# Artificial Intelligence in Radiology: Current Technology and Future Directions

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#### Abstract

#### Keywords

- artificial intelligence
- machine learning
- deep learning
- radiology
- informatics

Artificial intelligence (AI) has been heralded as the next big wave in the computing revolution and touted as a transformative technology for many industries including health care. In radiology, considerable excitement and anxiety are associated with the promise of AI and its potential to disrupt the practice of the radiologist. Radiology has often served as the gateway for medical technological advancements, and AI will likely be no different. We present a brief overview of AI advancements that have driven recent interest, offer a review of the current literature, and examine the most likely ways that AI will change radiology in the coming years.

It is unlikely that, in 2018, a practicing radiologist has managed to escape the constant hype of artificial intelligence (AI). Whether it is a prominent AI researcher advocating for the cessation of radiologist training,<sup>1</sup> a president citing radiologist displacement as an example of AI's impact on the economy,<sup>2</sup> or the constant articles in the literature and lay press,<sup>3</sup> the prominence of AI is everywhere. So, it may surprise some readers to learn that references to AI in radiology date back to at least 1994.<sup>4</sup> Despite the seemingly daily news regarding the promise of AI and its impending impact on radiology, true disruption to the practice of radiology has not occurred. Nevertheless, these technologies have the potential to elicit a paradigm shift within radiology and medicine as a whole. Unlike many prior technologies that have impacted radiology, AI may not only alter the interpretation of images but also affect every element of the clinical workflow of a radiology practice (**Fig. 1**).

#### What Is AI? A Brief Primer

Although many definitions for AI exist, the term is generally used in the medical context to refer to devices or systems that can perceive some element of their environment and use this information to achieve a predefined goal.<sup>5</sup> Most medical use cases comprise what is known as weak or narrow AI, indicating

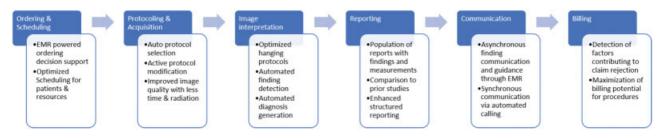
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the goal is the completion of a single task or set of tasks. Machine learning specifically is a subset of AI (Fig. 2) that focuses on the development of computer algorithms without the explicit encoding of decision-making rules.<sup>6</sup> Machine learning is often subdivided further into supervised and unsupervised learning. In supervised learning, the algorithm is given annotated data ("ground truth" data) that is used in the development of the algorithm. In unsupervised learning, the system is supplied with unlabeled data that it must classify itself.<sup>6</sup> Deep learning and specifically deep convolutional neural networks (also known as DCNNs or CNNs) represent a subset of supervised machine learning that has garnered the greatest amount of enthusiasm in recent years. DCNNs are a type of supervised learning that uses an algorithmic structure based on neural networks with many layers, that is, deep neural networks.<sup>7</sup> The power of this technique is in its scalability and the ability of the neural network architecture to extract its own relevant features from data without any direction other than labeled input data.

## AI in Scheduling and Protocoling

As mentioned earlier, AI is unique from many prior technological breakthroughs in radiology such as voice recognition or development of new modalities because it is capable of

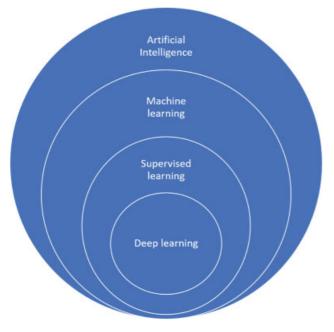
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**Fig. 1** Standard radiology workflow and opportunities for AI-powered disruption within each step. Unlike most new technologies in radiology, AI can potentially impact every step of a radiologist's value-adding activities.

affecting every portion of the radiologic workflow. For example, AI algorithms can be used at the point of care for medical decision support in requests for imaging by not only analyzing a patient's medical record and determining the appropriateness of imaging, but also in providing guidance for which imaging exam may be most appropriate.<sup>8</sup> The American College of Radiology (ACR) has developed rulebased appropriateness criteria to assist in this task, and deep learning algorithms can be applied to further tailor exams.<sup>9</sup> An example would be providing guidance for utilizing computed tomography (CT) or magnetic resonance imaging (MRI) rather than ultrasound in a patient with a body habitus that may preclude accurate sonographic diagnosis.

Al can also be used at the time of a patient's scheduling. Curtis et al demonstrated an Al model that could accurately predict wait times or appointment delays for CT, MRI, radiography, and ultrasound.<sup>10</sup> The ability to communicate these times to patients can result in improved patient satisfaction. Additionally, collection of data regarding wait times and appointment delays can be used to actively identify process improvement opportunities, which can increase the through-



**Fig. 2** Relationship of artificial intelligence, machine learning, supervised learning, and deep learning. Recent advances in machine learning in radiology have primarily come using deep learning techniques.

put of patient scanning and therefore increase the number of exams performed by any given resource.

Optimization of image acquisition using AI is also being targeted by industry and research parties alike. For example, some systems have shown promise in de-noising data acquired at significantly lower radiation levels than previously required, resulting in diagnostic imaging with dramatically low radiation exposure.<sup>11</sup> Similarly, AI-powered image processing can be applied during or after the reconstruction steps to minimize artifacts introduced during the acquisition process.<sup>12</sup> This includes a decreased radiation dose, particularly in the case of positron emission tomography (PET) and CT, and decreased scanning time for MRI.<sup>13</sup> The decrease in radiation dose offered by such approaches could serve to popularize exams such as PET/CT or multiphasic CT, which are often deferred or avoided due to concerns about radiation. Decreased radiation dose may also lower the threshold for imaging and increase the frequency of imaging, resulting in greater imaging volume. This may prove to be particularly useful in cancer screening programs. From an MRI perspective, deep learning algorithms have shown the ability to reduce scan time by improving reconstruction efficiency as well as improving scan quality.<sup>14</sup> Scanning protocols can also be dynamically adjusted before or during scanning, based on patient factors as well as imaging content from early sequences, to optimize sequence selection and decrease scanning time.<sup>15</sup> This decrease in necessary MRI scanner time to arrive at an accurate diagnosis could enable increased patient throughput.

### Al as a Tool to Optimize Radiology Workflow

Perhaps the greatest potential area of immediate disruption is in AI work list management. Classifiers have been developed to identify abnormal chest radiographs with the intent of expediting interpretation of an abnormal exam.<sup>16</sup> Similarly, classifiers have been developed to detect intracranial hemorrhage and stroke on noncontrast head CT and acute stroke on diffusionweighted MRI.<sup>17,18</sup> Again, these tools could be incorporated into the picture archiving and communication system (PACS) to develop a "smart work list" that flags the radiologist to interpret abnormal exams first, thereby reducing the time to diagnosis and treatment.<sup>17</sup> Similar techniques could also be used to flag studies that may potentially be nondiagnostic, such as improperly positioned radiographs or motion-degraded cross-sectional exams. By identifying these issues at the time of scanning, the technologist would be able to repeat the exam or confer with the radiologist, thereby minimizing issues in patient callbacks and delays in patient care.

Intuitive and useful hanging protocols are another preinterpretation step that AI can aid. Hanging protocols refer to the details of how a study, and relevant prior studies, are displayed when opened in a PACS. Among surveyed radiologists, automated hanging protocols was considered the biggest factor in improving efficiency.<sup>19</sup> Currently, hanging protocols rely on Digital Imaging and Communications in Medicine (DICOM) data generated by scanners that is inherently inhomogeneous and therefore introduces variability when images from multiple scanners are being reviewed at a single workstation. Ongoing research for this purpose leverages the ability of AI to identify structures within the image and integrate that information with image metadata to display images in a way that can minimize the time from exam loading to interpretation.

# Image Interpretation with AI: What Can It Really Do?

Some of the most excitement regarding deep learning techniques in radiology focuses on automated image interpretation. Rajpurkar et al demonstrated a model with similar diagnostic accuracy to radiologists for pneumonia on chest radiography in a public data set,<sup>20</sup> and similar studies were performed for fractures,<sup>21</sup> tuberculosis detection,<sup>22</sup> and bone age determination.<sup>23</sup> Despite these studies, there is currently no commercially available solution that will interpret images and generate a report. Thus this research really serves to demonstrate the potential of AI to augment the radiologist work flow by alerting the radiologist to possible findings. Advances in natural language processing (NLP) may also soon mean that a report can be auto-populated with the imaging findings that the machine sees, thereby reducing the time the radiologist spends in generating a report.<sup>23</sup> Another developing application for AI in image interpretation lies in the detection of incidental findings. It was shown that simple classifiers can be trained to detect shoulder dislocations on chest radiographs with a sensitivity of at least 70%. With AI helping to alert radiologists to incidental findings, greater time and cognitive effort can be dedicated to answering relevant clinical questions while the machine assistant can assess the remainder of the scan. As AI systems become more advanced, their role in assisting diagnosis will grow. It is relatively easy to envision a narrow AI engine tailored to bone tumor evaluation, for example, that can supply a differential diagnosis for an imaging finding and therefore assist the radiologist in interpretation.

### Intelligent Reporting Systems

Many additional opportunities within the realm of image interpretation exist that do not necessarily entail an automated diagnosis. For example, automated lesion measurements with volumetric calculations can be performed with advances in image segmentation driven by deep learning.<sup>24</sup> More precise and reproducible measurements could be used to provide better longitudinal data when following tumors while also significantly reducing imaging interpretation time by removing these tasks from the radiologist. This could apply to anatomical measurements such as the tibial tuberositytrochlear groove measurement or calculation of the  $\alpha$  angle in the hip. In fact, any task that is repeated with mild variation can likely be automated by AI. Simple versions of AI facilitating reporting can already be seen in applications such as Nuance PowerScribe that can be trained to recognize certain key phrases and utilize rule-based systems to automatically organize an unstructured dictation (Nuance, Burlington, MA, USA). As NLP techniques advance, it is likely that the process of reporting an exam can also be significantly automated without the need for specifying explicit rule sets beforehand.

NLP can also be used to extract relevant information from an electronic medical record (EMR).<sup>25</sup> An AI system could be trained to extract cancer history from the EMR if an osseous lesion is recognized in imaging. Again, providing the radiologist with the relevant information at the time of diagnosis would lead to improved workflow efficiency.

### **Radiology as Big Data**

Much of the excitement surrounding deep learning in radiology depends on the fact that radiology is a data-driven specialty. Given this reality, it is also quite likely that there is additional data within our imaging that is clinically relevant, although it may not be apparent at the time of interpretation. Radiomic analysis, which can be described as the quantitative analysis of images into mineable data that can be analyzed mathematically, will also become more commonplace as AI tools become more accessible.<sup>26</sup> Recently, Rajkomar et al demonstrated a deep learning model that could predict inhospital mortality, readmission, length of stay, and discharge diagnoses better than currently used clinical models.<sup>27</sup> Similarly, deep learning may enable large-scale radiomic analysis with the potential to identify disease characteristics based on imaging patterns that may not be readily apparent to the human eye.<sup>28</sup> "Big data" techniques, consisting of both deep learning and other machine learning strategies, may also allow for better prediction of response to therapy and provide information on which patients may benefit from percutaneous intervention as opposed to surgery.

# Real Communication with Artificial Intelligence

Al can also be used after the conclusion of imaging interpretation in communication. Google (Alphabet Inc., Mountain View, CA) recently demonstrated its Duplex digital assistant that can converse with humans in real time to make a reservation at a hair salon or restaurant.<sup>29,30</sup> Although calling in incidental and routine imaging findings may be more complicated than booking a table for six, it is apparent that such technology could at least be partially adapted to a radiology practice to expedite and perhaps automate the reporting of nonemergent findings. Similarly, an Al chat-bot has demonstrated the ability to advise referrers to select appropriate imaging studies without human intervention. The rise of personal digital assistants such as Siri (Apple, Cupertino, CA) and Alexa (Amazon.com, Inc., Seattle, WA), although currently predominantly for consumer use, hold some promise for facilitating various communication steps within the radiology workflow. As more of these tasks, which often do not require the extensive training that radiologists undergo, become automated, radiologists will again have increased time to dedicate to the remainder of their activities.

## **Business Aspects of Al**

Billing and coding, a complex but fundamentally necessary task in any radiology practice, can also be optimized using AI. Systems that evaluate both the images and incorporate information from reports using NLP can ensure that imaging exams are billed and coded appropriately. It was estimated that > 100 variables may contribute to denied claims, a number large enough to be tedious and expensive for humans but still easily handled by modern AI systems.<sup>31</sup> Thus machine learning may be able not only to identify rejected claims but also assess what could be added to resubmit the claim and reduce similar future denials.

What is a radiologist to do with the extra time and efficiency afforded by these possible AI solutions? The natural answer is to increase throughput, which of course would also serve to diagnose more patients, reduce delays in treatment, and augment the bottom line. But the AI-augmented radiologist will also have opportunities that radiologists lost several years ago: time to consult with referrers and patients. The ACR in recent years has pushed for greater visibility of radiologists with patients and patient-facing providers.<sup>32</sup> Perhaps AI will increase our efficiency to a point where it is cost effective for radiologists to provide in-person consultation to referrers and patients, increasing the visibility and health of our profession as a whole.

### AI Products: What Is the Fine Print?

Although the promise of AI in radiology has captured the imagination of the research community and many potential applications have been outlined here, finding truly disruptive AI that is currently commercially available yields startling few results (Fig. 3). It is true that some software packages may automatically incorporate measurements made into a report (iMorgon, San Mateo, CA) or that dictation software may automatically structure a dictation using rulebased methods (Nuance Communications, Burlington, MA), and that these applications could be considered very narrow AI. However, much of the groundbreaking tools that AI promises are not without their own issues. In the case of image interpretation and diagnostic support specifically, deep learning techniques notoriously suffer from the socalled black box problem: Many of their decisions cannot be explained. There has been some work in this space, particularly through the development of saliency and attention maps that can demonstrate what portions of an image contribute to neural network activation.<sup>33</sup> But these explanations do not come near the robustness of radiologists providing an explanation of their conclusions using a combination of anatomical knowledge and imaging physics. In fact, some authors debate whether deep learning systems will ever be capable of this level of explainability.<sup>34</sup>

In 2018, the U.S. Food and Drug Administration proposed classifying AI-powered computer-aided diagnosis software for breast imaging as class II devices, making it easier for similar AI products to come to market.<sup>35</sup> The coming wave of AI-driven systems will bring their evaluation metrics that have been borrowed from the computer science and statistics fields. Radiologists need to educate themselves on the evaluation of AI systems because they will be the initial targets of these vendors. Additionally, gaining knowledge in the evaluation of AI systems within health care can also give

#### Currently available products

- · Population of reports with measurements & worksheet findings
- · Rule-based structuring of free-form reports
- · Rule-based clinical decision support for exam ordering

#### Short term opportunities

- · Exam scheduling and wait time prediction
- · Worklist management to expedite abnormal study interpretation
- Protocol suggestion/selection
- · Hanging protocol optimization
- Billing optimization

#### Long term opportunities

- Automated finding detection
- Differential diagnosis augmentation
- Fully automated interpretation & report generation
- · Radiomic analysis to guide novel diagnosis and treatment

**Fig. 3** Consideration of currently available AI-powered products and summary of future directions. Short term opportunities are predominantly comprised of non-image interpretation tasks. Decisions that directly affect patient care, particularly without the possible intervention of a radiologist, have a longer time horizon as prospective studies proving safety will be necessary.

radiologists a unique niche in larger health care systems where decision making regarding AI systems even outside of the radiology department will need to be made. For example, radiologists commonly discuss diagnostic tests using the metrics of sensitivity and specificity. In machine learning, however, the metrics often quoted are precision (a synonym for positive predictive value) and recall (synonymous with sensitivity).<sup>36</sup>

Although there has been much speculation regarding the replacement of radiologists by AI, the fact is that most applications of AI in radiology are best served as adjuncts to a radiologist. The entire lifecycle of a radiology exam, from order placement to result communication, can be made more efficient by the incorporation of AI techniques. Advanced information synthesis, the combination of multiple findings, patient history, and clinical data to arrive at a diagnosis, remains the holy grail of AI but is still demonstrably far in the future. Radiologists are in a unique position to welcome the AI revolution in health care by virtue of their close relationship with an extraordinary amount of data. In fact, AI will grant radiologists new opportunities to participate in patient care both via increased time for consultation but also through improvements in imaging and extraction of useful data from those images. Radiologists who position themselves to use this technology to their benefit, rather than to avoid it out of fear, will gain a favorable position for themselves and for our specialty.

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