Artificial Intelligence: Review of Current and Future Applications in Medicine

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Background: The role of artificial intelligence (AI) in health care is expanding rapidly. Currently, there are at least 29 US Food and Drug Administration-approved AI health care devices that apply to numerous medical specialties and many more are in development.

Observations: With increasing expectations for all health care sectors to deliver timely, fiscally-responsible, high-quality health care, AI has potential utility in numerous areas, such as image analysis, improved workflow and efficiency, public health, and epidemiology, to aid in processing large volumes of patient and medical data. In this review, we describe basic terminology, principles, and general AI applications relating to health care. We then discuss current and future applications for a variety of medical specialties. Finally, we discuss the future potential of AI along with the potential risks and limitations of current AI technology.

Conclusions: AI can improve diagnostic accuracy, increase patient safety, assist with patient triage, monitor disease progression, and assist with treatment decisions.

Artificial Intelligence (AI) was first described in 1956 and refers to machines having the ability to learn as they receive and process information, resulting in the ability to "think" like humans.[1] AI's impact in medicine is increasing; currently, at least 29 AI medical devices and algorithms are approved by the US Food and Drug Administration (FDA) in a variety of areas, including radiograph interpretation, managing glucose levels in patients with diabetes mellitus, analyzing electrocardiograms (ECGs), and diagnosing sleep disorders among others.[2] Significantly, in 2020, the Centers for Medicare and Medicaid Services (CMS) announced the first reimbursement to hospitals for an AI platform, a model for early detection of strokes.[3] AI is rapidly becoming an integral part of health care, and its role will only increase in the future (Table).

As knowledge in medicine is expanding exponentially, AI has great potential to assist with handling complex patient care data. The concept of exponential growth is not a natural one. As Bini described, with exponential growth the volume of knowledge amassed over the past 10 years will now occur in perhaps only 1 year.[1] Likewise, equivalent advances over the past year may take just a few months. This phenomenon is partly due to the law of accelerating returns, which states that advances feed on themselves, continually increasing the rate of further advances.[4] The volume of medical data doubles every 2 to 5 years.[5] Fortunately, the field of AI is growing exponentially as well and can help health care practitioners (HCPs) keep pace, allowing the continued delivery of effective health care.

In this report, we review common terminology, principles, and general applications of AI, followed by current and potential applications of AI for selected medical specialties. Finally, we discuss AI's future in health care, along with potential risks and pitfalls.

AI OVERVIEW

AI refers to machine programs that can "learn" or think based on past experiences. This functionality contrasts with simple rules-based programming available to health care for years. An example of rules-based programming is the warfarindosing.org website developed by Barnes-Jewish Hospital at Washington University Medical Center, which guides initial warfarin dosing.[6,7] The prescriber inputs detailed patient information, including age, sex, height, weight, tobacco history, medications, laboratory results, and genotype if available. The application then calculates recommended warfarin dosing regimens to avoid over- or underanticoagulation. While the dosing algorithm may be complex, it depends entirely on preprogrammed rules. The program does not learn to reach its conclusions and recommendations from patient data.

In contrast, one of the most common subsets of AI is machine learning (ML). ML describes a program that "learns from experience and improves its performance as it learns."[1] With ML, the computer is initially provided with a training data set—data

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TABLE Key Historical Events in Artifical Intelligence Development With a Focus on Health Care Applications

Years	Events
1943	Neural network conceptual paper published[118]
1956	The term *artificial intelligence* is coined by John McCarthy[1]
1959	The term *machine learning* is coined by Arthur Samuel[119]
1983	First computer digitized X-ray developed for radiology[120]
1986	The term *deep learning* introduced by Rina Dechter[121]
1989	Convolutional neural networks invented by Yann LeCun[122]
2011	IBM Watson beats human contestants at *Jeopardy* game show[44]
2016	AlphaGo artificial intelligence system beats professional GO player[44]
2016	FDA approves the first artificial intelligence software for patient care[2]
2017	FDA approves the first whole slide scanner for clinical use in pathology (Philips IntelliSite)[123]
2018	FDA approves the first medical device for patient care without physician oversight (IDx-DR)[75]
2020	Centers for Medicare and Medicaid Services announces the first reimbursement to hospital for use of artificial intelligence technologies[3]

Abbreviation: FDA, US Food and Drug Administration.

with known outcomes or labels. Because the initial data are input from known samples, this type of AI is known as supervised learning.[8-10] As an example, we recently reported using ML to diagnose various types of cancer from pathology slides.[11] In one experiment, we captured images of colon adenocarcinoma and normal colon (these 2 groups represent the training data set). Unlike traditional programming, we did not define characteristics that would differentiate colon cancer from normal; rather, the machine learned these characteristics independently by assessing the labeled images provided. A second data set (the validation data set) was used to evaluate the program and fine-tune the ML training model's parameters. Finally, the program was presented with new images of cancer and normal cases for final assessment of accuracy (test data set). Our program learned to recognize differences from the images provided and was able to differentiate normal and cancer images with > 95% accuracy.

Advances in computer processing have allowed for the development of artificial neural networks (ANNs). While there are several types of ANNs, the most common types used for image classification and segmentation are known as convolutional neural networks (CNNs).[9,12-14] The programs are designed to work similar to the human brain, specifically the visual cortex.[15,16] As data are acquired, they are processed by various layers in the program. Much like neurons in the brain, one layer decides whether to advance information to the next.[13,14] CNNs can be many layers deep, leading to the term *deep learning*: "computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction."[1,13,17]

ANNs can process larger volumes of data. This advance has led to the development of unstructured or unsupervised learning. With this type of learning, imputing defined features (ie, predetermined answers) of the training data set described above is no longer required.[1,8,10,14] The advantage of unsupervised learning is that the program can be presented raw data and extract meaningful interpretation without human input, often with less bias than may exist with supervised learning.[1,18] If shown enough data, the program can extract relevant features to make conclusions independently without predefined definitions, potentially uncovering markers not previously known. For example, several studies have used unsupervised learning to search patient data to assess readmission risks of patients with congestive heart failure.[10,19,20] AI compiled features independently and not previously defined, predicting patients at greater risk for readmission superior to traditional methods.

A more detailed description of the various terminologies and techniques of AI is beyond the scope of this review.[9,10,17,21] However, in this basic overview, we describe 4 general areas that AI impacts health care (Figure).

Health Care Applications

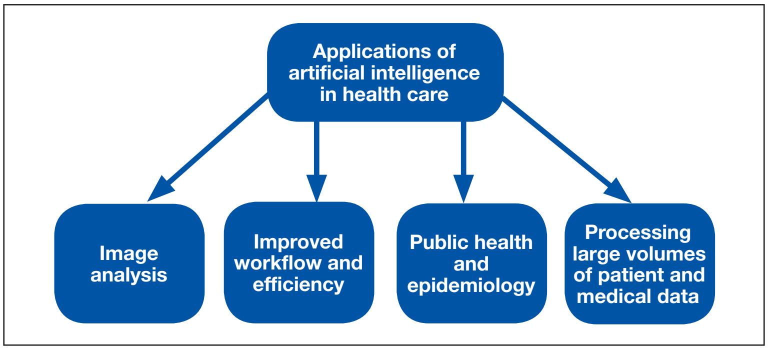
Image analysis has seen the most AI health care applications.[8,15] AI has shown potential in interpreting many types of medical images, including pathology slides, radiographs of various types, retina and other eye scans, and photographs of skin lesions. Many studies have demonstrated that AI can interpret these images as accurately as or even better than experienced clinicians.[9,13,22-29] Studies have suggested AI interpretation of radiographs may better distinguish patients infected with COVID-19 from other causes of pneumonia, and AI interpretation of pathology slides may detect specific genetic mutations not previously identified without additional molecular tests.[11,14,23,24,30-32]

The second area in which AI can impact health care is improving workflow and efficiency. AI has improved surgery scheduling, saving significant revenue, and decreased patient wait times for appointments.[1] AI can screen and triage radiographs, allowing attention to be directed to critical patients. This use would be valuable in many busy clinical settings, such as the recent COVID-19 pandemic.[8,23] Similarly, AI can screen retina images to prioritize urgent conditions.[25] AI has improved pathologists' efficiency when used to detect breast metastases.[33] Finally, AI may reduce medical errors, thereby ensuring patient safety.[8,9,34]

A third health care benefit of AI is in public health and epidemiology. AI can assist with clinical decision-making and diagnoses in low-income countries and areas with limited health care resources and personnel.[25,29] AI can improve identification of infectious outbreaks, such as tuberculosis, malaria, dengue fever, and influenza.[29,35-40] AI has been used to predict transmission patterns of the Zika virus and the current COVID-19 pandemic.[41,42] Applications can stratify the risk of outbreaks based on multiple factors, including age, income, race, atypical geographic clusters, and seasonal factors like rainfall and temperature.[35,36,38,43] AI has been used to assess morbidity and mortality, such as predicting disease severity with malaria and identifying treatment failures in tuberculosis.[29]

Finally, AI can dramatically impact health care due to processing large data sets or disconnected volumes of patient information—so-called big data.[44-46] An example is the widespread use of electronic health records (EHRs) such as the Computerized Patient Record System used in Veteran Affairs medical centers (VAMCs). Much of patient information exists in written text: HCP notes, laboratory and radiology reports, medication records, etc. Natural language processing (NLP) allows platforms to sort through extensive volumes of data on complex patients at rates much faster than human capability,

FIGURE Artificial Intelligence Health Care Applications



which has great potential to assist with diagnosis and treatment decisions.[9]

Medical literature is being produced at rates that exceed our ability to digest. More than 200,000 cancer-related articles were published in 2019 alone.[14] NLP capabilities of AI have the potential to rapidly sort through this extensive medical literature and relate specific verbiage in patient records guiding therapy.[46] IBM Watson, a supercomputer based on ML and NLP, demonstrates this concept with many potential applications, only some of which relate to health care.[1,9] Watson has an oncology component to assimilate multiple aspects of patient care, including clinical notes, pathology results, radiograph findings, staging, and a tumor's genetic profile. It coordinates these inputs from the EHR and mines medical literature and research databases to recommend treatment options.[1,46] AI can assess and compile far greater patient data and therapeutic options than would be feasible by individual clinicians, thus providing customized patient care.[47] Watson has partnered with numerous medical centers, including MD Anderson Cancer Center and Memorial Sloan Kettering Cancer Center, with variable success.[44,47-49] While the full potential of Watson appears not yet realized, these AI-driven approaches will likely play an important role in leveraging the hidden value in the expanding volume of health care information.

MEDICAL SPECIALTY APPLICATIONS

Radiology

Currently > 70% of FDA-approved AI medical devices are in the field of radiology.[2] Most radiology departments have used AI-friendly digital imaging for years, such as the picture archiving and communication systems used by numerous health care systems, including VAMCs.[2,15] Gray-scale images common in radiology lend themselves to standardization, although AI is not limited to black-and-white image interpretation.[15]

An abundance of literature describes plain radiograph interpretation using AI. One FDA-approved platform improved X-ray diagnosis of wrist fractures when used by emergency medicine clinicians.[2,50] AI has been applied to chest X-ray (CXR) interpretation of many conditions, including pneumonia, tuberculosis, malignant lung lesions, and COVID-19.[23,25,28,44,51-53] For example, Nam and colleagues suggested AI is better at diagnosing malignant pulmonary nodules from CXRs than are trained radiologists.[28]

In addition to plain radiographs, AI has been applied to many other imaging technologies, including ultrasounds, positron emission tomography, mammograms, computed tomography (CT), and magnetic resonance imaging (MRI).[15,26,44,48,54-56] A large study demonstrated that ML platforms significantly reduced the time to diagnose intracranial hemorrhages on CT and identified subtle hemorrhages missed by radiologists.[55] Other studies have claimed that AI programs may be better than radiologists in detecting cancer in screening mammograms, and 3 FDA-approved devices focus on mammogram interpretation.[2,15,54,57] There is also great interest in MRI applications to detect and predict prognosis for breast cancer based on imaging findings.[21,56]

Aside from providing accurate diagnoses, other studies focus on AI radiograph interpretation to assist with patient screening, triage, improving time to final diagnosis, providing a rapid "second opinion," and even monitoring disease progression and offering insights into prognosis.[8,21,23,52,55,56,58] These features help in busy urban centers but may play an even greater role in areas with limited access to health care or trained specialists such as radiologists.[52]

Cardiology

Cardiology has the second highest number of FDA-approved AI applications.[2] Many cardiology AI platforms involve image analysis, as described in several recent reviews.[45,59,60] AI has been applied to echocardiography to measure ejection fractions, detect valvular disease, and assess heart failure from hypertrophic and restrictive cardiomyopathy and amyloidosis.[45,48,59] Applications for cardiac CT scans and CT angiography have successfully quantified both calcified and noncalcified coronary artery plaques and lumen assessments, assessed myocardial perfusion, and performed coronary artery calcium scoring.[45,59,60] Likewise, AI applications for cardiac MRI have been used to quantitate ejection fraction, large vessel flow assessment, and cardiac scar burden.[45,59]

For years ECG devices have provided interpretation with limited accuracy using preprogrammed parameters.[48] However, the application of AI allows ECG interpretation on par with trained cardiologists. Numerous such AI applications exist, and 2 FDA-approved devices perform ECG interpretation.[2,61-64] One of these devices incorporates an AI-powered stethoscope to detect atrial fibrillation and heart murmurs.[65]

Pathology

The advancement of whole slide imaging, wherein entire slides can be scanned and digitized at high speed and resolution, creates great potential for AI applications in pathology.[12,24,32,33,66] A landmark study demonstrating the potential of AI for assessing whole slide imaging examined sentinel lymph node metastases in patients with breast cancer.[22] Multiple algorithms in the study demonstrated that AI was equivalent or better than pathologists in detecting metastases, especially when the pathologists were time-constrained consistent with a normal working environment. Significantly, the most accurate and efficient diagnoses were achieved when the pathologist and AI interpretations were used together.[22,33]

AI has shown promise in diagnosing many other entities, including cancers of the prostate (including Gleason scoring), lung, colon, breast, and skin.[11,12,24,27,32,67] In addition, AI has shown great potential in scoring biomarkers important for prognosis and treatment, such as immunohistochemistry (IHC) labeling of Ki-67 and PD-L1.[32] Pathologists can have difficulty classifying certain tumors or determining the site of origin for metastases, often having to rely on IHC with limited success. The unique features of image analysis with AI have the potential to assist in classifying difficult tumors and identifying sites of origin for metastatic disease based on morphology alone.[11]

Oncology depends heavily on molecular pathology testing to dictate treatment options and determine prognosis. Preliminary studies suggest that AI interpretation alone has the potential to delineate whether certain molecular mutations are present in tumors from various sites.[11,14,24,32] One study combined histology and genomic results for AI interpretation that improved prognostic predictions.[68] In addition, AI analysis may have potential in predicting tumor recurrence or prognosis based on cellular features, as demonstrated for lung cancer and melanoma.[67,69,70]

Ophthalmology

AI applications for ophthalmology have focused on diabetic retinopathy, age-related macular degeneration, glaucoma, retinopathy of prematurity, age-related and congenital cataracts, and retinal vein occlusion.[71-73] Diabetic retinopathy is a leading cause of blindness and has been studied by numerous platforms with good success, most having used color fundus photography.[71,72] One study showed AI could diagnose diabetic retinopathy and diabetic macular edema with specificities similar to ophthalmologists.[74] In 2018, the FDA approved the AI platform IDx-DR. This diagnostic system classifies retinal images and recommends referral for patients determined to have "more than mild diabetic retinopathy" and reexamination within a year for other patients.[8,75] Significantly, the platform recommendations do not require confirmation by a clinician.[8]

AI has been applied to other modalities in ophthalmology such as optical coherence tomography (OCT) to diagnose retinal disease and to predict appropriate management of congenital cataracts.[25,73,76] For example, an AI application using OCT has been demonstrated to match or exceed the accuracy of retinal experts in diagnosing and triaging patients with a variety of retinal pathologies, including patients needing urgent referrals.[77]

Dermatology

Multiple studies demonstrate AI performs at least equal to experienced dermatologists in differentiating selected skin lesions.[78-81] For example, Esteva and colleagues demonstrated AI could differentiate keratinocyte carcinomas from benign seborrheic keratoses and malignant melanomas from benign nevi with accuracy equal to 21 board-certified dermatologists.[78]

AI is applicable to various imaging procedures common to dermatology, such as dermoscopy, very high-frequency ultrasound, and reflectance confocal microscopy.[82] Several studies have demonstrated that AI interpretation compared favorably to dermatologists evaluating dermoscopy to assess melanocytic lesions.[78-81,83]

A limitation in these studies is that they differentiate only a few diagnoses.[82] Furthermore, dermatologists have sensory input such as touch and visual examination under various conditions, something AI has yet to replicate.[15,34,84] Also, most AI devices use no or limited clinical information.[81] Dermatologists can recognize rarer conditions for which AI models may have had limited or no training.[34] Nevertheless, a recent study assessed AI for the diagnosis of 134 separate skin disorders with promising results, including providing diagnoses with accuracy comparable to that of dermatologists and providing accurate treatment strategies.[84] As Topol points out, most skin lesions are diagnosed in the primary care setting where AI can have a greater impact when used in conjunction with the clinical impression, especially where specialists are in limited supply.[48,78]

Finally, dermatology lends itself to using portable or smartphone applications (apps) wherein the user can photograph a lesion for analysis by AI algorithms to assess the need for further evaluation or make treatment recommendations.[34,84,85] Although results from currently available apps are not encouraging, they may play a greater role as the technology advances.[34,85]

Oncology

Applications of AI in oncology include predicting prognosis for patients with cancer based on histologic and/or genetic information.[14,68,86] Programs can predict the risk of complications before and recurrence risks after surgery for malignancies.[44,87-89] AI can also assist in treatment planning and predict treatment failure with radiation therapy.[90,91]

AI has great potential in processing the large volumes of patient data in cancer genomics. Next-generation sequencing has allowed for the identification of millions of DNA sequences in a single tumor to detect genetic anomalies.[92] Thousands of mutations can be found in individual tumor samples, and processing this information and determining its significance can be beyond human capability.[14] We know little about the effects of various mutation combinations, and most tumors have a heterogeneous molecular profile among different cell populations.[14,93] The presence or absence of various mutations can have diagnostic, prognostic, and therapeutic implications.[93] AI has great potential to sort through these complex data and identify actionable findings.

More than 200,000 cancer-related articles were published in 2019, and publications in the field of cancer genomics are increasing exponentially.[14,92,93] Patel and colleagues assessed the utility of IBM Watson for Genomics against results from a molecular tumor board.[93] Watson for Genomics identified potentially significant mutations not identified by the tumor board in 32% of patients. Most mutations were related to new clinical trials not yet added to the tumor board watch list, demonstrating the role AI will have in processing the large volume of genetic data required to deliver personalized medicine moving forward.

Gastroenterology

AI has shown promise in predicting risk or outcomes based on clinical parameters in various common gastroenterology problems, including gastric reflux, acute pancreatitis, gastrointestinal bleeding, celiac disease, and inflammatory bowel disease.[94,95] AI endoscopic analysis has demonstrated potential in assessing Barrett's esophagus, gastric *Helicobacter pylori* infections, gastric atrophy, and gastric intestinal metaplasia.[95] Applications have been used to assess esophageal, gastric, and colonic malignancies, including depth of invasion based on endoscopic images.[95] Finally, studies have evaluated AI to assess small colon polyps during colonoscopy, including differentiating benign and premalignant polyps with success comparable to gastroenterologists.[94,95] AI has been shown to increase the speed and accuracy of gastroenterologists in detecting small polyps during colonoscopy.[48] In a prospective randomized study, colonoscopies performed using an AI device identified significantly more small adenomatous polyps than colonoscopies without AI.[96]

Neurology

It has been suggested that AI technologies are well suited for application in neurology due to the subtle presentation of many neurologic diseases.[16] Viz LVO, the first CMS-approved AI reimbursement for the diagnosis of strokes, analyzes CTs to detect early ischemic strokes and alerts the medical team, thus shortening time to treatment.[3,97] Many other AI platforms are in use or development that use CT and MRI for the early detection of strokes as well as for treatment and prognosis.[9,97]

AI technologies have been applied to neurodegenerative diseases, such as Alzheimer and Parkinson diseases.[16,98] For example, several studies have evaluated patient movements in Parkinson disease for both early diagnosis and to assess response to treatment.[98] These evaluations included assessment with both external cameras as well as wearable devices and smartphone apps.

AI has also been applied to seizure disorders, attempting to determine seizure type, localize the area of seizure onset, and address the challenges of identifying seizures in neonates.[99,100] Other potential applications range from early detection and prognosis predictions for cases of multiple sclerosis to restoring movement in paralysis from a variety of conditions such as spinal cord injury.[9,101,102]

Mental Health

Due to the interactive nature of mental health care, the field has been slower to develop AI applications.[18] With heavy reliance on textual information (eg, clinic notes, mood rating scales, and documentation of conversations), successful AI applications in this field will likely rely heavily on NLP.[18] However, studies investigating the application of AI to mental health have also incorporated data such as brain imaging, smartphone monitoring, and social media platforms, such as Facebook and Twitter.[18,103,104]

The risk of suicide is higher in veteran patients, and ML algorithms have had limited success in predicting suicide risk in both veteran and nonveteran populations.[104-106] While early models have low positive predictive values and low sensitivities, they still promise to be a useful tool in conjunction with traditional risk assessments.[106] Kessler and colleagues suggest that combining multiple rather than single ML algorithms might lead to greater success.[105,106]

AI may assist in diagnosing other mental health disorders, including major depressive disorder, attention deficit hyperactivity disorder (ADHD), schizophrenia, posttraumatic stress disorder, and Alzheimer disease.[103,104,107] These investigations are in the early stages with limited clinical applicability. However, 2 AI applications awaiting FDA approval relate to ADHD and opioid use.[2] Furthermore, potential exists for AI to not only assist with prevention and diagnosis of ADHD, but also to identify optimal treatment options.[2,103]

General and Personalized Medicine

Additional AI applications include diagnosing patients with suspected sepsis, measuring liver iron concentrations, predicting hospital mortality at the time of admission, and more.[2,108,109] AI can guide end-of-life decisions such as resuscitation status or whether to initiate mechanical ventilation.[48]

AI-driven smartphone apps can be beneficial to both patients and clinicians. Examples include predicting nonadherence to anticoagulation therapy, monitoring heart rhythms for atrial fibrillation or signs of hyperkalemia in patients with renal failure, and improving outcomes for patients with diabetes mellitus by decreasing glycemic variability and reducing hypoglycemia.[8,48,110,111] The potential for AI applications to health care and personalized medicine are almost limitless.

DISCUSSION

With ever-increasing expectations for all health care sectors to deliver timely, fiscally-responsible, high-quality health care, AI has the potential to have numerous impacts. AI can improve diagnostic accuracy while limiting errors and impact patient safety such as assisting with prescription delivery.[8,9,34] It can screen and triage patients, alerting clinicians to those needing more urgent evaluation.[8,23,77,97] AI also may increase a clinician's efficiency and speed to render a diagnosis.[12,13,55,97] AI can provide a rapid second opinion, an ability especially beneficial in underserved areas with shortages of specialists.[23,25,26,29,34] Similarly, AI may decrease the inter- and intraobserver variability common in many medical specialties.[12,27,45] AI applications can also monitor disease progression, identifying patients at greatest risk, and provide information for prognosis.[21,23,56,58] Finally, as described with applications using IBM Watson, AI can allow for an integrated approach to health care that is currently lacking.

We have described many reports suggesting AI can render diagnoses as well as or better than experienced clinicians, and speculation exists that AI will replace many roles currently performed by health care practitioners.[9,26] However, most studies demonstrate that AI's diagnostic benefits are best realized when used to supplement a clinician's impression.[8,22,30,33,52,54,56,69,84] AI is not likely to replace humans in health care in the foreseeable future. The technology can be likened to the impact of CT scans developed in the 1970s in neurology. Prior to such detailed imaging, neurologists spent extensive time performing detailed physicals to render diagnoses and locate lesions before surgery. There was mistrust of this new technology and concern that CT scans would eliminate the need for neurologists.[112] On the contrary, neurology is alive and well, frequently being augmented by the technologies once speculated to replace it.

Commercial AI health care platforms represented a $2 billion industry in 2018 and are growing rapidly each year.[13,32] Many AI products are offered ready for implementation for various tasks, including diagnostics, patient management, and improved efficiency. Others will likely be provided as templates suitable for modification to meet the specific needs of the facility, practice, or specialty for its patient population.

AI Risks and Limitations

AI has several risks and limitations. Although there is progress in explainable AI, at times we still struggle to understand how the output provided by machine learning algorithms was created.[44,48] The many layers associated with deep learning self-determine the criteria to reach its conclusion, and these criteria can continually evolve. The parameters of deep learning are not preprogrammed, and there are too many individual data points to be extrapolated or deconvoluted for evaluation at our current level of knowledge.[26,51] These apparent lack of constraints cause concern for patient safety and suggest that greater validation and continued scrutiny of validity is required.[8,48] Efforts are underway to create explainable AI programs to make their processes more transparent, but such clarification is limited presently.[14,26,48,77]

Another challenge of AI is determining the amount of training data required to function optimally. Also, if the output describes multiple variables or diagnoses, are each equally valid?[113] Furthermore, many AI applications look for a specific process, such as cancer diagnoses on CXRs. However, how coexisting conditions like cardiomegaly, emphysema, pneumonia, etc, seen on CXRs will affect the diagnosis needs to be considered.[51,52] Zech and colleagues provide the example that diagnoses for pneumothorax are frequently rendered on CXRs with chest tubes in place.[51] They suggest that CNNs may develop a bias toward diagnosing pneumothorax when chest tubes are present. Many current studies approach an issue in isolation, a situation not realistic in real-world clinical practice.[26]

Most studies on AI have been retrospective, and frequently data used to train the program are preselected.[13,26] The data are typically validated on available databases rather than actual patients in the clinical setting, limiting confidence in the validity of the AI output when applied to real-world situations. Currently, fewer than 12 prospective trials had been published comparing AI with traditional clinical care.[13,114] Randomized prospective clinical trials are even fewer, with none currently reported from the United States.[13,114] The results from several studies have been shown to diminish when repeated prospectively.[114]

The FDA has created a new category known as Software as a Medical Device and has a Digital Health Innovation Action Plan to regulate AI platforms. Still, the process of AI regulation is of necessity different from traditional approval processes and is continually evolving.[8] The FDA approval process cannot account for the fact that the program's parameters may continually evolve or adapt.[2]

Guidelines for investigating and reporting AI research with its unique attributes are being developed. Examples include the TRIPOD-ML statement and others.[49,115] In September 2020, 2 publications addressed the paucity of gold-standard randomized clinical trials in clinical AI applications.[116,117] The SPIRIT-AI statement expands on the original SPIRIT statement published in 2013 to guide minimal reporting standards for AI clinical trial protocols to promote transparency of design and methodology.[116] Similarly, the CONSORT-AI extension, stemming from the original CONSORT statement in 1996, aims to ensure quality reporting of randomized controlled trials in AI.[117]

Another risk with AI is that while an individual physician making a mistake may adversely affect 1 patient, a single mistake in an AI algorithm could potentially affect thousands of patients.[48] Also, AI programs developed for patient populations at a facility may not translate to another. Referred to as overfitting, this phenomenon relates to selection bias in training data sets.[15,34,49,51,52] Studies have shown that programs that underrepresent certain group characteristics such as age, sex, or race may be less effective when applied to a population in which these characteristics have differing representations.[8,48,49] This problem of underrepresentation has been demonstrated in programs interpreting pathology slides, radiographs, and skin lesions.[15,32,51]

Admittedly, most of these challenges are not specific to AI and existed in health care previously. Physicians make mistakes, treatments are sometimes used without adequate prospective studies, and medications are given without understanding their mechanism of action, much like AI-facilitated processes reach a conclusion that cannot be fully explained.[48]

CONCLUSIONS

The view that AI will dramatically impact health care in the coming years will likely prove true. However, much work is needed, especially because of the paucity of prospective clinical trials as has been historically required in medical research. Any concern that AI will replace HCPs seems unwarranted. Early studies suggest that even AI programs that appear to exceed human interpretation perform best when working in cooperation with and oversight from clinicians. AI's greatest potential appears to be its ability to augment care from health professionals, improving efficiency and accuracy, and should be anticipated with enthusiasm as the field moves forward at an exponential rate.

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