ORIGINAL ARTICLE

Machine Learning in Radiology: Applications Beyond Image Interpretation

SA-CME

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Abstract

Much attention has been given to machine learning and its perceived impact in radiology, particularly in light of recent success with image classification in international competitions. However, machine learning is likely to impact radiology outside of image interpretation long before a fully functional "machine radiologist" is implemented in practice. Here, we describe an overview of machine learning, its application to radiology and other domains, and many cases of use that do not involve image interpretation. We hope that better understanding of these potential applications will help radiology practices prepare for the future and realize performance improvement and efficiency gains.

Key Words: Artificial intelligence, machine learning, deep learning, radiology, workflows

J Am Coll Radiol 2017;■:■-■. Copyright © 2017 American College of Radiology

INTRODUCTION

Machine learning is a branch of artificial intelligence that has been employed in a variety of applications to analyze complex data sets and find patterns and relationships among such data without being explicitly programmed [1]. Arthur Samuel was among the first researchers to apply machine learning, teaching a computer to improve playing checkers based on training with a human counterpart in 1959 [2]. Machine learning algorithms analyze data features as inputs, and by the process of iterative improvement can produce linear and nonlinear predictive models that detect signals, classify patterns, or prognosticate outcomes [3]. Machine learning is sometimes categorized into two main types, supervised and unsupervised [4,5]. In supervised learning, the data set is already annotated with ground truth labels from which the algorithm learns. In unsupervised learning, the algorithm detects patterns in data when the outcome is unknown.

There are many types of machine learning algorithms, including artificial neural networks (ANNs), support vector machines, k-nearest neighbors, and random forest [4,6,7]. More recently, there has been a resurgence of interest in multilayered or deep ANNs, given their ability to work well with complex and high-dimensional data sets [8].

The relatively recent success of machine learning, particularly ANNs, can be attributed to three primary factors: (1) availability of Big Data—very large data sets that exceed the capability of conventional data analysis; (2) requisite parallel processing power that exists in

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This work is from of a group of authors working on behalf of the ACR within the Commission on Informatics on the Innovation Advisory Council.

The authors have no conflicts of interest related to the material discussed in this article.

1546-1440/17/$36.00 ■ https://doi.org/10.1016/j.jacr.2017.09.044

modern-day graphics-processing units, which facilitates training of modern machine learning algorithms; and (3) advanced deeper algorithms and optimization techniques for training [9-11].

Machine learning has been used across many industries, including banking and finance, manufacturing, marketing, and telecommunications [11]. Some more common every day examples include e-mail spam filters, face recognition, search engines, speech recognition, and language translation. Many large capital corporations in the digital world including Microsoft (Microsoft Corp, Redmond, Washington, USA), Google (Menlo Park, California, USA), Apple (Apple Inc, Cupertino, California, USA), Facebook (Facebook, Inc, Menlo Park, California, USA), Baidu (Baidu Inc, Beijing, China), and Amazon (Amazon Inc, Seattle, Washington, USA) incorporate machine learning in their products [12-17].

MACHINE LEARNING WITHIN RADIOLOGY

One recent success in machine learning has been the ability to classify images [7]. Much of this success can be attributed to the availability of large annotated data sets for machine learning researchers. For example, Pascal Visual Object Classes, CIFAR-10, and ImageNet contain up to millions of annotated images. In particular, the ImageNet Large Scale Visual Recognition Competition challenge that began in 2008 has led to breakthroughs in artificial intelligence [18-21]. The use of deep or multilayered ANNs, often now broadly referred to as "deep learning," led to an increase in performance of the top-five accuracy (percent of cases where the answer was within the top-five predictions) from approximately 75% in 2011 to 97% in 2016 [22,23]. Since 2012, all of the winning entries in international challenges have used some variant of deep ANNs, with current accuracy comparable or exceeding human performance.

Machine learning and deep neural networks have had similar success with other high-dimensional complex data sets for performing speech recognition and language translation [15,16]. Accordingly, machine learning has the potential to solve many challenges that currently exist in radiology beyond image interpretation. One of the reasons there is great excitement in radiology today is the access to digital Big Data [9]. Many institutions have implemented electronic health care databases over the past two decades, including for images in PACS, radiology reports and ordering information in Radiology Information Systems, and electronic health records that encompass information from other sources, including clinical notes, laboratory data, and pathology records. Moreover, radiology images themselves are rich in metadata stored in the DICOM format, which may be leveraged as well. As such, there are great opportunities to uncover complex associations within the data using machine learning that would otherwise be difficult for a human to do [24]. This has potential implications for population health, earlier prediction of disease, and improvement in quality, efficiency, and cost-effectiveness of care [25-27].

There are a number of ways in which machine learning can help radiology practices today, including many tasks that are frequently performed by radiologists and ordering clinicians, such as imaging appropriateness assessment, creating study protocols, and standardization of radiology reporting, that could benefit from automation [28-30]. Although many of these examples could be implemented using conventional procedural programming methodologies, the machine learning approach holds the promise to perform these tasks with a higher level of proficiency that can improve over time as the system "learns" new data.

USE CASES IN RADIOLOGY (BEYOND IMAGE INTERPRETATION)

Machine learning has potential to assist radiologists with many of the tasks that they perform in addition to image interpretation, particularly in scenarios in which current IT solutions may not be optimal. The following are some use cases where machine learning technologies can have an impact in radiology. It should be noted that many of the following cases would require clinical validation before use.

Creating Study Protocols

One of the roles of a radiologist is to appropriately create study protocols based on their order indication and other relevant clinical parameters [29]. This involves reviewing clinical and ordering information stored in an electronic health record, referencing relevant lab values, prior images, and radiology reports. This can be a time-consuming but important task. However, recent studies demonstrate that machine learning algorithms utilizing information extracted from the provided study indications can be accurate in determining protocols of studies in both brain and body MRIs [31,32]. Tools like these could be useful and time-saving in clinical practice (Fig. 1).

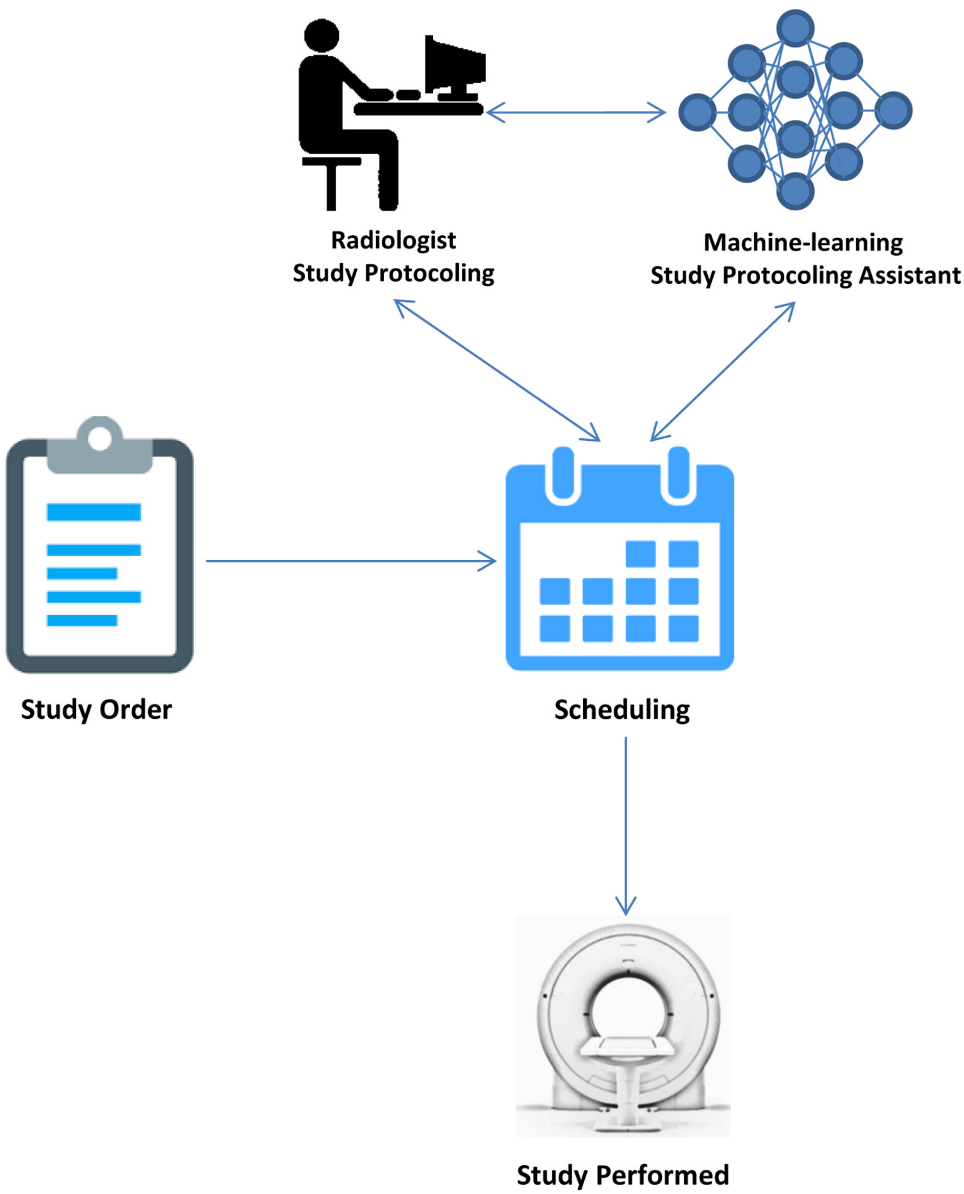

Fig 1. Sample workflow of a machine learning assistant for creating a study protocol. A study is initially ordered that routes into a scheduling system. A radiologist creates a protocol for the scheduled studies, with assistance from the machine learning software, which can make suggestions or predict an imaging protocol based on various input parameters.

Moreover, they can assist the clinician at the time of order entry by integration into decision-support systems.

Hanging Protocols

Many modern PACS leverage DICOM metadata to appropriately display or "hang" radiology studies so that they can be optimally interpreted by radiologists in a timely fashion. This becomes even more important with complex studies that have many parameters and series, such as MRI, in which there may be dozens of pulse sequences to be displayed in various anatomic planes. Moreover, with different scanner brands and naming conventions, an automated method to appropriately display these studies can be a difficult task. In addition, sometimes metadata are inaccurate due to manual entry, leading to hanging protocol errors. However, if a machine can accurately identify the modality, body part, image plane, and other pieces of information (eg, pulse sequence), such an algorithm may be used to more accurately automatically derive hanging protocols. A survey of radiologists indicated that creating hanging protocols had the highest perceived impact on radiologist's productivity, with some work already addressing this challenge with machine learning [33,34]. An example showing how machine learning may be incorporated into clinical workflow for this purpose is provided in Figure 2.

Improve Image Quality and Decrease Radiation Dose in CT

There has been a desire to reduce radiation dose in CT, although this results in a tradeoff with increased image noise and therefore poorer-quality images, because there are limitations of the commonly used filtered back projection reconstruction techniques. Some of the newer iterative reconstruction technologies have helped reduce noise in images generated with lower doses [35]. However, deep learning has the potential to reduce radiation dose even further. The idea is to train a classifier to map "noisy" images generated from ultra-low-dose CT protocols to high-quality images from regular protocols, using deep learning techniques [36,37]. This is akin to creating "super-resolution" photo-realistic images from down-sampled versions, which has already shown exciting results in every-day color images [38,39]. This technique teaches the network what normal anatomy and abnormal pathology looks like at low doses compared with that at regular doses, thereby being able to recreate the image from ultra-low-dose scans (Fig 3). This type of algorithm demonstrated positive results in a survey-based multicenter study that had over 60 radiologists assess the diagnostic quality of low-dose scans reconstructed by an ANN versus the same scan at standard doses. They found over 90% of evaluators felt the ANN-reconstructed low-dose images were of greater or equal diagnostic quality than the standard-dose images [40].

Increase Image Quality and Decrease Scan Time in MRI

MRIs require more time to acquire than other imaging modalities to achieve a certain image quality. In some scenarios, such as in stroke or cerebral hemorrhage detection, there is a need for rapid acquisition protocols. Researchers have already used deep learning to reconstruct anatomic MRIs using sparse raw data from the scanner, which can reduce acquisition time by half or more [41,42]. Another group used deep learning to improve image quality of thicker MR brain scans similar to that of thin-section, high-quality research scans. This is performed by interpolating sparse data from

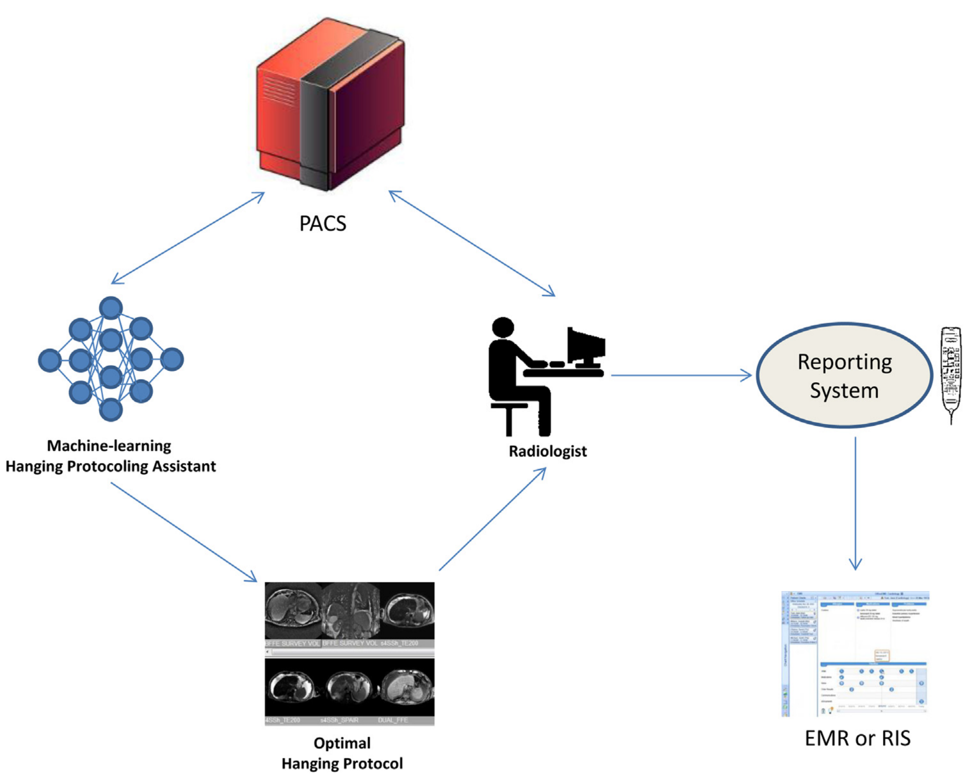

Fig 2. Example workflow using machine learning for hanging protocols. A radiologist opens a study on the PACS, and a machine learning assistant automatically creates an optimal hanging protocol for the radiologist to view. The radiologist then reports the findings and finalizes the report to the electronic medical record (EMR) or radiology information system (RIS).

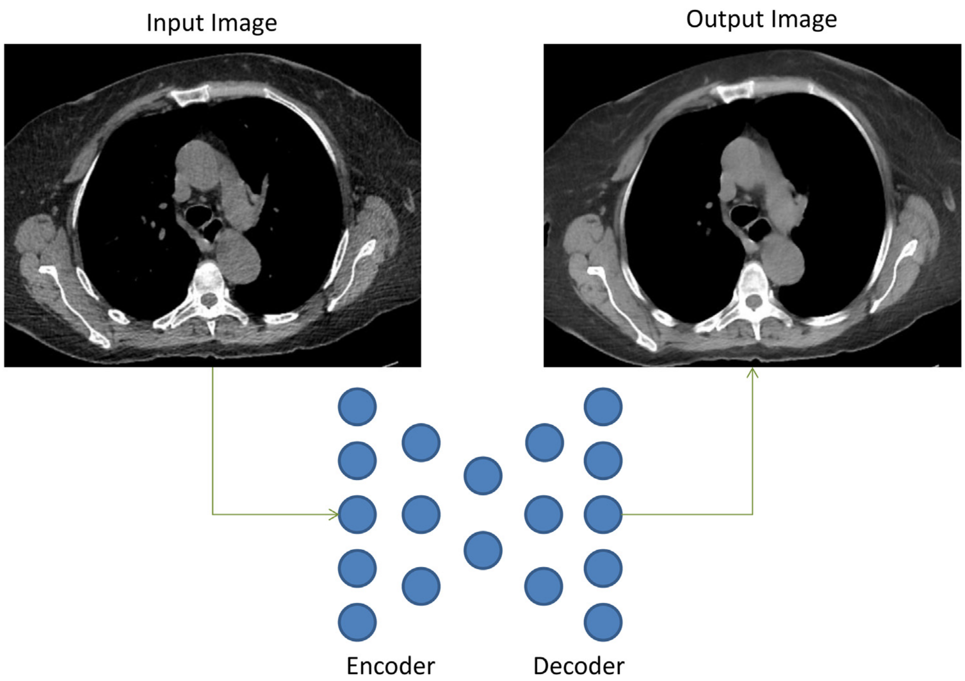

Fig 3. Example of a trained convolutional autoencoder (encoder-decoder) artificial neural network (ANN) transforming a relatively noisy input image from a low-dose CT to a corresponding image with less noise. The image on the left is taken from a low-dose CT scan, and the image on the right is a simulation of what a transformed de-noised image could look like. In this example, the input image is fed into the network, and then mapped into an encoded representation, which is subsequently used by the decoder network to create an output image. Such ANNs need to be trained on low dose CTs as well as corresponding routine dose CTs, and learn the mapping between the two.

larger axial slice intervals at 5 to 7 mm apart using deep learning to map such images into higher-resolution, anatomically plausible volumetric outputs [43]. The higher-resolution restored scans could improve the performance of basic image-processing tasks, such as skull-stripping and registration, which sometimes is difficult to perform on routine thicker-cut brain MRs.

Optimize MR Scanner Utilization

Because MRIs typically take the longest to acquire, maximizing the number of scans performed per shift could result in cost savings. A recent preliminary study used neural networks to help determine the optimal time slot per scan based on various input parameters (scan protocol, patient age, contrast usage, and protocol mean of unplanned sequence repeats). This has the potential to optimize scanner utilization and thereby reduce costs [44].

Assessment of Image Quality

Technologists and physicists routinely check medical image quality for various quality-related factors including appropriate penetration, exposure, coverage, artifacts, and image clarity. These evaluations are typically performed via visual inspection and phantoms. However, occasionally suboptimal images are not recognized until many hours after an exam is completed during image interpretation by the radiologist. With advances in machine and deep learning, there is now potential to instantly recognize, or perhaps even predict, poor image quality, allowing technologists to correct such errors before ending the imaging exam [45].

Scheduling Patients and Staffing Optimization

Particularly for large practices, scheduling the appropriate amount of staff for shift coverage can be a complex problem. Many factors are involved, including time of day, day of the week, coverage location (emergency department, inpatient, outpatient), exam complexity, volume of studies, variety of modalities (MR, CT, ultrasound, x-ray), and referring clinician practice patterns. Sometimes radiologists feel overwhelmed with the volume and complexity of studies on a given shift, and other times they are overstaffed. Outside of radiology, there is already an interest in using machine learning to optimize staffing, which has implications for increased profitability and cost reduction [46]. Another known problem that involves radiology and all health care practices are patient “no-shows.” This is a complex problem that may involve many factors including time, day of the week, and various patient demographics. Machine learning has already been applied in this area in the clinical domain, and similar solutions for radiology appointments may be valuable to improve cost-effectiveness [47].

Billing and Collections

Advances in natural language processing (NLP) and machine learning can be used to better interpret and classify reports from image-based procedures such that more accurate claims can be submitted for reimbursement. Insurance denials have been reported to cost health care organizations as much as 3% to 5%. Denials may be related to a combination of inputs, rather than due to just one alone, which can be difficult to decipher. As a result, hospitals and health care systems are turning to artificial intelligence to reduce denials, prioritize work queues for claims resubmissions, and alter processes to help prevent future denials [48].

Natural Language Understanding of Radiology Reports

There has been a movement toward standardized radiology reporting templates, such as in RadReport, and use of a standardized radiology lexicon, such as Radlex [49,50]. However, wide variation persists between radiologists and institutions, and reports continue to contain a large amount of semistructured prose text. Studies have shown that this can lead to differences in interpretation among radiologists and referring clinicians [51-53]. With advances in NLP, there have been ways to extract clinically meaningful data from such text including critical findings, BI-RADS categories and findings, and Fleischner Society recommendations often using heuristic techniques [53-57]. Machine learning approaches have shown promise in achieving high accuracy and being generalizable to many domains [58,59]. Recent advances in deeper machine learning methods may allow for better semantic understanding of free text and automatic generation of standardized reports, which can then be cycled back to machine learning algorithms as annotated or labeled data [7,60,61]. A potential application of natural language understanding is the development of an application that could generate radiology reports tailored to different audiences, such as the patient, primary care doctor, or subspecialty surgeon, for example. Moreover, intelligent text-understanding systems can recognize important findings such as critical results, pulmonary nodules, or lesion measurements; provide standardized terminology; and automatically insert appropriate recommendation statements.

Text Summarization

There is an overabundance of data in today’s EMRs, and consequently it can be time-consuming for the radiologist to find relevant information. Machine learning and NLP can extract pertinent clinical information from the EMR and present the information in a contextualized fashion to assist in imaging interpretation [62].

Speech Recognition and Text Translation

Speech recognition systems are widely used in radiology [63]. Newer advances with deep learning could further improve speech recognition systems and reduce errors commonly encountered with current technologies [15,64]. Also, there has been interest in machine translation of radiology report templates, and translation of finalized radiology reports themselves into various languages that could be beneficial to patients [49].

Image-Based Search Engines

As opposed to traditional search engines using text searches, advances in image understanding via deep learning could permit searches using images directly as an input [65]. For example, one could input an image of the lungs containing a ground-glass opacity and see other CT scans containing similar findings, matched with corresponding radiology reports (or even pathology if known). This technology could augment electronic teaching files and result in diagnostic assistance technologies.

Population Health and Disease Prevention

Images could be used as an input along with other measures not only to detect disease presence but to predict future disease. Already, there are example methods to match dual energy X-ray absorptiometry scores to CT images, and coronary calcium scores to nongated CT chest studies, but future work could be done to create many other models [66,67]. Much of this would require building data sets where a disease outcome is known, along with all available medical data—images, pathology, laboratory, and clinical notes. Similarly, one could create a seemingly limitless number of prediction models, such as tolerance to medication, probability of tumor response to chemotherapy, and survival odds of a particular disease or surgery.

Radiomics and Image Quantification

Radiomics (or radiogenomics) is the correlation between the imaging appearance of cancer and the genomics of such [68]. Advances in traditional machine learning and more novel deep learning approaches in this area have shown promising results [69-71]. Moreover, deep learning techniques has achieved state-of-the-art results in biomedical image segmentation, which can be used to automatically segment and extract volumes of organs, specific tissues, and regions of interest [72]. The radiology report of the future may automatically include such quantitative information, which could be used to assess disease and guide treatment decisions.

SYMBIOSIS OF ARTIFICIAL INTELLIGENCE AND MEDICAL SUBSPECIALISTS

Human experts and machines have different strengths. Accordingly, there are tasks that are better suited for machines and others for humans. Some advantages of machines are that they can work 24 hours per day and contemporaneously. Also, machines may be designed to provide consistent analysis for a given input or series of input parameters. This allows for precision and potential for quantification in results reporting. Machines can analyze large volumes of data and find complex associations hidden within these data that may be otherwise difficult for a human to do [9].

In contradistinction, humans can make inferences and innovate from very little training data and solve a wide variety of problems. They are more likely to better tailor and adjust practice patterns to regional variations, fostering relationships, and optimally communicate findings to referring physicians and patients [73-75]. Finally, radiologists may be better able to perceive a broader scope of patient care and intentionally not mention an incidental finding that could lead to "overdiagnosis"—and potentially negatively impact the global use of medical imaging [76].

Despite success with everyday image classification, currently available artificially intelligent models for medical image analysis represent artificial narrow intelligence, as they focus on narrow specific tasks [21,77-79]. On the other hand, it will take many more years before such machines could attain artificial general intelligence, with the ability to apply intelligence to any problem, similar to that of medical subspecialists.

In addition, there is a relative lack of transparency and understanding as to how newer, more complex algorithms actually work [80]. For example, in a recent study, models based on deep learning were better able to predict the probability of patients developing various diseases such as diabetes, congestive heart failure, and schizophrenia from clinical records than other pre-existing models and physician-expert diagnosis. However, the study authors could not explain what the exact associations were, or how the machines arrived at their conclusions [27]. The machine learning research community is actively working on tools to improve understanding of these algorithms, and saliency and attention maps can be helpful to address some of these challenges, but more research is needed in this area [81-83]. Understanding how machine learning algorithms come to medical conclusions is important, because ultimately physicians will be explaining such results to patients.

An additional obstacle to machine learning implementation in health care is that although there is a framework to validate such models (as in C-statistics), this does not fully address the high degree of dependency on the underlying data to influence the performance of machine learning models. Although a model may perform well in a research environment, it may behave differently when deployed in a "real-world" situation and poorly generalize to other populations and regions. Prospective studies will be helpful to address this. In addition, multi-institutional well-curated data sets sponsored by national organizations would be helpful to facilitate creation of more robust models for testing and validation in the clinical setting.

Ultimately, machine learning has the potential to dramatically improve patient care. Importantly for radiologists, machine learning algorithms can help address many problems in current-day radiology practices that do not involve image interpretation. Although much of the attention in the machine learning space has focused on the ability of machines to classify image findings, there are many other useful applications of machine learning that will improve efficiency and utilization of radiology practices today. Moreover, we may see a world where a symbiosis of subspecialty experts and machines lead to better care than could be provided by either one alone. Those practices that implement these technologies today are likely to better position themselves for the future.

TAKE-HOME POINTS

- Machine learning is a powerful tool with many applications that can help radiology practices today beyond image interpretation.
- Some applications include creating study protocols or decision support, hanging protocols, improving image quality, decreasing MR scanner time, optimizing staffing and scanner utilization, billing and collections, reporting, text understanding, image quantification, radiomics, and population health.
- Current machine learning models consist of narrow artificial intelligence and can provide value in solving specific tasks.
- Integrating human general intelligence and narrow artificially intelligent models holds promise for improving radiology practices and patient care.

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