Noninterpretive Uses of Artificial Intelligence in Radiology

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We deem a computer to exhibit artificial intelligence (AI) when it performs a task that would normally require intelligent action by a human. Much of the recent excitement about AI in the medical literature has revolved around the ability of AI models to recognize anatomy and detect pathology on medical images, sometimes at the level of expert physicians. However, AI can also be used to solve a wide range of noninterpretive problems that are relevant to radiologists and their patients. This review summarizes some of the newer noninterpretive uses of AI in radiology.

Key Words: Artificial intelligence; Deep learning; Radiology applications; Radiology education.

INTRODUCTION

When a computer performs a task that would normally require intelligent action by a human, we term that behavior artificial intelligence (AI). Much of the recent excitement about AI in the radiology literature has revolved around the ability of AI models to recognize anatomy and detect pathology on medical images, sometimes at the level of expert physicians [1−5]. However, AI can also be used to solve a wide range of noninterpretive problems that are relevant to radiologists and their patients. Despite a number of excellent recent reviews on this topic [6−9], subsequent developments have continued at such a pace that these reviews are already somewhat out of date. With one exception [8], these reviews have given little attention to issues specific to academic radiology, such as the impact of AI on radiology education and residency training. The purpose of this review is to stake a new set of banners in the sand along the current edges of this rapidly expanding field. The topics covered in this review are shown in Figure 1.

IMAGE PRODUCTION AND QUALITY CONTROL

There have been a number of recent developments in the use of AI for image reconstruction for a variety of image modalities (e.g., CT, PET, and MRI) [9]. These techniques have led to decreases in imaging time, radiation dose, and contrast dose while also improving image quality.

Noise Reduction

Deep learning has been used to reduce noise and artifacts, enhance contrast and thus improve visualization of pathology [10,11]. Initial deep learning techniques resulted in over-smooth images with loss of details and compromised visibility of essential structures [12−14]. However, this has been addressed with more recent techniques involving the use of convolutional neural networks (CNN) [15] and generative-adversarial networks (GAN), resulting in de-noised images without loss of critical information [13,16−19].

AI can improve image quality either by acting on the processed image or by directly transforming the raw sensor scanner data into images. A postprocessing stage is then added to minimize artifacts and noise [20−23]. AI based algorithms such as AUTOMAP have been developed, which can be directly applied on the sensor data to improve performance. AUTOMAP uses deep learning to produce higher-quality MR images with superior immunity to noise and reduction in reconstruction artifacts compared to conventional

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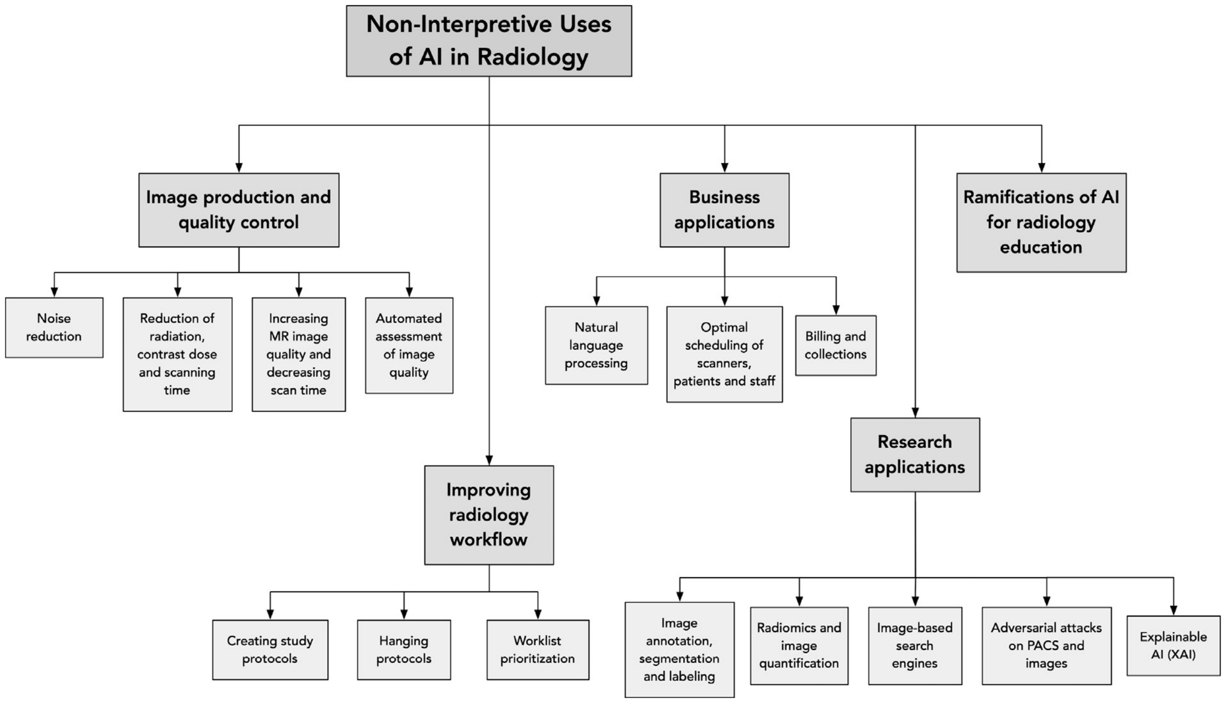

Figure 1. Flowchart of topics covered in this review.

reconstruction methods, without having to collect additional data [21].

Reduction of Radiation, Contrast Dose, and Scanning Time

Increased utilization of computed tomography (CT) and positron-emission tomography (PET) imaging has led to significant concerns about radiation dose, especially when considered on a population scale. Although magnetic resonance (MR) images do not employ ionizing radiation, there are similar concerns about the wide usage of gadolinium-based contrast agents.

The classic method for CT dose reduction is to reduce the X-ray tube current. However, this results in fewer X-ray photons utilized per scan and thus noisier images. Multiple algorithmic approaches have been implemented to reduce this noise, and iterative reconstruction techniques are currently offered by most vendors. More recently, deep learning techniques have demonstrated the potential to decrease radiation and contrast doses without loss of image quality. Initial machine learning approaches to dose reduction resulted in fuzzy, over-smoothed images. However, as the field has evolved, techniques such as CNNs or GAN have offered a balance between smoothing and feature preservation [7].

One such deep learning technique teaches an AI model what normal anatomy and abnormal pathology look like at both low and standard radiation doses. The AI model can then create high-quality images directly from low-dose raw sensor data [12,18]. A multi-center study compared the diagnostic quality of low-dose scans created in this manner with CT scans of the same patient at standard radiation doses. Over 90% of the radiologists in this study felt the AI-reconstructed low-dose images were of greater or equal diagnostic quality than the standard-dose images [24].

Similar techniques can be used to generate high-quality PET images, with significant reductions in radiation dose to the patient. One early study combined low-quality, low-dose PET images with high-quality T1-weighted MR images to produce high-quality PET images, at only 1/4 of the radiation dose [25]. Subsequent studies have used GANs to produce high-quality PET images with only 1% of the standard dose of radiation [26,27]. Yet another study achieved a 200-fold decrease in the radiotracer dose for ^{18}F-fluorodeoxyglucose PET scans in the evaluation of glioblastoma by using deep learning [28].

Another use of deep learning is to learn the artifacts produced from low-dose CT and subtract these artifacts from reconstructed low-dose images. Using a technique called residual learning, this has been applied to low-dose CT to remove streak artifacts [29].

Deep learning techniques have been used to create good quality postcontrast MRI images from images obtained using only 10% of the standard dose of gadolinium [30]. These images did not have any significant image degradation compared to full contrast dose images and also had lower motion artifacts.

Increasing MR Image Quality and Decreasing Scan Time

Deep learning has been used to improve other aspects of image quality in CT and MR [31], such as the removal of CT metal artifact [32], MR banding artifact [33], and MR motion artifact [34]. CNNs have also been used to enhance spatial resolution [35,36].

The relatively long acquisition times of MRI often require one to sacrifice image quality to meet the constraints of limited scanning time. Another problem is that MR sequences with incomplete sampling of k-space (a technique used to shorten MR scan acquisition times) can result in lengthy reconstruction times. Deep learning has been used in MR image reconstruction from undersampled k-space data by training a CNN to learn a mapping between zero-filled and fully sampled MR images [37]. Deep learning has also been used for MR image reconstruction from clinical multicoil MR data, an adaptation that reduces scan time through the use of parallel imaging [38]. These techniques can substantially decrease the time needed to produce acceptable MR images. For example, diffusion MR imaging can be accelerated by a factor of 12 when deep learning is used to optimize q-space data processing [39].

Automated Assessment of Image Quality

Technologists routinely screen medical images for quality as they are created. They check these images for adequacy of penetration, exposure, coverage, and the presence of motion or other imaging artifacts. They also assess the need for image retake or sequence repetition. The need for this type of quality control is especially critical in MR imaging, where sequence repetition may be needed in up to 55% of exams [40]. Sometimes suboptimal images are not identified until after an exam has been completed and the patient has left the department. Recalling these patients for repeat imaging results in delayed diagnoses, increased costs to the health care system, and in some cases, increased radiation exposure. There is therefore great interest as to whether deep learning models can be trained to instantly recognize image quality problems, allowing technologists to correct them before the exam is completed [41]. One recent study was able to train an AI model to recognize quality problems on abdominal T2-weighted images with a negative predictive value of 86−94% [42].

IMPROVING RADIOLOGY WORKFLOW

Creating Study Protocols

Radiology study protocoling is an important task in routine clinical practice, and ensures that patients undergo the correct and optimal study. However, this process is tedious, time-consuming, and susceptible to human errors. Nascent work on automating this process has shown promising results. At one large academic center, rule-based machine learning applied to order entry information substantially decreased the number of studies manually protocoled and improved emergency department order turn-around-time [43]. Using non-deep learning-based natural language processing algorithms applied to order entry data, neuroradiology MRI protocol selection can also be automated [44] and can even allow selection of specific MRI sequences [45]. Such automation of MRI sequence-level protocol information could potentially allow for dynamic sequence selection, instead of a one-size-fits-all approach. Deep learning-based natural language processing algorithms have been applied to musculoskeletal MRI protocol selection [46] and general radiology protocol selection [47] with some success.

Another facet of protocol optimization is the experimental determination of the optimal pulse sequence for a particular clinical indication. Currently, optimal sequences are chosen following a tedious side-by-side comparison between pulse sequences by one or more radiologists. However, a properly trained CNN might provide an acceptable surrogate for human readers when performing a protocol optimization study [48]. Use of a CNN could not only reduce the tedious aspects of such studies but could also greatly increase the practical number of sequence combinations that could be tested.

Hanging Protocols

Hanging protocols can have a large impact on a radiologist's workflow. An efficient hanging protocol can reduce the lag time between study selection and when the radiologist can actually view the images. Most major commercial picture archival and communication systems (PACS) offer some form of automated hanging protocol. However, PACS vendors continue to strive for even more efficient tools, such as GE Healthcare's "Smart Reading Protocols" technology, which learns the user's preferences based on what the user explicitly teaches the algorithm [49]. Academic work has been completed to create hanging protocols based on the user's previously manually corrected hanging protocols, without explicit user input to the algorithm [50]. Creating optimal hanging protocols can be challenging because of diverse individual preferences, inconsistencies in the DICOM metadata, and differences between vendors. For example, a brain MRI acquired using one vendor's scanner will have different sequence names, which prevents simple rule-based machine learning approaches from inferring the correct hanging protocol. Using AI to dynamically create the hanging protocol based on image content as opposed to the metadata alone could provide one solution to this problem.

Worklist Prioritization

AI can also help optimize radiologist workflow by means of worklist prioritization. A radiologist's worklist is often populated based on a set of rules related to exam type, subspecialty focus, location, or other variables, with studies assigned varying levels of priority. However, algorithms that might modify these rules or alter priority of individual exams on a worklist have the potential to optimize efficiency or other outcome metrics within a given practice. For example, one group practice reported improved group turnaround times by using analytics-driven worklists in which studies from a shared worklist were distributed to individual radiologists' worklists based on empirical measures of each individual's reading speed for each study type [51]. Deep learning approaches can also assist radiologists by assigning higher priorities to cases on the worklist that may contain emergent abnormalities. Such prioritization has been proposed in the setting of triage or screening systems to detect abnormalities on chest radiographs [5], abdominal CT [52], or head CT [53]. In these paradigms, there is an image interpretation component to the AI's tasks, but the role of the AI is not to primarily render an interpretation but to alert radiologists to potential critical findings and improve turnaround time for reporting of potentially actionable abnormalities.

BUSINESS APPLICATIONS

NATURAL LANGUAGE PROCESSING

"Natural language processing" (NLP) is a term that is often used synonymously with the terms "text mining" or "information extraction." Tang et al. state that NLP typically refers to conversion of unstructured text into a structured format, which can facilitate automated information extraction [54−56]. Principal applications of natural language processing include improvement in the quality of radiology reports and in improving communication with clinicians and patients.

It has been proposed that clinicians prefer itemized reporting because specific information or findings can be found more easily in reports with this format than in unstructured, narrative reports [57]. Many radiology practices have already adopted speech recognition software which enables radiologists to utilize templates with such subheadings. Indeed, the Radiological Society of North America (RSNA) hosts a website, radreport.org, which effectively serves as a library for radiology report templates [58]. RSNA members can submit new reporting templates, and this collection of templates is reviewed by the RSNA Reporting Subcommittee.

The extent to which itemized reporting has been adopted varies considerably among different radiology practices. For practices with persistent heterogeneity in reporting format and style, NLP may be a promising means to automatically generate standardized radiology reports from free text reports [55]. NLP may also provide an automated method for converting nonstandard terminology into a standardized lexicon [58,59].

A majority of referring clinicians prefer that radiology reports include follow-up imaging recommendations and adhere to published management guidelines for managing imaging findings. One survey found that 67% of clinicians believed that radiology reports should indicate whether imaging follow-up is indicated for incidental 5 mm hepatic lesions [60]. Another study found that in CT scans of the chest or abdomen, only 34% of recommendations for pulmonary nodules adhered to Fleischner Society Guidelines [61]. NLP could enable "computer-assisted reporting" in which published clinical guidelines and recommendations are automatically inserted into radiology reports based on application of the algorithm to freely dictated findings [7,55,58].

Recent studies have shown that NLP can be applied to the unstructured text of a radiology report to detect actionable imaging findings, such as the presence of a pulmonary embolus [62]. Detection of such findings could trigger more timely communication of results to referring clinicians [62−64].

An additional use of NLP is to improve communications of results with patients. Patients have increasing access to their diagnostic testing results, including radiology reports. It may be difficult for patients without a medical background to understand their imaging findings and their clinical importance. It has been suggested that NLP could automatically convert a radiology report into a jargon-free format, either by converting it into "plain" English for English-speaking patients or by converting it into various other languages for non-English-speaking patients [7].

Other NLP applications include extraction of pertinent clinical information from the electronic medical record to aid imaging interpretation [7,55] and embedding calculators to aid interpretation (such as adrenal nodule washout calculations) [58]. Other clinical support tools may improve reporting quality by prompting a dictating radiologist to consider a second site of fracture [54] or suggesting a differential diagnosis for the reported findings [55].

Optimal Scheduling of Scanners, Patients, and Staff

AI applications have the potential to address complex issues such as scanner utilization and schedule optimization. In the United States, medical imaging utilization continues to increase in most age groups, with a 1−5% annual increase in advanced imaging utilization (CT and MRI) reported between 2012 and 2016 [65]. MRIs are time consuming to acquire [7], and significant time-length variability is observed in identically protocoled MRI examinations [66]. Given the high capital expense and labor costs of performing MRIs, utilization rate of the scanner becomes a significant factor in determining the cost of an MRI exam [67]. These factors, in an environment of declining reimbursements, are driving the development of AI applications in the optimization of scanner utilization and prospective determination of optimal time allocation per scan. The transition of the US healthcare system to electronic medical records systems, digitized radiology ordering, reporting, and image storage have created rich data sources that may be used by AI applications to address inefficiencies in utilization and scheduling [7] and to predict patient wait times and appointment delays [68].

One preliminary study developed a machine learning based approach using a feed-forward type of neural network to predict length of MRI exam based on patient demographics and exam type [67]. This algorithm created an optimized schedule simulation using dynamic slot lengths as compared to the traditional method of fixed slot lengths based only on MRI exam type. Using this method, the authors report decreased patient wait times and increased scheduling density, allowing accommodation of 2.78 more exams per day per scanner in their schedule simulation when compared to historical data [67]. This approach has the potential to improve MRI efficiency, increase patient satisfaction through lower wait times, and reduce costs.

Missed scheduled medical appointments are a problem observed in all healthcare systems, leading to clinical mismanagement and consumption of substantial resources [69]. AI models have been used to predict missed appointments and determine which missed appointments are most likely to result in treatment discontinuation [69,70]. One study concluded that missed appointments are the result of complex interactions between patient, environmental, and operational factors — their optimal AI prediction model required 81 variables [69]. Another prediction model for a cohort of diabetic patients used demographics, clinical condition, and prior appointment attendance [70]. When the predictions were compared against true historical data, the algorithm accurately predicted missed appointments with an AUC of 0.958, with the ultimate goal of targeting interventions designed to increase compliance.

Scheduling the appropriate staffing level and workforce composition can be complex in any industry, particularly healthcare. Interest in leveraging AI to optimize staffing is long standing with publications dating back to the late 1980s [71]. One recent report projected a 3−5% increase in profitability by using a machine learning-based framework trained on historical data that predicted the staffing needs of a professional services company [72]. An optimized or "intelligent" radiology schedule may be able to predict fluctuations in volume, exam complexity, "no shows," and referring practice patterns while determining the ideal number and composition of requisite staff [7].

BILLING AND COLLECTIONS

Insurance claim denials can account for as much as a 3−5% loss in revenue [73]. This has led healthcare organizations to turn to AI techniques such as NLP and other machine learning (ML) tools for innovative solutions to optimize billing, report classification, and claim denial reconciliation [7,73]. There has long been interest in the automated prediction of diagnosis (International Classification of Diseases, version 10) and procedural codes (Current Procedural Terminology) based on unstructured free text entries in the medical record. Currently, this task is expensive and time-consuming, and is performed by experts trained in the nuances of these coding systems. Most published research has focused on the application of diagnostic codes rather than billing codes due to the sensitive nature of billing code prediction. Errors related to under- or over-coding could potentially lead to inaccurate revenue realization or billing compliance risk [74].

One recent report described a neural network trained to automatically assign International Classification of Diseases, Tenth Revision (ICD-10) codes to the morbid disease/conditions reported on death certificates, based on the interpretation of multilanguage free text [75]. This AI model represents an important initial step in developing AI applications for diagnosis code prediction, which could help improve billing accuracy and reduce insurance claim denials.

NLP techniques can be used to analyze radiology reports for administrative coding and quality assurance within a radiology practice. NLP could either analyze a free-text radiology report and automatically generate a billing code, or it could convert a free-text radiology report into a structured report that is more amenable to analysis by a separate algorithm used to generate a billing code [54,55]. NLP could also be used to assess for completeness of a radiology report, documentation of use of comparison studies, documentation of timely non-routine communications, and assuring that recommendations in a radiology report adhere to published guidelines [54,58].

RESEARCH APPLICATIONS

Image Annotation, Segmentation, and Labeling

Traditionally, positive imaging findings are described in the diagnostic report, often with the use of specific series and image numbers. However, further effort is required to localize subtle or small findings on a given image. Radiologists have therefore long used annotations such as arrows, circles, flags, and other markings placed on the DICOM images [76]. Such annotations may help a referring clinician to discuss the findings with patients and plan treatment. They can also greatly assist radiologists following findings on subsequent studies or during multidisciplinary boards.

Segmentation is the process of partitioning an image into multiple segments, each of which represents a cell, a tissue or an organ of choice. Labeling refers to text labels assigned to each of these segments of interest.

Image segmentation, labeling, and volumetric assessment are being increasingly used, and are becoming an important component of diagnostic imaging interpretation. These tasks are mostly performed by radiologists or specially-trained technologists on dedicated workstations under a radiologist's supervision. Annotation, segmentation, and labeling can be tedious and time-consuming tasks, and while they do not directly impact diagnosis by human radiologists, are helpful to convey imaging findings. Segmentation and annotations are also useful when referencing a finding relative to standard anatomic structure in the human body, such as vertebrae, hepatic lobes, brain anatomy, prostate, etc.

AI models have been used to successfully localize and annotate organs such as the kidney, segmental anatomy such as lobes of the liver or lung, and automated detection and labeling of vertebral bodies [77,78]. This is extremely useful when volumetric assessment of a lesion or organ is needed. Examples include automated estimate of renal volume in a potential donor, liver volumes in patients with potential segmental or lobar resection and volumetric assessment in tumor treatment response. Prostate segmentation is used by urologists for targeted biopsy in suspected MR findings of high-risk prostate cancer. Studies have shown high accuracy in prostate segmentation using deep learning [79,80].

One concern with annotation is that annotations permanently embedded in images may alter the original dataset and may impact its use for other projects. However, annotation metadata can be stored independently (e.g., medical imaging research management and associated information database format) or embedded within the dataset as needed [81].

Image annotation and segmentation remains an important component in oncologic clinical trials where lesions (target or nontarget) are followed from baseline at various time points to assess treatment response. These studies require precise and consistent evaluation of the lesions across different readers at different time points, and can be best optimized using annotations and in some instances automated/semiautomated segmentation or volumetric assessment. Studies have shown that deep learning can efficiently monitor changes and perform quantitative analysis before, during, and after treatment and can also help to predict prognostic endpoints [82−84].

Radiomics and Image Quantification

Radiomics refers to the extraction of features from medical images to be used to support decision-making [85]. Following imaging acquisition, images are segmented to reduce the image to a set of essential components by manual, automated, or semiautomated methods. The segmentation process itself can be fully automated through use of deep learning algorithms, particularly those using the U-Net architecture [14]. Subsequently, feature extraction is performed to obtain quantitative data to characterize the volumes of interest. The imaging-derived data can be combined with clinical or genomic data to build databases that can be later mined. AI can be applied to these databases in either unsupervised learning approaches (e.g., to identify patterns) or supervised learning approaches (in which outcome data or confirmed pathological diagnoses are used to train a learning model).

Radiomics is often used in oncological scenarios, such as for identification of imaging features that predict specific subtypes or grades of tumors [86]. Applying a discovery radiomics approach to chest CT resulted in better prediction of pathologically proven lung cancer than current state-of-the-art approaches [87]. Combining radiomics signatures of non-small cell lung cancers with clinical variables can predict overall survival [88]. Deep learning has also been used in attempts to identify MR features that could help classify molecular subtypes of [89,90] and estimate patient prognosis in [91] patients with intracranial gliomas. A systematic review in neuro-oncology found that AI models could predict patient outcomes such as survival with higher accuracy than conventional staging and clinical risk parameters [92]. For instance, AI can predict prognosis in patients with high-grade glioma with accuracies of 91% [93].

AI models based on radiomics have been used to estimate severity or risk of progression in certain disease states in a variety of nononcological settings [94], including coronary artery disease, dental disease, gastrointestinal disease, endocrinopathies, neurological disorders, ophthalmology, fractures, and pulmonary disease. For example, conversion of mild cognitive impairment to Alzheimer disease can be predicted by combining multimodal neuroimaging data with other biomarkers such as cerebrospinal fluid analyses and cognitive performance assessments with up to 81% accuracy (AUC of 0.86) [95].

Image-Based Search Engines

As machine learning techniques have matured, search engines using images as input have been developed for commercial and academic use [96−99]. Unlike traditional search systems that use text input and search databases based on image tags and keywords, image-based search engines search using the visual content of the image. This can provide more accurate and complete results given that text searches are limited by the textual annotation of images [100].

In radiology, image-based search engines can provide valuable opportunities for education as well as research [7]. Large volumes of medical imaging are accumulating in shared and public databases, and image-based search engines connected to these databases may allow easy discovery and comparison of visually similar cases. As opposed to text searches, which are likely to find cases with similar diagnoses, image searches may also find visually similar cases with different diagnoses. Correlation of visual and textual features of images found using image-based search engines may also provide interesting research opportunities [101].

Explainable Artificial Intelligence

One problem that may delay both widespread clinical adoption and regulatory approval is the relative lack of transparency about how AI systems make their decisions. Patients and physicians should both feel uneasy about trusting important medical decisions to opaque pronouncements from a "black box" [9]. AI algorithms in nonmedical fields have been shown to make problematic decisions based on training data biased for ethnicity, age, or gender [6,8,102]. Furthermore, medical deep learning models may be susceptible to adversarial attacks [103−105]. If a medical AI system makes an incorrect decision, it is critical to find out why and to prevent future errors of the same type. To help address these concerns, the European Commission High-Level Expert Group on Artificial Intelligence recently presented its Ethics Guidelines for Trustworthy AI [106]. Among these guidelines are the principles of explicability and transparency, which state that "technical explainability requires that the decisions made by an AI system can be understood and traced by human beings." There are speculations that the European Union may go on to require that companies providing automated systems be able to explain to users how their systems reach a decision [107]. These concerns have prompted research into explainable artificial intelligence. Explainable artificial intelligence techniques such as saliency maps [108] and local interpretable model-agnostic explanations [109] provide some early steps toward this goal.

Adversarial Attacks on PACS and Images

An adversarial attack is another name for the more colloquially familiar term "cyberattack." Motivations to attack healthcare systems are wide and varied. One obvious motivation for an adversarial attack is monetary, as the healthcare system represents a large portion (17.8% in 2016) of the US gross domestic product [104]. However, other possible motivations may include political influence, fame or attention, or infliction of personal harm.

Well-publicized cases of cyberattacks on national healthcare systems already exist, such as the 2017 attack on the National Health System in the United Kingdom [110]. In this case, an attack was designed to infiltrate a healthcare system and hold data or access to the data for ransom. One can imagine similar types of attacks which would target images or other patient data. A malicious actor might hold this data for ransom or publicly expose potentially damaging private health details.

There are also potential political motivations for adversarial attacks. Persons hoping to effect political regime change could target a particular politician's or candidate's imaging or other health data by inserting or deleting abnormal imaging findings. This contaminated data might cause that politician to resign from office or drop out of a race. Other individuals might be personally targeted, with the intent to cause harm or death. Altered images could lead to the withholding of critical care or to unnecessary and possibly harmful treatments.

One cybersecurity study found that a typical PACS may be intentionally or inadvertently exposed to the internet, and that more than 1100 PACS directly connected to the Internet without any layer of security or virtual private network [111]. Even PACS not directly connected to the internet could be indirectly exposed to the internet via a healthcare facility's internal network, for example, through web-based PACS viewers. Furthermore, it is not common practice for hospitals to encrypt internal PACS traffic, largely due to outdated hardware, infrastructure, or information technology (IT) policies [105]. Infiltration of a hospital's PACS system without exploiting a direct exposure to the internet has been shown to be shockingly easy [105]. With permission of a hospital participating in their study, investigators performed a penetration test (i.e., an ethical hacking test). In their test, they were able to install a small device between the hospital's CT scanner and the hospital PACS system that enabled them to intercept and manipulate all scan data transmitted in the PACS. The device installation process took 30 seconds to complete, and within 10 minutes, they obtained usernames and passwords of 27 staff members and physicians in addition to access to PACS data.

With rapidly advancing progress in the development of algorithms for detecting and classifying imaging findings, more attention has turned towards limitations of these algorithms and particularly to vulnerabilities in these algorithms. To date, adversarial algorithms have been developed that can systematically deceive a trained AI model or a human radiologist. Notable examples include one algorithm that tricked an AI model into misclassifying pneumothorax on chest radiographs [103] and another that misled human radiologists by adding fake pulmonary nodules and removing real pulmonary nodules from chest CT exams [105].

Research is ongoing to develop methods to prevent and detect image tampering. Methods such as digital image watermarking [105] and ML algorithms to detect tampered images [112], such as "feature squeezing" [113] or "defensive distillation" [114], have been proposed for the detection of manipulated images.

In the meantime, prevention of an adversarial attack begins with recognition of the problem and by adopting some simple standards of practice. Exposure of a hospital's PACS to the internet should be minimized. Antivirus, security software on workstations and servers, and all medical devices connected to a hospital network should be kept updated. Data encryption should be enabled on every hospital's PACS, and as a corollary to this recommendation, hospitals and clinics should avoid using PACS with no encryption.

RAMIFICATIONS OF AI FOR RADIOLOGY EDUCATION

AI has promise for improving the quality and efficiency of radiology education. In the current training model for radiology residency, residents operate as apprentices, dictating studies from the diagnostic work list, which are then reviewed by the attending radiologist for accuracy and clarity. However, the studies that residents are exposed to over the course of residency training can vary substantially. To address this problem, Chen et al. developed an NLP tool that operates on electronic medical records to track resident progress, and can be used to assign future cases to residents for a more balanced curriculum [115]. Applications like this one have the potential to help radiology residents identify knowledge gaps and areas in which the resident needs greater clinical exposure [116].

The difficulty of assigned cases can also potentially be matched to a resident's individual ability, using AI tools that dynamically evaluate cases for their level of difficulty [117]. Interesting cases could be identified using NLP tools applied to radiology reports [118], and then used to build and index teaching files [58]. One could use an NLP algorithm to search free-text, unstructured reports to retrieve imaging studies for educational files [54]. Automated correlation of radiology findings with pathology results, operative reports, and clinical outcomes using AI tools would be another area in which the educational experience could be improved.

During a case conference, an experienced radiologist varies the difficulty of a case to match the ability of a student or other trainee. This is in contrast to current physical and electronic media used for radiology education, which are static with respect to a student's ability [117]. However, by adapting a video game AI technique called dynamic difficulty [119−122], educators may be able to create teaching materials that adapt to a student's abilities in real-time.

AI tools might also help in tracking radiology resident performance and evaluate competency. AI tools are being developed and implemented across medical specialties to evaluate physician competence [123], and radiology training should be particularly amenable given the highly digitized nature of radiology practice. Metrics used for evaluation of resident competency, such as the ACGME/American Board of Radiology milestone project [124], could incorporate AI-based assessments in the future.

While AI tools may help improve radiology training, there are potential downsides to the resident's educational experience. As interpretive AI tools begin to be incorporated in radiology practice, residency programs will need to decide how residents should use these tools. For example, pulmonary nodule detection on chest CTs is a time-consuming task and an active area of research for deep learning algorithms. Should radiology residents first learn to interpret chest CTs without the algorithm in order to develop their own perceptive skills or should they use the algorithm and focus on learning what the algorithm's blind spots are? Does manually segmenting cardiac chambers by drawing circles on a cardiac MRI serve an educational purpose or should that be left to deep learning software? Skills such as these that are currently learned by radiologists will likely atrophy as radiologists become more dependent on automated tools. However, deciding which skills should be allowed to atrophy and the subsequent impact on clinical performance will be important questions moving forward. In addition, it will be important that AI tools do not replace residents in the interpretive workflow for educational activities [116]. For example, much work is focused on the identification of normal studies, with the idea that the radiologist can focus his or her time on the more complex cases. If radiology residents are directed to only examine cases with positive findings, those residents will lose experience in identifying negative cases, which are important for learning the spectrum of normal variation. Communicating that a study is normal to the clinical team or patient can be one of the most challenging but useful tasks in radiology. Attention to possible unintended consequences of AI tools such as these will be important for radiology residency programs in the future.

A substantial number of radiology residents at one US program felt that they lacked exposure to the current literature on AI, and expressed doubts about whether they would have gone into radiology had they known of AI's potential impact on their specialty [125]. A majority of the radiology faculty at the same institution admitted they neither had familiarity with big data analytics nor used AI or machine learning in their daily work [125].

Academic radiologists need to consider other effects of AI on their residents and residency programs. Anxiety about the potential displacement of radiologists by AI has discouraged some Canadian medical students from going into radiology [126]. This anxiety may also be shared by US medical students. Despite these fears, medical student interest in radiology remains at its highest level in 10 years [127]. Radiology residents in some institutions have embraced the need to learn and use AI by instituting multi-institutional resident-driven AI journal clubs [128]. Others have crafted their own year-long pathway to teach themselves the arcana of machine learning. Attending radiologists at these institutions are also rising to the challenge by devoting considerably more time to teaching AI techniques to their residents and by performing their own AI research. Tools such as Google's Colab Notebook system (https://colab.research.google.com/notebooks/welcome.ipynb) allow radiologists to get their feet wet with deep learning without having to buy a high-end workstation [129]. The ACR Data Science Institute has developed a freely-available, user-friendly platform called ACR AI-LAB, which is designed to enable radiologists to develop AI algorithms at their own institutions and use their own data to meet their own specific clinical needs [130].

It therefore behooves all radiology educators to follow these examples, and to teach their medical students and residents about AI as an opportunity for radiology, rather than as a threat [127,131]. The European Society of Radiology has called for AI and informatics to be included in the curricula for future radiology residents [8]. This approach could be strengthened by dedicated rotations in information technology (IT) during residency training, and fellowships in AI and IT post-residency.

CONCLUSIONS

The ultimate goal of AI in medical imaging is to improve patient outcomes. In this review, we have summarized some of the many ways in which noninterpretive AI is relevant to radiologists and their patients. At this time, only a few of these techniques are ready to translate into clinical practice. Regardless of which of these techniques are ultimately adopted, we hope that this review will provoke thought in the wider community of academic radiologists, and to help lead us to even newer and more intriguing applications.

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