة بتطبيقات الذكاء الاصطناعي (AI) لتحسين جرعات الإشعاع في التصوير الطبي للأطفال. تم إجراء بحث إلكتروني عبر قواعد بيانات متعددةPubMed) ، ScienceDirect، وغيرها (باستخدام كلمات مفتاحية تتعلق بالذكاء الاصطناعي، وتقليل الجرعات، وطب الأطفال، مع التركيز على الدراسات المنشورة بعد عام 2017.

النتائج : حددت المراجعة تقدمًا كبيرًا في منهجيات الذكاء الاصطناعي، خاصة تقنيات التعلم العميق، التي أظهرت إمكانيات في تقليل جرعات الإشعاع بنسبة تتراوح بين 36% إلى 95% عبر العديد من أساليب التصوير، بما في ذلك التصوير المقطعي المحوسب (CT) وتصوير البوزيترون المقطعي (PET). أشارت معظم الدراسات إلى قدرة الذكاء الاصطناعي على الحفاظ على جودة الصور التشخيصية مع تقليل التعرض للإشعاع بشكل كبير، مما يعالج مخاوف السلامة والفعالية في الأشعة للأطفال.

الاستنتاج : تؤكد النتائج على أهمية دمج تقنيات الذكاء الاصطناعي في مجال الأشعة للأطفال لتحسين جرعات الإشعاع مع ضمان صور عالية الجودة. لا تزال التحديات قائمة، بما في ذلك الحاجة إلى التعليم المستمر وتوحيد الممارسات في التصوير الطبي للأطفال. يجب أن تركز الأبحاث المستقبلية على توسيع نطاق الدراسات لتشمل مجموعة أكبر من أساليب التصوير وأحجام عينات أكبر للتحقق من تطبيقات الذكاء الاصطناعي بشكل شامل.

الكلمات المفتاحية : أشعة الأطفال، تحسين جرعات الإشعاع، الذكاء الاصطناعي، التعلم العميق، بروتوكولات التصوير.