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Review Article

Current and potential applications of artificial intelligence in medical imaging practice: A narrative review

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ABSTRACT

Background and purpose: Artificial intelligence (AI) is present in many areas of our lives. Much of the digital data generated in health care can be used for building automated systems to bring improvements to existing workflows and create a more personalised healthcare experience for patients. This review outlines select current and potential AI applications in medical imaging practice and provides a view of how diagnostic imaging suites will operate in the future. Challenges associated with potential applications will be discussed and healthcare staff considerations necessary to benefit from AI-enabled solutions will be outlined.

Methods: Several electronic databases, including PubMed, ScienceDirect, Google Scholar, and University College Dublin Library Database, were used to identify relevant articles with a Boolean search strategy. Textbooks, government sources and vendor websites were also considered.

Results/Discussion: Many AI-enabled solutions in radiographic practice are available with more automation on the horizon. Traditional workflow will become faster, more effective, and more user friendly. AI can handle administrative or technical types of work, meaning it is applicable across all aspects of medical imaging practice.

Conclusion: AI offers significant potential to automate most of the manual tasks, ensure service consistency, and improve patient care. Radiographers, radiation therapists, and clinicians should ensure they have adequate understanding of the technology to enable ethical oversight of its implementation.

RÉSUMÉ

Contexte et objectif: L'intelligence artificielle (IA) est présente dans de nombreux domaines de notre vie. Une grande partie des données numériques générées dans les soins de santé peut être utilisée pour construire des systèmes automatisés afin d'améliorer les flux de travail existants et de créer une expérience de soins de santé plus personnalisée pour les patients. Cette étude présente une sélection d'applications actuelles et potentielles de l'IA dans la pratique de l'imagerie médicale et donne un aperçu du fonctionnement futur des salles d'imagerie diagnostique. Les défis associés aux applications potentielles seront discutés et les considérations du personnel de santé nécessaires pour bénéficier des solutions basées sur l'IA seront décrites.

Méthodologie: Plusieurs bases de données électroniques, dont PubMed, ScienceDirect, Google Scholar et la base de données de la bibliothèque de l'University College Dublin, ont été utilisées pour identifier les articles pertinents à l'aide d'une stratégie de recherche booléenne. Les manuels, les sources gouvernementales et les sites web des fournisseurs ont également été pris en compte.

Résultats/Discussion: De nombreuses solutions basées sur l'IA sont disponibles pour la pratique de la radiographie et l'automatisation se poursuit à l'horizon. Le flux de travail traditionnel deviendra plus rapide, plus efficace et plus convivial. L'IA peut prendre en charge des tâches administratives ou techniques, ce qui signifie qu'elle est applicable à tous les aspects de la pratique de l'imagerie médicale.

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Conclusion: L'IA offre un potentiel considérable pour automatiser la plupart des tâches manuelles, assurer la cohérence du service et améliorer les soins aux patients. Les radiographes, les radiothérapeutes et les cliniciens doivent s'assurer qu'ils ont une compréhension suffisante de la technologie pour permettre une surveillance éthique de sa mise en œuvre.

Keywords: Artificial Intelligence; Medical imaging; Radiography; Radiation therapy; Radiology

Introduction

Medical imaging practice is undoubtedly subject to significant changes due to the impressive performance of clinical artificial intelligence (AI). Whilst technological developments of medical imaging equipment are continuously improving, clinical integration of AI has introduced new ways of optimisation and refinement of the diagnostic imaging workflow. With the increased capabilities of medical imaging equipment, and a significant increase in its utilisation, radiographers and clinicians are under increasing work pressure [1-5].

AI is an umbrella term that encompasses various algorithmic learning techniques, including machine learning (ML), its subcategory deep learning (DL), and natural language processing (NLP). ML allows computers to learn from data either through supervised, unsupervised, semi-supervised, or reinforcement learning [6]. In supervised learning, the algorithm learns patterns from datasets containing a set of descriptive features and associated class labels. In contrast, unsupervised learning algorithms learn from unlabelled datasets. A typical unsupervised learning task is anomaly detection, the process of finding outliers in a given dataset [7]. Semi-supervised learning algorithms attempt to learn patterns from partially labelled datasets, mostly consisting of unlabelled examples. Such algorithms are mainly combinations of supervised and unsupervised algorithms. In reinforcement learning, a software agent takes actions, based on observations within an environment, to maximize its positive reward. If an action results in a negative outcome, such as misdiagnosis, or worsened patient outcome, the agent receives a negative reward. DL models are deep neural networks, and like ML, DL can be supervised, unsupervised, or semi-supervised. Due to its superior performance, DL is the most popular learning technique in the medical imaging field for image segmentation, image and text classification, and object detection [8,9]. NLP, on the other hand, enables computers to understand unstructured text, including sensor data, by converting it into a structured form suitable for subsequent ML or DL.

With technological advancements in data storage, graphics processing units and advances in algorithmic training techniques, state-of-the-art AI systems are being increasingly built. Each AI-enabled device intended for clinical use within Europe, US or Canada must undergo a rigorous approval process conducted by either the European Commission, Food and Drug Administration or Health Canada, respectively [10-12]. In this review, we aim to summarize certain current and potential applications of AI in medical imaging practice to raise healthcare professionals' awareness of how AI powers state-of-the-art medical imaging workflows, its associated potentials, challenges, and highlight the importance of knowledge and cautiousness when utilising AI-enabled solutions.

Methodology

The Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines were used as a guide. We performed a review of articles and other resources pertinent to AI applications for technical use in medical imaging practice published from 2000 to March 2023. A search strategy incorporating Boolean "AND" and "OR" logic was used to gather articles across multiple electronic databases such as PubMed, ScienceDirect, Google Scholar, and University College Dublin Library Database. Different combinations of keywords searched included "artificial intelligence", "machine learning", "deep learning", "natural language processing", "radiography", "medical imaging", "diagnostic imaging", "computed tomography", "magnetic resonance imaging", "fluoroscopy", "interventional radiology", "radiation therapy", "radiotherapy". Vendors included in our search were Siemens Healthineers (Erlangen, Germany), General Electric (GE Healthcare, Chicago, IL), and Philips (Amsterdam, NL). Keywords "artificial intelligence", "ethics", "privacy", and "health care" were used to gather resources on AI ethics.

Articles published in English language journals with an impact factor greater than two were selected. This review also included articles that provide grounds for discussing AI-enabled solutions. Hence, specific search terms such as "imaging trends", "dose" etc. were included. Commercial applications of AI were identified through official vendor websites. The search of potential AI applications focused on tasks required prior to image acquisition, namely patient identification and justification of medical exposures. Articles on CT metal artefact reduction (MAR) and synthetic contrast enhancement were of interest due to the high number of articles being available in databases. Articles discussing risks and concerns of AI for healthcare were included. Paediatric, nuclear medicine- and mammography-specific articles were excluded due to subspecialty and to narrow the scope of our review, however certain applications discussed may be applicable to them. Initially, titles and content of retrieved articles were reviewed by a single researcher to identify AI applications for inclusion or exclusion. Eligibility for inclusion in the final review was confirmed

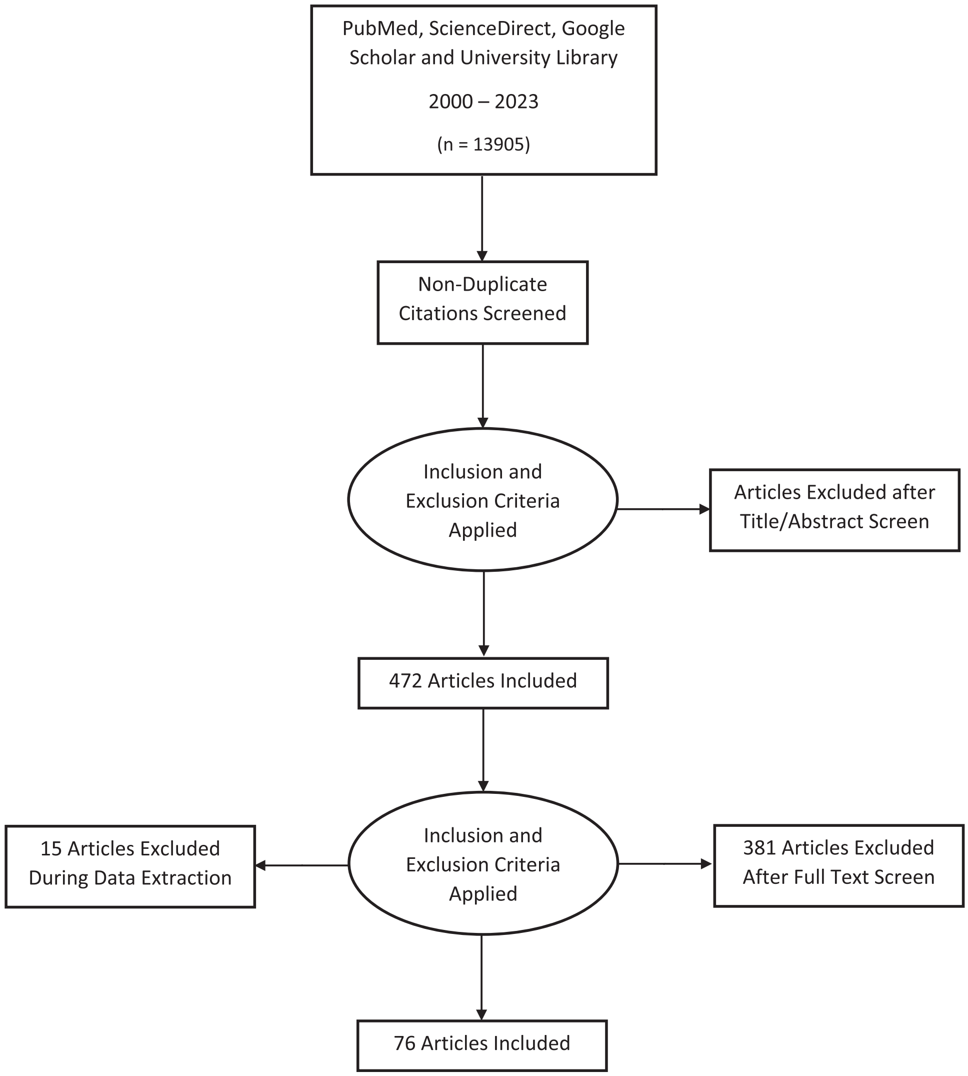

Fig. 1. The PRISMA flow diagram of articles included in our review.

upon full-text review. This process is illustrated in a PRISMA flowchart (Fig.1).

Current clinical applications of artificial intelligence

Commercial clinical applications for technical use discussed are summarized in Fig. 2.

General radiography

General radiography is often used as the initial tool for answering clinical questions. When radiographic images of poor diagnostic quality are accepted, the standard of care may be greatly reduced – repeat radiographs may be warranted, time to establish diagnosis may be prolonged, patient safety may be compromised, and the costs of care may increase [13]. Since chest radiographs are the most frequently performed examinations in hospitals, the development of AI-enabled devices was initiated in this area of practice [14-16]. Radiographers may decide not to repeat mobile chest studies despite poor radiographic technique and image quality and potentially send radiographs of inferior diagnostic quality for reporting [17]. In addition, critical studies often remain concealed in large worklists without any flags indicating that the patient is at higher risk. GE has developed Critical Care Suite 2.0™, a collection of AI algorithms embedded on mobile X-ray systems for assessing antero-posterior chest radiographs [18]. The algorithms can assess endotracheal tube positioning, detect a pneumothorax, and triage studies based on AI findings. Furthermore, the system can automatically rotate a radiograph, detect anatomy cut-off, underexposure or overexposure and make suggestions to radiographers accordingly. These image evaluation features support radiographer decision making in determining diagnostic acceptability of radiographic images. Studies with AI critical findings are automatically flagged and prioritised, as they appear at the top of radiologists' worklist.

Philips has integrated an AI-enabled solution (Radiology Smart Assistant™) which analyses erect postero-anterior chest

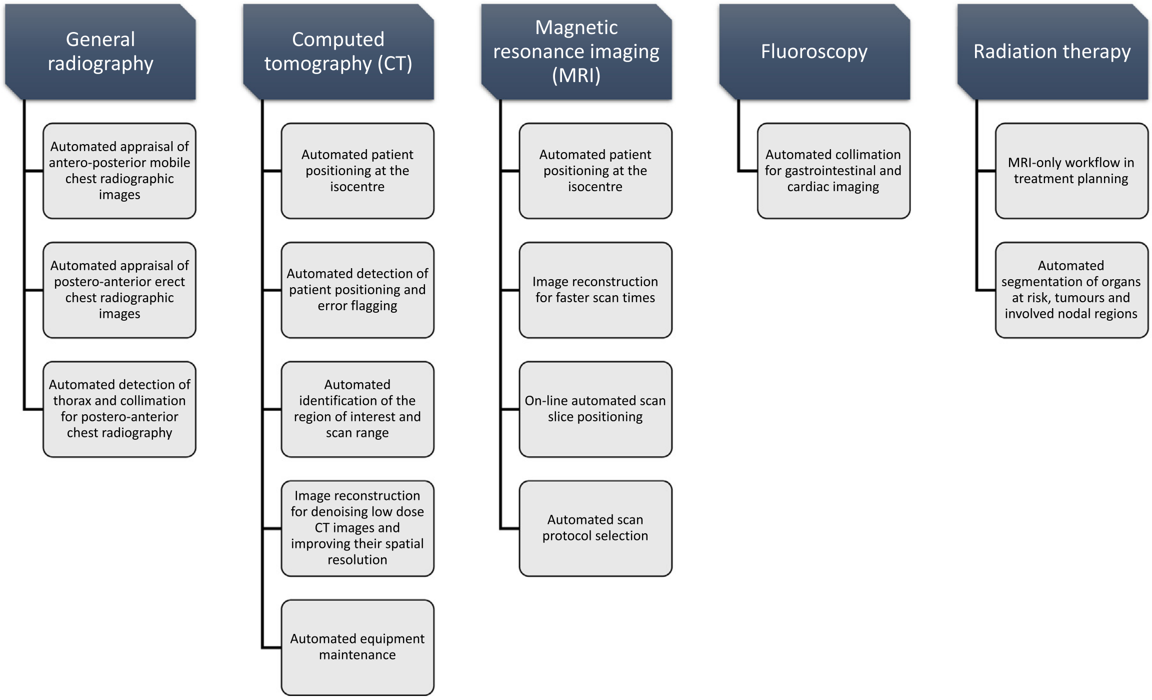

Fig. 2. Current clinical applications of artificial intelligence in medical imaging addressed in our review.

radiographic images in real-time, at the point of acquisition, in terms of collimation, rotation, inspiration, and provides feedback to radiographers to assist their decision making [19]. It has been shown that AI-based image analysis of postero-anterior chest examinations enhances departmental productivity by 30%, reduces unnecessarily exposed areas by 34%, and increases the rate of images with appropriate collimation by 28% [20]. If a radiographer and AI disagree on the image analysis outcome, the Radiology Smart Assistant™ requires the radiographer to provide a reason for accepting an inadequate image. Radiographers can access individual statistics on their performance and how many studies in their department are in accordance with positioning standards, making this particular feature useful for tracking their progress over time, or auditing performance and workload of the diagnostic imaging department.

Siemens Healthineers have developed a ceiling-mounted X-ray system YSIO X.pree™ that takes advantage of the myExam 3D Camera to expedite image acquisition [21]. An AI algorithm embedded in the system automatically detects the thorax, even when patients are clothed, and collimates accordingly [22]. Such automation assists with dose optimisation while allowing radiographers to dedicate more time to their patients [23].

Computed tomography

Wide detector computed tomography (CT) scanners have markedly reduced scan times; however, radiographer variance in patient positioning may contribute to varying dose reference levels for certain anatomical areas and clinical indications [24,25]. Several studies revealed negative impacts on organ dose and image quality when patients are not positioned at isocentre [26-28]. Considering the human factor, workload pressure, patient size and presentation, radiographers may neglect to position the patient correctly in the isocentre of the gantry which results in dose and image quality errors. Modern CT scanners take advantage of a ceiling mounted 3D camera utilising DL to capture the patients' shape, contours, position – head or feet first, height and width, to automatically position patients at the isocentre [29]. The system can detect incorrect patient positioning, for a given CT scan, and warn radiographers about the error. At this specific task, AI significantly outperforms human experts, leading to more consistent radiation output, improved image quality and reduced scan times [30-32].

Localiser radiographs are acquired to manually identify the anatomy of interest and define the scan range of the subsequent CT scan. Operator-to-operator variations can cause inconsistencies in defining the scan range and may lead to overscanning or missing pertinent anatomy and may cause unnecessary patient dose [33]. State-of-the-art workflows utilise DL to accurately identify specific anatomy from localisers and determine the scan range that is optimally centred around the required anatomical coverage [34]. Examples of AI-enabled CT include Siemens FAST Integrated Workflow™, Philips CT Precise Suite™, and GE Revolution™ Maxima [35-37].

CT is known for its fast scan times and excellent spatial resolution, but at the cost of higher radiation exposures. Certain approaches with the aim to reduce radiation dose to patients undergoing chest CT have been developed which often result in reduced image quality [38-40]. It has been demonstrated that DL-based reconstruction outperforms iterative reconstruction in denoising ultra low-dose chest CT images and improving their spatial resolution [41-43]. Similar observations were noted in imaging of the abdomen [44]. TrueFidelity™ is the first image reconstruction technique available that utilises DL to generate high quality CT images from low-dose scans [45].

Experiencing CT equipment failure during busy periods can pose a significant threat to patient care, hospital reputation and finances. For example, if the average number of scans per hour is four, a hospital loss equates to approximately $6,000 per day [46]. Fortunately, ML gives an opportunity to turn long, unexpected downtimes into scheduled maintenance by predicting equipment failure in advance [47,48]. Glassbeam (Santa Clara, US) offers implementation of the Clinsights™ feature within diagnostic imaging workflows to automate CT and magnetic resonance imaging (MRI) equipment maintenance utilising ML for anomaly detection [49]. Radiographers can view alerts and warnings across all modalities from a single workstation or their smartphone.

Magnetic resonance imaging

Long MRI scan times inspired the development of AI-based DL image reconstruction methods for accelerating the scan time, while maintaining diagnostic image quality and perceived benefits in signal to noise ratio and artifact reduction [50,51]. GE and Philips have made DL image reconstruction available allowing for sharper images and up to a 50% and 66% reduction in scan times, respectively [52,53]. Siemens Healthineers is offering a deployment of Deep Resolve™ functionalities to each of their MRI scanners resulting in up to 70% shorter scan times [54]. In combination with the Simultaneous Multi-Slice technology, the scan time can be accelerated by up to 80%. For example, a knee MRI on a three Tesla system takes approximately 10 minutes, whereas DL imaging takes less than two minutes.

AI-powered MRI workflows have undergone further development to automate manual labour and eliminate operator-to-operator variations, including patient positioning at the isocentre. On-line automatic scan slice positioning research dates back to early 2000s and is relevant to today's practice [55,56]. Furthermore, variations in protocol selection are noticeable among institutions and physicians – with the help of AI, protocol selection is becoming automated [57,58] including guidance on recommended patient position, coil and scan parameter selection, and even automated breathing instructions for consistent timing, when required. (e.g., AIR™ Workflow by GE, Philips SmartWorkflow™, and myExam Companion™ by Siemens [59-61]).

Fluoroscopy

Radiographer and physician experience greatly influence radiation dose delivered to patients undergoing fluoroscopy guided procedures, and staff involved due to scattered radiation [62,63]. In extreme cases, patients may suffer from tissue effects due to overexposure, such as skin erythema or ulcers and hair loss [64,65]. Therefore, operators utilising fluoroscopy must ensure appropriate radiation protection for their patients and staff. This includes using lower fluoroscopy frame and pulse rates when possible, keeping the height of an x-ray detector low, limited use of magnification, and adjusting collimation to the anatomical region of interest [66-68]. The latter has become automated for fluoroscopic gastrointestinal endoscopy and cardiac interventional procedures. An AI-enabled fluoroscopy system (Omega Medical Imaging, Sanford, FL) can utilise DL to automatically collimate to the size of the field of view necessary to visualize the anatomy of interest and procedural activity at ultra-fast pace without compromising image quality [69]. AI-based ultra-fast collimation, in comparison with traditional methods, contributes to more than 60% reduction in patient and staff dose [70].

Radiation therapy

Patients undergoing radiation therapy may undergo both CT and MRI prior to treatment. CT provides information on the soft tissue electron density necessary for dosimetric calculations, while MRI is a complementary modality that offers better soft tissue contrast and delineation accuracy [71]. The bimodal approach comes with certain disadvantages including radiation, time difference between the two acquisitions and internal organ movements, gas volatility, bowel loops displacement in the abdomen, and artifacts such as fiducials, hip prosthesis, or contrast agent. DL-based software for MRI-only radiation therapy planning for head, neck and pelvis has been developed (e.g., Synthetic CT™ by Siemens Healthineers, Spectronic Medical Synthetic CT™ from GE, and MRCAT™ by Philips[72-74]) which automatically generates synthetic CT images, thus saving on both radiation dose and cost of an additional CT examination.

Perhaps the most laborious, yet crucial task in radiation therapy is manual contouring of organs at risk (OAR), primary tumour and involved nodal regions. Any inaccuracies and inconsistencies in this step may lead to underdosing of the tumour or increased toxicity directly impacting patient survival and quality of life. It has been demonstrated that DL (e.g., DirectORGANS™ by Siemens Healthineers, Vysioneer Vbrain™ by GE, and RTdrive™ by Philips) can automate this manual task providing a high degree of accuracy for OAR segmentation and clinical target volume generation in a clinical setting [75-78]. Another study showed the majority of oncologists believed that this particular clinical application of AI would have a positive impact on radiation therapy, although only being used by less than half of survey sites [79]. Some participants had concerns associated with user deskilling, retaining own planning skills and training future oncologists.

Potential applications of artificial intelligence and challenges

Considering current clinical applications of AI, it is reasonable to expect more automation across all imaging modalities and extensions of automated features. The question is how else AI can enhance radiography practice.

Prior to diagnostic imaging procedures, radiographers need to verify patient identity. Systems for establishing and verifying personal identity are particularly central in forensic science and criminal justice [80]. During the COVID-19 pandemic, direct patient contact had to be minimized to minimize the virus spread [81]. Patient identity might be difficult to establish for patients with cognitive decline, unconscious patients or deceased trauma victims. AI algorithms establishing personal identity based on the facial and eye region have been developed [82-84]. In the future, AI could play a big role in timely personal identification of such individuals, particularly during a crisis, by contactless means. However, AI algorithms for face recognition have varying accuracy and tend to be biased. For example, darker-skinned women tend to be misclassified more often than lighter-skinned men [85]. For this reason, only diverse datasets that capture marginalized groups should be used to train such systems, and thorough evaluation is required prior to implementation within health care. Moreover, the electronic databases containing identity pictures of individuals should be stored in a cyber-attack proof system to protect the identity and theft of personal data. The vulnerability of the national system was exposed on the 14th of May 2021 when the Conti ransomware shut down the Irish healthcare IT system and stole sensitive data from 520 patients, hence safety and data privacy concerns regarding automated personal identification in health care are reasonable [86].

Justification of medical exposures is a key principle in ensuring that the benefits of the examination outweigh the associated risks [87]. There is potential to efficiently implement clinical imaging guidelines within clinical practice by automating justification analysis of unstructured CT and MRI radiology referrals with AI. This could serve radiographers and clinicians as a clinical decision support at conducting both retrospective justification audits and real-time analysis [88,89]. Since AI can analyse thousands of referrals within seconds, regular retrospective audits would become more feasible, as significant funding would no longer be needed, as well as recruiting human experts and dedicating months of time to manually assess the compliance of referrals with the guidelines. This application of AI could result in a higher rate of justified examinations, locally and nationally, reduced radiation dose and CT and MRI waiting lists burden. Datasets for training automated systems for justification should also be diverse to capture the inter-physician, inter-institutional varieties in medical language and common spelling mistakes.

Orthopaedic and dental implants cause streak artifacts and skewed information on x-ray beam attenuation in CT imaging. Consequently, the impact on visual assessment of reconstructed CT images is hard to ignore. MAR techniques attempt to limit this effect, inaccurate estimations may still be produced, valuable information may be lost and as a result, additional postprocessing artifacts may occur [90,91]. Given longer image post-processing times and, often, increased patient dose, using dual-energy CT as a MAR technique is not optimal [92]. On the other hand, due to its accuracy, faster processing times and no requirements for additional patient dose, DL-based CT image reconstruction tends to outperform iterative, interpolation, and dual energy-based reconstruction methods [93-95]. In the future, it is very likely to see an emergence in commercialisation of DL-based MAR.

Contrast-enhanced CT involves intravenous or intra-arterial administration of contrast media to enhance anatomy and pathology of interest. Adverse reactions do occur, and complications associated with extravasation and air embolism pose further risk [96]. Additionally, there is a worldwide shortage of contrast material with many clinical sites reducing the volume injected [97]. In chest CT, contrast enhancement is required for detailed evaluation of the mediastinum, pleura, and vessels. A DL technique for generating synthetic contrast-enhanced chest CT from non-contrast chest CT was developed [98]. The contrast differentiation, between mediastinal lymph nodes and surrounding vascular structures, was enhanced on the synthetic contrast-enhanced images, allowing readers to detect a higher number of nodes than on non-contrast CT alone. However, the model fails to clearly delineate hilar and segmental lymph nodes adjacent to pulmonary vessels. Another study investigated feasibility of DL for generating synthetic contrast-enhanced abdomen CT from non-contrast abdomen CT [99]. Patients presenting with acute abdominal pain often undergo a non-contrast abdomen CT to identify the cause of symptoms; the diagnostic value of non-contrast CT can be increased with DL-based synthetic contrast enhancement. The outputs of a developed DL model significantly improved diagnostic accuracy in half of the readers involved in the study, and the majority of readers reported increased confidence in diagnosis when interpreting synthetic contrast-enhanced scans. All readers agreed that the image quality of synthetic CT was sufficient with moderate limitations for clinical use. Synthetic contrast enhancement methods exhibit potential to be used as a type of post-processing technique to additionally inform non-contrast scans. Evaluation standards regarding diagnostic image quality of synthetic CT need to be developed and image quality of synthetic CT must be improved. As of now, iodinated contrast media in CT imaging will remain, which may not be the case in a distant future.

Knowledge and cautiousness are prerequisites to benefit from automation

With so many benefits that AI delivers to medical imaging practice and patients, there are certain limitations that healthcare professionals should be aware of. First, when relying solely on AI recommendations, instead of evaluating AI outputs against the evidence-based knowledge, the risk of human expert deskilling is hard to ignore [100]. If the healthcare professionals accept that the automated systems are always correct, an over-reliance on AI might worsen outcomes and trust in health care systems. AI in radiography practice is a clinical decision support system that assists clinical staff in decision-making, and should always be treated as such. Second, AI systems make decisions without providing explanations as to how and why a certain decision was made. Most state-of-the-art systems are based on DL whose inputs and operations are unavailable to users. This makes explainability challenging, therefore such algorithms are known as 'black box' algorithms. Third, as discussed above, inaccurate or incomplete training datasets can lead to biased algorithms favouring certain social groups over others and intensify inequity. AI systems should be able to learn and evolve over time, to ensure their development and usage is ethical for everyone and everywhere. Last, the rise and availability of big data accelerated safety and privacy concerns among the general public [101]. Inadvertent disclosure of identifying information can take place owing to malicious acts or poor data handling such as merging deidentified datasets consisting of several columns of big data [102,103]. For example, merging data on patient age, their blood group and body mass index may be sufficient to identify a person who would not be identifiable through each of the features alone. Healthcare professionals should engage only with lawful, ethical, and robust AI-enabled solutions [104].

Limitations

The literature search filtered articles published in journals with the impact factor lower than two, and without impact factor. Moreover, only certain commercially available technical clinical applications of AI have been discussed. It is important to acknowledge that there are more technical and image-based applications available, or under development by more than the three vendors included in our review.

Conclusion

There is a wide range of AI-enabled solutions available in medical imaging practice. Imaging professionals can expect automation of many previously manual tasks pertinent to pre-examination, patient positioning, imaging protocol selection, image acquisition, image evaluation, post-processing, and even equipment maintenance. Radiographers, clinicians and radiation therapists should acquaint themselves with the new technology, demonstrate readiness to actively contribute towards development, implementation, and adoption of AI-enabled solutions. However, it is vital to benefit from AI safely through evidence-based practice and ethical oversight. Users should monitor impact of the AI applications that they utilise to provide clinical evidence and support implementation of AI in more settings.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmir.2023.03.033.

References

[1] National Council on Radiation Protection and Measurements. Report No. 184 – Medical Radiation Exposure of Patients in the United States (2019). Bethesda, MD. Report No.: 184. Available at: https://ncrponline.org/shop/reports/report-no-184-medical-radiation-exposure-of-patients-in-the-united-states-2019/

[2] Smith-Bindman R, Kwan ML, Marlow EC, Theis MK, Bolch W, Cheng SY, et al. Trends in use of medical imaging in us health care systems and in Ontario, Canada, 2000-2016. *JAMA*. 2019;322(9):843 Sep 3.

[3] National health service england diagnostic imaging dataset 2012-13 Data. Available at: https://www.england.nhs.uk/statistics/statistical-work-areas/diagnostic-imaging-dataset/diagnostic-imaging-dataset-2012-13-data-2/

[4] National Health Service England and National Health Service Improvement. *Diagnostic Imaging Dataset Statistical Release: Provisional Monthly Statistics, September 2018 to September 2019*. London: Performance Analysis Team; 2020 Available at *https://www.england.nhs.uk/statistics/wp-content/uploads/sites/2/2020/01/Provisional-Monthly-Diagnostic-Imaging-Dataset-Statistics-2020-01-23.pdf* .

[5] Gilligan P, Darcy L, Maguire G, Lindsay R, Rowan M, et al. Irish national 2017 CT population and dose reference level survey: A novel gender and aged based survey using spreadsheet templates and clinical indications. Poster presented at: ESR EuroSafe Imaging; 2018 Feb 28 – Mar 4. Available at: https://epos.myesr.org/poster/eurosafe/eurosafeimaging2018/ESI-0055

[6] Aurélien Géron. *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. "O'Reilly Media, Inc.; 2019.

[7] Patel AA. *Hands-On Unsupervised Learning Using Python: how to Build Applied Machine Learning Solutions From Unlabeled Data*. Sebastopol: Ca O'reilly Media; 2019.

[8] Aggarwal R, Sounderajah V, Martin G, Ting DSW, Karthikesalingam A, King D, et al. Diagnostic accuracy of deep learning in medical imaging: a systematic review and meta-analysis. *npj Digital Medicine*. 2021 Apr 7;4(1).

[9] Sorin V, Barash Y, Konen E, Klang E. Deep learning for natural language processing in radiology-fundamentals and a systematic review. *J Am Coll Radiol*. 2020;17(5):639–648.

[10] European Commission. A European approach to artificial intelligence. Available at: https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence [Accessed 22 October 2022]

[11] Food and Drug Administration. Artificial intelligence and machine learning (AI/ML)-enabled medical devices. Available at: https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices [Accessed 22 October 2022]

[12] Health Canada. Guidance document: software as a medical device (SaMD): definition and classification. Available at: https://www.canada.ca/content/dam/hc-sc/documents/services/drugs-health-products/medical-devices/application-information/guidance-documents/software-medical-device-guidance-document/software-medical-device-guidance-document.pdf [Accessed 24 March 2023]

[13] Kjelle E, Chilanga C. The assessment of image quality and diagnostic value in X-ray images: a survey on raographers' reasons for rejecting images. *Insights Imaging*. 2022;13(1):36.

[14] National Health Service England and National Health Service Improvement. *Diagnostic Imaging Dataset Annual Statistical Re-*

lease 2020/21. London: Performance Analysis Team; 2021 Available at *https://www.england.nhs.uk/statistics/wp-content/uploads/sites/2/2021/11/Annual-Statistical-Release-2020-21-PDF-1.3MB-1.pdf* .
[15] Gershengorn HB, Wunsch H, Scales DC, Rubenfeld GD. Trends in use of daily chest radiographs among US adults receiving mechanical ventilation. *JAMA Network Open*. 2018;1(4):e181119 Aug 10.
[16] Ganapathy A, Adhikari NK, Spiegelman J, Scales DC. Routine chest x-rays in intensive care units: a systematic review and meta-analysis. *Critical Care*. 2012;16(2):R68.
[17] Saade C, Siblini L, Karout L, Khalife S, Hilal H, Abbas S, et al. To repeat or not to repeat: Radiologists demonstrated more decisiveness than their fellow radiographers in reducing the repeat rate during mobile chest radiography. *Radiography*. 2021;27(2):304–309.
[18] General Electric Company. Critical care suite 2.0*. Available at: https://www.gehealthcare.com/products/radiography/mobile-xray-systems/critical-care-suite-on-optima-xr240amx [Accessed 24 October 2022]
[19] Philips. Radiology smart assistant. Available at: https://www.usa.philips.com/healthcare/product/712093/radiology-smart-assistant [Accessed 1 November 2022]
[20] Poggenborg J, Yaroshenko A, Wieberneit N, Harder T, Gossmann A. Impact of AI-based real time image quality feedback for chest radiographs in the clinical routine. 2021 Jun 10;
[21] Siemens Healthineers. YSIO X.pree with myExam companion: a leap forward in intelligent X-ray imaging. Available at: https://www.siemens-healthineers.com/en-us/radiography/digital-x-ray/ysio-xpree [Accessed 1 November 2022]
[22] Siemens Healthineers. Auto thorax collimation. Available at: https://www.siemens-healthineers.com/nl-be/infrastructure-it/artificial-intelligence/ai-campaign/auto-thorax-collimation [Accessed 1 November 2022]
[23] Siemens Healthineers. Siemens Healthineers uses artificial intelligence to take X-ray diagnostics to a new level. Available at: https://www.siemens-healthineers.com/press/releases/ysioxpree-ai-chest.html
[24] Paulo G, Damilakis J, Tsapaki V, Schegerer AA, Repussard J, Jaschke W, et al. Diagnostic reference levels based on clinical indications in computed tomography: a literature review. *Insights into Imaging*. 2020 Aug 17;11(1).
[25] Kanal KM, Butler PF, Chatfield MB, Wells J, Samei E, Simanowith M, et al. U.S. diagnostic reference levels and achievable doses for 10 pediatric CT examinations. *Radiology*. 2022;302(1):164–174.
[26] Habibzadeh MA, Ay MR, Asl ARK, Ghadiri H, Zaidi H. Impact of miscentering on patient dose and image noise in x-ray CT imaging: phantom and clinical studies. *Phys Med*. 2012;28(3):191–199.
[27] Shaffiq Said Rahmat SM, Abdul Karim MK, Che Isa IN, Abd Rahman MA, Noor NM, Hoong NK. Effect of miscentering and low-dose protocols on contrast resolution in computed tomography head examination. *Comput Biol Med*. 2020;123(103840):103840.
[28] Ishita Y, Urikura A, Yoshida T, Takiguchi K, Ikegaya M. Inaccurate table height setting affects the organ-specific radiation dose in computed tomography. *Eur J Radiol*. 2022;151(110317).
[29] Singh V, Ma K, Tamersoy B, Chang Y-J, Wimmer A, O'Donnell T, et al. DARWIN: Deformable patient avatar representation with deep image network. *Lecture Notes in Computer Science*. Cham: Springer International Publishing; 2017:497–504.
[30] Booij R, van Straten M, Wimmer A, Budde RPJ. Automated patient positioning in CT using a 3D camera for body contour detection: accuracy in pediatric patients. *Eur Radiol*. 2021;31(1):131–138.
[31] Dane B, O'Donnell T, Liu S, Vega E, Mohammed S, Singh V, et al. Radiation dose reduction, improved isocenter accuracy and CT scan time savings with automatic patient positioning by a 3D camera. *Eur J Radiol*. 2021;136(109537):109537.
[32] Gang Y, Chen X, Li H, Wang H, Li J, Guo Y, et al. A comparison between manual and artificial intelligence-based automatic positioning in CT imaging for COVID-19 patients. *Eur Radiol*. 2021;31(8):6049–6058.
[33] Schwartz F, Stieltjes B, Szucs-Farkas Z, Euler A. Over-scanning in chest CT: comparison of practice among six hospitals and its impact on radiation dose. *Eur J Radiol*. 2018;102:49–54.
[34] Salimi Y, Shiri I, Akhavanallaf A, Mansouri Z, Saberi Manesh A, Sanaat A, et al. Deep learning-based fully automated Z-axis coverage range definition from scout scans to eliminate overscanning in chest CT imaging. *Insights Imaging*. 2021;12(1):162.
[35] Siemens Healthineers. FAST integrated workflow. Available at: https://www.siemens-healthineers.com/en-ie/computed-tomography/technologies-and-innovations/fast-integrated-workflow [Accessed 30 October 2022]
[36] Philips. AI to save time and improve precision in CT patient positioning. Available at: https://www.philips.com/c-dam/b2bhc/master/resource-catalog/landing/precise-suite/incisive_precise_position.pdf [Accessed 30 October 2022]
[37] General Electric Company. Revolution™ Maxima: overall, a top performer. Available at: https://www.gehealthcare.com/products/computed-tomography/revolution-maxima [Accessed 30 October 2022]
[38] Kubo T, Ohno Y, Kauczor HU, Hatabu H. Radiation dose reduction in chest CT–review of available options. *Eur J Radiol*. 2014;83(10):1953–1961.
[39] Lee SW, Kim Y, Shim SS, Lee JK, Lee SJ, Ryu YJ, et al. Image quality assessment of ultra low-dose chest CT using sinogram-affirmed iterative reconstruction. *Eur Radiol*. 2014;24(4):817–826.
[40] Agostini A, Floridi C, Borgheresi A, Badaloni M, Esposto Pirani P, Terilli F, et al. Proposal of a low-dose, long-pitch, dual-source chest CT protocol on third-generation dual-source CT using a tin filter for spectral shaping at 100 kVp for CoronaVirus Disease 2019 (COVID-19) patients: a feasibility study. *Radiol Med*. 2020;125(4):365–373.
[41] Klug M, Shemesh J, Green M, Mayer A, Kerpel A, Konen E, et al. A deep-learning method for the denoising of ultra-low dose chest CT in coronary artery calcium score evaluation. *Clin Radiol*. 2022;77(7):e509–e517.
[42] Kim JH, Yoon HJ, Lee E, Kim I, Cha YK, Bak SH. Validation of deep-learning image reconstruction for low-dose chest computed tomography scan: emphasis on image quality and noise. *Korean J Radiol*. 2021;22(1):131–138.
[43] Franck C, Zhang G, Deak P, Zanca F. Preserving image texture while reducing radiation dose with a deep learning image reconstruction algorithm in chest CT: a phantom study. *Phys Med*. 2021;81:86–93.
[44] Nam JG, Hong JH, Kim DS, Oh J, Goo JM. Deep learning reconstruction for contrast-enhanced CT of the upper abdomen: similar image quality with lower radiation dose in direct comparison with iterative reconstruction. *Eur Radiol*. 2021;31(8):5533–5543.
[45] General Electric Company. TrueFidelity: how the best see better. Available at: https://www.gehealthcare.com/products/truefidelity [Accessed 5 November 2022]
[46] Siemens Healthineers. Downtime calculator. Available at: https://www.siemens-healthineers.com/en-us/customer-services/valuebeyondcost1/downtime-calculator [Accessed 5 November 2022]
[47] Zamzam AH, Al-Ani AKI, Wahab AKA, Lai KW, Satapathy SC, Khalil A, et al. Prioritisation assessment and robust predictive system for medical equipment: A comprehensive strategic maintenance management. *Front Public Health*. 2021;9:782203.
[48] Liao H-Y, Cade W, Behdad S. Forecasting repair and maintenance services of medical devices using Support Vector Machine. *J Manuf Sci Eng*. 2022;144(3):1–14.
[49] Glassbeam Inc. Clinsights service analytics. Available at: https://www.glassbeam.com/clinsights [Accessed 6 November 2022]
[50] Bash S, Johnson B, Gibbs W, Zhang T, Shankaranarayanan A, Tanenbaum LN. Deep learning image processing enables 40% faster spinal MR scans which match or exceed quality of standard of care : a prospective multicenter multireader study. *Clin Neuroradiol*. 2022;32(1):197–203.
[51] Gassenmaier S, Küstner T, Nickel D, Herrmann J, Hoffmann R, Almansour H, et al. Deep learning applications in magnetic resonance imaging: has the future become present? *Diagnostics (Basel)*. 2021;11(12):2181.

[52] General Electric Company. A bold new world: GE healthcare's pioneering deep learning image reconstruction technology benefits more than 2 million patients globally. Available at: https://www.ge.com/news/press-releases/a-bold-new-world-ge-healthcares-pioneering-deep-learning-image-reconstruction#_edn1 [Accessed 6 November 2022]

[53] Philips. Philips SmartSpeed. Available at: https://www.philips.com.au/healthcare/resources/landing/smartspeed [Accessed 6 November 2022]

[54] Siemens Healthineers. Siemens healthineers accelerates and improves magnetic resonance imaging with artificial intelligence. Available at: https://www.siemens-healthineers.com/press/releases/deepresolve [Accessed 6 November 2022]

[55] van der Kouwe AJW, Benner T, Fischl B, Schmitt F, Salat DH, Harder M, et al. On-line automatic slice positioning for brain MR imaging. *Neuroimage*. 2005;27(1):222–230.

[56] Zhan Y, Dewan M, Harder M, Krishnan A, Zhou XS. Robust automatic knee MR slice positioning through redundant and hierarchical anatomy detection. *IEEE Trans Med Imaging*. 2011;30(12):2087–2100.

[57] Glazer DI, DiPiro PJ, Shinagare AB, Huang RY, Wang A, Boland GW, et al. CT and MRI protocol variation and optimization at an academic medical center. *J Am Coll Radiol*. 2018;15(9):1254–1258.

[58] Brown AD, Marotta TR. Using machine learning for sequence-level automated MRI protocol selection in neuroradiology. *J Am Med Inform Assoc*. 2018;25(5):568–571.

[59] General Electric Company. AIR™ workflow. Available at: https://www.gehealthcare.com/products/magnetic-resonance-imaging/air-technology/workflow-applications [Accessed 14 November 2022]

[60] Philips. SmartWorkflow solutions: patient-centered productivity. Available at: https://www.philips.com/c-dam/b2bhc/master/resource-catalog/landing/smartworkflow/philips_mr_smartworkflow_brochur.pdf [Accessed 14 November 2022]

[61] Siemens Healthineers. myExam companion: intelligence that works with you. Available at: https://www.siemens-healthineers.com/en-ie/magnetic-resonance-imaging/technologies-and-innovations/my-exam-companion [Accessed 14 November 2022]

[62] Weyland CS, Hemmerich F, Möhlenbruch MA, Bendszus M, Pfaff JAR. Radiation exposure and fluoroscopy time in mechanical thrombectomy of anterior circulation ischemic stroke depending on the interventionalist's experience-a retrospective single center experience. *Eur Radiol*. 2020;30(3):1564–1570.

[63] Javed M, Rahman N, Adnan G, Nizar Z, Shah I. Differing radiation exposure in scrub technicians and rotating staff in cardiac catheterization laboratory: occupation matters. *Eur Heart J*. 2022;43(1).

[64] Stahl CM, Meisinger QC, Andre MP, Kinney TB, Newton IG. Radiation risk to the fluoroscopy operator and staff. *Am J Roentgenol*. 2016;207(4):737–744.

[65] Liao J-B, Chen W, Lee H-S, Wu S-R, Wei K-C. Histopathology of fluoroscopy-induced radiation ulcer: a case series study in comparison with morphea. *J Dtsch Dermatol Ges*. 2020;18(5):447–454.

[66] Mahesh M, Gingold E, Jones A. MO-G-18A-01: Radiation dose reducing strategies in CT, fluoroscopy and radiography. *Med Phys*. 2014;41(1):431.

[67] Yamashita K, Higashino K, Hayashi H, Hayashi F, Fukui Y, Sairyo K. Pulsation and collimation during fluoroscopy to decrease radiation: A cadaver study. *JB JS Open Access*. 2017;2(4):e0039.

[68] Gupta A, Chhikara S, Vijayvergiya R, Barwad P, Prasad K, Datta R, et al. Radiation exposure reduction and patient outcome by using very low frame rate fluoroscopy protocol (3.8 + 7.5 fps) during percutaneous coronary intervention. *Front Cardiovasc Med*. 2021;8:625873.

[69] Omega Medical Imaging. FluoroShield™ reduces dose area product (DAP) during interventional procedures. Available at: https://www.omegamedicalimaging.com/fluoroshield/ [Accessed 20 November 2022]

[70] Bang JY, Hough M, Hawes RH, Varadarajulu S. Use of artificial intelligence to reduce radiation exposure at fluoroscopy-guided endoscopic procedures. *Am J Gastroenterol*. 2020;115(4):555–561.

[71] Pathmanathan AU, McNair HA, Schmidt MA, Brand DH, Delacroix L, Eccles CL, et al. Comparison of prostate delineation on multimodality imaging for MR-guided radiotherapy. *Br J Radiol*. 2019;92(1095):20180948.

[72] Siemens Healthineers. MR-based Synthetic CT reimagined: An AI-based algorithm for continuous Hounsfield units in the pelvis and brain – with syngo.via RT Image Suite (VB60). Available at: https://marketing.webassets.siemens-healthineers.com/14a780979ccdde45/657cf9efc589/White-Paper-MR-based-Synthetic-CT.PDF [Accessed 20 November 2022]

[73] General Electric Company. Leveraging AI technology to enable MRI-only radiation therapy planning. Available at: https://www.gehealthcare.com/insights/article/leveraging-ai-technology-to-enable-mrionly-radiation-therapy-planning [Accessed 20 November 2022]

[74] Philips. MR-only simulation. Available at: https://www.philips.ie/healthcare/product/HCNMRF171/mr-only-simulation-unleash-the-real-power-of-mr-simulation [Accessed 20 November 2022]

[75] Wong J, Huang V, Wells D, Giambattista J, Giambattista J, Kolbeck C, et al. Implementation of deep learning-based auto-segmentation for radiotherapy planning structures: a workflow study at two cancer centers. *Radiation Oncol*. 2021;16(101).

[76] Siemens Healthineers. Deep learning-based autocontouring. Available at: https://www.siemens-healthineers.com/en-ie/radiotherapy/software-solutions/autocontouring [Accessed 25 February 2023]

[77] General Electric Company. Radiation oncology. Available at: https://www.gehealthcare.com/products/radiation-oncology [Accessed 25 February 2023]

[78] Philips. RTdrive MR prostate. Available at: https://www.philips.ie/healthcare/product/HCNMRF143/rtdrive-mr-prostate [Accessed 25 February 2023]

[79] Hindocha S, Zucker K, Jena R, Banfill K, Mackay K, Price G, et al. Artificial intelligence for radiotherapy auto-contouring: current use, perceptions of and barriers to implementation. *Clinical Oncology*. 2023 In Press, Corrected Proof. DOI. doi:10.1016/j.clon.2023.01.014.

[80] de Boer HH, Obertová Z, Cunha E, Adalian P, Baccino E, Fracasso T, et al. Strengthening the role of forensic anthropology in personal identification: position statement by the board of the forensic anthropology society of Europe (FASE). *Forensic Sci Int*. 2020;315(110456).

[81] World Health Organization. Coronavirus disease (COVID-19). Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019 [Accessed 30 November 2022]

[82] Ranjan R, Patel VM, HyperFace Chellappa R. A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition. *IEEE Trans Pattern Anal Mach Intell*. 2019;41(1):121–135.

[83] Wang K, Kumar A. Toward more accurate Iris recognition using dilated residual features. *IEEE Trans Inf Forensics Secur*. 2019;14(12):3233–3245.

[84] Chen X, Qing L, He X, Su J, Peng Y. From eyes to face synthesis: A new approach for human-centered smart surveillance. *IEEE Access*. 2018;6:14567–14575.

[85] Buolamwini J, Gebru T. Gender shades: intersectional accuracy disparities in commercial gender classification. In: Friedler SA, Wilson C, eds. *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*; Feb 2018:77–91.

[86] Health Service Executive. HSE publishes independent report on Conty cyber attack. Available at: https://www.hse.ie/eng/services/news/media/pressrel/hse-publishes-independent-report-on-conti-cyber-attack.html [Accessed 30 November 2022]

[87] Ebdon-Jackson S, Frija G. European Society of Radiology. Improving justification of medical exposures using ionising radiation: considerations and approaches from the European Society of Radiology. *Insights Imaging*. 2021;12(1):2.

[88] Potočnik J, Thomas E, Killeen R, Foley S, Lawlor A, Stowe J. Automated vetting of radiology referrals: exploring natural language processing and traditional machine learning approaches. *Insights Imaging*. 2022;13(1):127.

[89] Alanazi AH, Cradock A, Ryan J, Rainford L. Machine learning and deep learning-based natural language processing for auto-vetting the appropriateness of lumbar spine magnetic resonance imaging referrals. *Inform Med Unlocked*. 2022;30(100961).

[90] Meyer E, Raupach R, Lell M, Schmidt B, Kachelriess M. Normalized metal artifact reduction (NMAR) in computed tomography. *Med Phys*. 2010;37(10):5482–5493.

[91] Meyer E, Raupach R, Lell M, Schmidt B, Kachelrieß M. Frequency split metal artifact reduction (FSMAR) in computed tomography. *Med Phys*. 2012;39(4):1904–1916.

[92] Wellenberg RHH, Hakvoort ET, Slump CH, Boomsma MF, Maas M, Streekstra GJ. Metal artifact reduction techniques in musculoskeletal CT-imaging. *Eur J Radiol*. 2018;107:60–69.

[93] Liang K, Zhang L, Yang H, Yang Y, Chen Z, Xing Y. Metal artifact reduction for practical dental computed tomography by improving interpolation-based reconstruction with deep learning: MAR for dental CT with deep learning. *Med Phys*. 2019;46(12):e823–e834.

[94] Huang X, Wang J, Tang F, Zhong T, Zhang Y. Metal artifact reduction on cervical CT images by deep residual learning. *Biomed Eng Online*. 2018;17(1):175.

[95] Arabi H, Zaidi H. Deep learning-based metal artefact reduction in PET/CT imaging. *Eur Radiol*. 2021;31(8):6384–6396.

[96] Beckett KR, Moriarity AK, Langer JM. Safe use of contrast media: What the radiologist needs to know. *Radiographics*. 2015;35(6):1738–1750.

[97] Eibschutz LS, Gholamrezanezhad A. How low can we go? Strategies and recommendations to combat the iodinated contrast shortage. *Emerg Radiol*. 2022;29(5):925–928.

[98] Choi JW, Cho YJ, Ha JY, Lee SB, Lee S, Choi YH, et al. Generating synthetic contrast enhancement from non-contrast chest computed tomography using a generative adversarial network. *Sci Rep*. 2021;11(1):20403.

[99] Kim SW, Kim JH, Kwak S, Seo M, Ryoo C, Shin C-I, et al. The feasibility of deep learning-based synthetic contrast-enhanced CT from nonenhanced CT in emergency department patients with acute abdominal pain. *Sci Rep*. 2021;11(1):20390.

[100] Carter SM, Rogers W, Win KT, Frazer H, Richards B, Houssami N. The ethical, legal and social implications of using artificial intelligence systems in breast cancer care. *Breast*. 2020;49:25–32.

[101] Mai J-E. Three models of privacy: New perspectives on informational privacy. *NORD Rev Nord res Media Commun*. 2016;37(s1):171–175.

[102] Rothstein MA. Is deidentification sufficient to protect health privacy in research? *Am J Bioeth*. 2010;10(9):3–11.

[103] Tolich M. Internal confidentiality: When confidentiality assurances fail relational informants. *Qual Sociol*. 2004;27(1):101–106.

[104] Crigger E, Reinbold K, Hanson C, Kao A, Blake K, Irons M. Trustworthy augmented Intelligence in health care. *J Med Syst*. 2022;46(2):12.