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CADTH ISSUES IN EMERGING HEALTH TECHNOLOGIES

Informing Decisions About New Health Technologies

Issue 174 September 2018

An Overview of Clinical Applications of Artificial Intelligence

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Cite As: An Overview of Clinical Applications of Artificial Intelligence. Ottawa: CADTH; 2018 Sep. (CADTH issues in emerging health technologies; issue 174)

ISSN: 1488-6324 (online)

Funding: CADTH receives funding from Canada's federal, provincial, and territorial governments, with the exception of Quebec.

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Background

Like many industries, health care is generating increased volumes of data and becoming increasingly reliant on it.[1] Applications that use artificial intelligence (AI) may offer opportunities to make better use of health care's increasingly data-driven environment and could change the way health care is delivered to Canadians.

What is Artificial Intelligence?

AI is a branch of computer science concerned with the development of systems that can perform tasks that would usually require human intelligence, such as problem-solving, reasoning, and recognition.[2-5] With theory and work dating back to the 1950s, AI is not a new concept, but advances in computing power and connectivity during the past two decades led to the expansion of AI research and applications.[1,3] AI is anticipated to impact multiple areas of health care including, but not limited to, process optimization, preclinical research, clinical pathways, and patient-facing, and population-level applications.[3,6]

Scope of this Bulletin

The proposed and current uses of AI in health care are myriad. This bulletin focuses on clinical applications of AI that may impact the care of patients, including tools that have been proposed, are in development, or are currently being used by health care providers. It is intended as an overview for readers and not as a comprehensive review of the literature. Discussion of the clinical- and cost-effectiveness of specific AI technologies described within the report is not within the scope of the bulletin. Select, non-clinical applications are briefly discussed. A review of potential implications for health human resources is not included.

Methods

These bulletins are not systematic reviews and do not involve critical appraisal or a detailed summary of study findings. Rather, they present an overview of the technology and available evidence. They are not intended to provide recommendations for or against a particular technology.

Literature Search Strategy

A limited literature search was conducted using PubMed and the Cochrane Library (2018, Issue 2). Grey literature was identified by searching relevant sections of the *Grey Matters* checklist (https://www.cadth.ca/grey-matters). Search filters for health technology assessments, systematic reviews, and meta-analyses were applied. The search was limited to English-language documents published between January 1, 2013, and February 28, 2018. Targeted supplemental searches were also conducted in PubMed at authors' requests.

Stakeholder Review

A draft version of this bulletin was posted publicly for stakeholder review.

The Technology

AI is an umbrella term encompassing a number of subfields and approaches.[2] In health care, AI systems often include, but are not limited to, one or more of the following:

Machine Learning

The health care sector has a historic interest in prediction, making a subset of AI — machine learning — of particular relevance, particularly for the detection of disease and for personalized treatment planning.[7] Machine learning involves training an algorithm to perform tasks by learning from patterns in data rather than performing a task it is explicitly programmed to do.[2] To train a machine learning program, data are typically divided into training sets (where a human indicates whether an outcome of interest is present or absent) and validation sets (where the system uses what it learns to indicate the presence or absence of outcomes of interest).[7] Typically, machine learning approaches are used when the number of patient traits of interest is small.[8]

Support Vector Machine

A support vector machine is a type of machine learning that is used mainly to classify subjects into two groups,[8] often used for the diagnosis or prediction of disease.[8]

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Artificial Neural Networks

An artificial neural network is a method of mimicking the way the human brain learns, through its connection of neurons, using a computer model.[3] This form of AI can evaluate complex relationships between inputs and outputs through a hidden layer (or layers) of calculations.[8] The network adapts to the information that it is provided (such as images) and, through a series of layered calculations, learns on its own what features can be used to determine specified outputs such as the presence or absence of a condition.[1,2,5,9]

Deep Learning

Deep learning is a form of artificial neural network with many hidden layers between inputs and outputs that allow the program to analyze complex data of various structures.[8] In health care, a common form of deep learning is the convolutional neural network.[8] Approaches to deep learning can be supervised, with the goal of accurately predicting known outcomes (such as the presence or absence of a disease) from sets of labelled data, or unsupervised with the goal of summarizing or explaining patterns observed in a set of data.[1]

Natural Language Processing

Natural language processing (NLP) is a branch of AI concerned with understanding and interpreting human language.[6,10,11] In health care, NLP could be used to analyze the content of electronic medical records or as an automated agent to respond to patient questions.[6]

Emergence of AI in Canada

The availability of powerful, low-cost computers has led to a burst of innovation in AI systems.[12,13] In health care, this innovation is supported by the increased availability of data from sources such as electronic health records, clinical and pathological images, and wearable connected sensors. This data can be used to train algorithms and provide more opportunities for these systems to practice and learn.[4,7,12] The current health care landscape in Canada has been noted to be conducive to the adoption of AI.[13] For example, the Canadian Association of Radiologists (CAR) stated that, "The integrated nature of the Canadian health care system makes it ideal for pooling anonymized medical data from several institutions or provinces, which is required to improve and validate AI tools for patient management."[13]

Past funding and research efforts have provided Canada with a robust network of AI labs, including hubs in Edmonton (Alberta Machine Intelligence Institute), Montreal (Institute Québecois d'intelligence artificielle), and Toronto (Vector Institute).[3] This developing infrastructure is complemented by various networking and funding initiatives. For instance, the Canadian Institute for Advanced Research is leading a pan-Canadian strategy to promote collaboration between the provincial hubs.[14] To attract and retain students, post-graduates, and researchers to these hubs, the federal government also provided a one-time funding of C$125 million to create the Pan-Canadian Artificial Intelligence Strategy through the Canadian Institute for Advanced Research in the 2017 budget.[3] The next Collaborative Health Research Project (CHRP) competition has earmarked C$6 million to support collaborative projects on "Artificial Intelligence, Health and Society" with Tri-Agency funding provided through the Natural Sciences and Engineering Research Council of Canada, the Canadian Institutes of Health Research, and the Social Sciences and Humanities Research Council of Canada.[15] Additional funding and investment in AI is occurring both provincially and regionally across Canada and plays an important role in the development of the country's AI ecosystem.[16] Further integration of AI in the Canadian system was discussed in a 2017 report by the Senate's Standing Committee on Social Affairs, Science and Technology, which outlined some of the challenges and opportunities for AI in Canada's health care system.[3]

Regulatory Considerations and Standardization

A key question that has been raised is whether AI should be regulated as a distinct area, or whether existing regulated areas should incorporate considerations for AI.[17]

Health Canada has indicated that Canada's *Food and Drug Act and Medical Devices Regulations* have already informed issuing of licenses to technologies that use AI.[3] In April 2018, Health Canada announced the establishment of the Digital Health Review Division within the Therapeutic Products Directorate's Medical Devices Bureau. The division is intended to allow for a more targeted review of rapidly changing and innovating digital health technologies, including AI technologies.[18]

Other countries, including the US[19,20] and the UK,[21] have started planning for the regulation of AI in health care. In April 2018, the

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FDA announced that it will develop a new regulatory framework for these AI applications.[22] Of note, the FDA intends to apply its new Pre-Cert program to AI applications which would focus on the developer rather than the product and allow minor changes to software to be approved without the need for resubmissions, an issue of particular concern with self-learning and self-adapting software.[22] The program is intended to go through pilot testing for products classified as software as a medical device in 2019.[23]

Regulation of specialized AI applications may require additional considerations. For example, CAR recommends that AI tools with radiology applications must consider the principles of evidence-based medicine and should receive the same level of clinical assessment as all other innovative drugs or devices before adoption.[24] They advise that consideration is given to potential ethical, medicolegal, and bias-related issues associated with the use of AI tools.[24] As well, the CAR working group suggests that all AI tools developed for diagnostic purposes should follow the Standards for Reporting Diagnostic Accuracy (STARD) guidelines when reporting studies of diagnostic accuracy.[24] Similarly, the group also recommended that studies reporting predictive models should be compliant with the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) statement.[24]

As well, to ensure that the performance on training datasets is generalizable to target hospital sites, CAR recommends that communications on patient cohort criteria should be comprehensive and transparent.[24] In addition, CAR encourages the development of standards for validating and testing processes for AI tools with an emphasis on stability of performance over different settings, equipment and protocols, and reproducible techniques.[24]

Privacy, ethical, and social issues are addressed in more detail in the Implementation Issues section of this report.

Who Might Benefit?

AI has the potential to improve patient care and the delivery of health services across a broad range of clinical specialties. Some specialties have incorporated AI for some time. In other cases, AI tools are just emerging or are in earlier stages of development. The next section of the report outlines some clinical specialty areas for which health technologies involving AI are being developed, studied, and incorporated into patient care.

Clinical Uses of Artificial Intelligence

Radiology, pathology, and dermatology are anticipated to be the first clinical specialties to experience large-scale change due to the incorporation of AI into work practices. These specialties have been targeted because their work involves the collection of data in the form of image interpretation and analysis.[25] Beyond these disciplines, there are numerous AI-related developments for other clinical specialties. Some of the developments outlined involve multiple clinical specialties or illustrate AI applications that have potential relevance across numerous clinical areas. For simplicity, they are presented according to the clinical specialty that the AI tool has a most direct impact upon.

Radiology and Imaging

Key Issues

Machine learning in radiology can be used to facilitate automated disease detection that enables clinicians to more quickly characterize disease.[26] Machine learning has increased rapidly in the field of medical imaging, especially in the areas of computer-aided detection, image analysis,[27] and radiomics — the applied conversion of medical images into complex quantitative data, which can be analyzed to support diagnoses and develop new decision support systems.[28,29]

The current focus of AI in medical imaging is on assisting imaging professionals in the reading and interpretation of images. Recent studies suggest that AI can make predictions when interpreting images at a level of competence comparable to that of a physician.[30] Given radiologist error rates at around 3% to 5% in image interpretations,[31] AI may play an important role in preventing medical errors. This is because AI applications are able to process large amounts of data, without being affected by lapses in memory, emotional response, or fatigue.[32] In addition to the interpretation and reading of imaging exams, AI tools may also help radiologists by coordinating and integrating information, identifying patients for screening examinations, prioritizing patients for immediate interpretation, and standardizing reporting.[33,34]

While AI in radiology is currently concentrated in the research domain,[24] deep learning algorithms are anticipated to diffuse into widespread clinical use,[33,35] as is evident by the FDA's recent approval of two AI-driven technologies.[36-38] As well, numerous manufacturers of imaging equipment are integrating AI into their medical imaging software systems.[24] For example, one large device manufacturer has 400 patents and patent applications in the field of AI.[35]

There is a spectrum of thought regarding the role of AI in radiology. It is anticipated that over the next 10 years there will be a gradual conversion to AI that will have significant implications for the work of radiologists.[39] The extent of the impact on radiology is unclear with some stakeholders predicting that AI tools will improve radiologist's contribution to patient care, enhance their workflow, and make their work easier and more interesting.[24] Others speculate that AI will one day supersede radiologists.[34]

As AI tools become more sensitive and are able to identify small image variances that are not visually discernible by the human eye, they may have the potential to enable earlier diagnosis of disease.[40] This could lead to the identification of previously unrecognized image features that correlate with a patient's prognosis and potentially guide treatment decisions that were previously not possible.[34] AI can also be used to track treatment progress, and record changes in the size and density of tumours over time.[41] This process can inform treatment decisions, and verify progress in clinical studies.[41]

Applications in Medical Imaging

In 2017 the FDA provided 510(k) clearance for the first machine learning application to be used in a clinical setting. The tool uses MRI to assist physicians in diagnosing heart problems by providing accurate measurements of the volume of each ventricle, allowing for more precise assessment.[42] In 2018, the FDA permitted the marketing of AI enhanced clinical decision support software designed to analyze computed tomography (CT) results to notify providers of a patient's potential stroke. The software is intended to benefit patients by reducing the time to treatment by notifying a specialist earlier in the emergency setting.[36] Also in 2018, the FDA approved an AI tool to be used with X-ray by a physician to support reviews of imaging exams for the detection of wrist fractures.[37]

Researchers have leveraged machine learning and deep learning in radiology to create tools that can improve the diagnosis and classification of cancer, including the identification of pulmonary nodules with CT,[27] polyp detection in CT colonography,[27,43] screening for breast cancer,[44] detection of microcalcification clusters (early signs of breast cancer) in mammography,[27] and the detection of masses and whether they are classified as benign or malignant in mammography.[27] AI is now being combined with computer-aided detection systems in mammography to improve diagnostic accuracy for the classification of breast cancer.[45]

Deep learning tools that automate extraction and classification of imaging features with speed and power are assisting in the diagnosis of stroke using neuroimaging with CT and MRI.[46-52] Key areas of development are radiomics, image segmentation, and multimodal prognostication.[46] On the CT front, a similar decision support tool to the one recently approved by the FDA is in development that automates the Alberta Stroke Program Early CT Score (ASPECTS) assessment tool for early ischemic changes.[47] As well, AI is used with CT angiography to differentiate free-floating intraluminal thrombus from carotid plaque[48] and to predict recovery after stroke by providing an accurate measure of cerebral edema severity, which may aid in early triaging of suitable stroke patients for craniectomy.[49]

With MRI, AI is being used to improve the overall image quality of scans, which due to time constraints of managing stroke patients, are usually done quickly and are of lower quality, making precise diagnosis a challenge.[50] A new technique uses high-resolution scans of different patients taken previously to improve the image quality of new stroke patients.[50] The technique fills in the space between the scanned slices so that an algorithm can confirm that the image looks similar to comparable high-quality scans. The data from the original image and the previous images are separated so that measurements can be compared against the actual image. Data from functional MRI may allow the classification of individual motor impairment after a stroke, which may play a role in predicting neurological outcomes and optimizing rehabilitation.[51] As well, AI data are being used with MRI to identify the extent and volume of stroke lesions with the aim of reducing the amount of time and effort dedicated to this task.[52]

There are other imaging-related AI algorithms on the horizon[53] For example, AI is combined with both X-ray and MRI to provide automatic delineation of tumours.[54] In addition, AI is coupled with chest X-ray to improve tuberculosis diagnosis,[26,55] and with positron emission tomography (PET) to assist in the early diagnosis of Alzheimer's disease.[56] AI is also used with MRI to identify multiple sclerosis patients who are likely to benefit from proactive treatment,[57] to determine Parkinson's disease using computer-based diagnosis of the brain,[27,58] and to differentiate Parkinson's disease from progressive supranuclear palsy.[58] As well, AI is being used as a decision support tool in endoscopy to predict the pathology of lesions and prevent unnecessary polypectomy of non-cancerous polyps.[59,60]

Concurrent developments in medical imaging relate to AI tools that are intended to improve patient and clinician safety, and patient experience. These include applications that enable CT to be performed at ultra-low radiation dose, MRI exams that can be conducted in two-thirds of current time frames, and PET that uses radio-tracer dose reduction of up to 99%.[61]

Pathology

Pathology is a clinical area in which AI innovations are emerging, albeit at a somewhat slower rate than radiology.[25,62]

Current interest in AI for pathology may, in part, be linked to the emergence of whole slide digital scanners and the interest in digital pathology (digitization of histology slides to produce high-resolution images).[25,63] Use of AI in pathology may also be linked to the fact that digital pathology creates large volumes of data that can be used in algorithms to recognize predictive patterns.[64] Given the world shortage of pathologists,[65] AI may be welcome in this discipline, particularly given the potential to enhance patient safety and contribute to workflow efficiencies.[64] To assist pathologists, AI may be leveraged to:

- automate some of the complex and time-consuming tasks involved in pathology such as object quantification, tissue classification based on morphology, and rare target identification.[64]
- determine personalized treatments for patients by using the data available to enable more personalized treatment decisions.[26]
- minimize the risk of misdiagnosis and the incorrect prescribing of medicines.[66]
- improve standardization and the consistency of decision-making.[26]
- facilitate the sharing of images to other readers to help reduce inter-reader variability.[66]
- speed up the process of image analysis.[26]

AI in combination with digital pathology can also promote telepathology (the practice of pathology at a distance) by allowing physicians in rural and remote communities to access and consult with specialized pathologists. These two technologies used together can also help reduce inter-reader variability amongst pathologists by allowing images to be easily shared so that a second reader can confirm findings.[66,67] Incorporation of AI into digital pathology practices may enable identification of data in images that is not visually discernable by the human eye — such as molecular markers in tumours. Such findings could lead to new microclassifications of diseases, and support early diagnosis.[33]

Numerous organizations are developing pattern-recognition algorithms for use with digital pathology to help interpret features in tissue and make predictions about disease progression (such as metastasis and recurrence).[25,26,67-69] In cases where cancer is present, AI software can classify the characteristics of the condition in terms of staging, grading, and differential diagnosis.[67,68] One such tool is intended to assist pathologists by providing precise methods to differentiate malignant from benign cells, and to determine the most effective treatment for a patient. The tool is currently being used to detect breast, prostate, lung and colorectal cancers, but it is anticipated that, over time, it may have the ability to identify any solid tumour.[26]

AI software that integrates histology and genomic biomarkers has been designed to predict the overall survival of patients with brain tumours. The predictive accuracy of the software is reported to be comparable or exceed the accuracy of a human pathologist.[69]

Dermatology

AI has the potential to play a role in supporting dermatologists' clinical decision-making for general skin conditions and specific cancers. Most of the current and emerging applications of AI in dermatology are aimed at diagnosing and preventing the onset of skin disease.[70]

For patients, innovations in AI may help to minimize unnecessary biopsies and increase the early detection of skin diseases.[71] For clinicians, AI may be able to assist in the diagnosis of disease. Considering current workforce shortages in dermatology,[70] AI may assist dermatologists in the management of demanding workloads and competing priorities.

AI enhanced software has been developed that can distinguish malignant melanomas from benign lesions. A recent study demonstrated that an AI algorithm was more accurate than 21 dermatologists participating in the study at identifying melanomas from non-cancerous lesions.[72] In addition, AI has been shown to be capable of identifying some new lesion characteristics such as border demarcation features particularly in the identification of cancerous lesions, which are often subtle and difficult to determine using visual diagnosis,[71] the primary method used to diagnose skin conditions.[72]

Machine learning is being used to analyze and track the changes and development of skin moles for the purpose of early detection of serious skin conditions. Individuals can use a mobile device to scan their body using an AI application to identify suspicious marks and send images to their dermatologist for further analysis.[70] AI is also being used to diagnose acne, psoriasis, seborrheic dermatitis,[73] and nail fungus.[74]

Genetics and Genomics

It is anticipated that AI may play a role in the further refinement of genomics-informed precision medicine.[75,76] AI can identify patterns in large data sets to provide greater insight into how the human physiology reacts to different chemicals, viruses, and the environment, and to inform tailored treatment.[75,76]

Machine learning is being used to recognize patterns in DNA sequences, that may help predict a patient's probability of developing an illness and identify underlying causes to facilitate the development of targeted therapies.[76] Machine learning is also being used to help inform the design of potential drug therapies to identify the genetic causes of disease and help understand the mechanisms underlying gene expression.[77]

Liquid biopsies that incorporate AI are in development.[78] They enable physicians to better predict patient outcomes by determining whether their current therapy is optimal or if an alternative therapy may be more beneficial to a patient.[78]

Liquid biopsies remove the need for invasive biopsy procedures by analyzing DNA from a blood sample. One such innovation is intended to predict relapse an average of seven months earlier than the current standard of care in patients diagnosed with cancer.[79]

AI may also be used to improve accuracy in gene editing (a method of altering DNA at the cellular or organism level).[80] The use of large datasets and machine learning may, in the future, be able to predict optimal locations to edit DNA to alleviate suboptimal gene editing outcomes, enabling researchers to focus efforts on genes that are less likely to be of risk to patients.[81] It is anticipated that this could prevent the genetic risk of developing a disease before it occurs by editing the genome of an egg, sperm, or embryo and thus lowering the risk of disease even before birth. Genome editing may also be able to correct mutations such as Huntington's disease or cystic fibrosis. In the UK, genome editing of human embryos was approved by regulatory authorities in 2017,[82] and in the US, gene editing research is also under way. However, before AI and gene editing can advance, important ethical, legal, and social considerations will need to be addressed. In the US, the National Academies of Sciences, Engineering, and Medicine recently released a report recommending to authorize the use of AI with gene editing under the condition that it is used exclusively to prevent severe diseases for which no existing treatments exists.[83]

Oncology

Innovation in AI for oncology has been addressed elsewhere in this bulletin, in sections covering radiology, pathology, dermatology, and genomics. Innovations not yet addressed are covered here.

AI is increasing its presence in oncology especially in the field of cancer-oriented cognitive computing systems.[84] Cognitive computing mimics the working of the human brain by applying machine learning algorithms to simulate human thought processes using data mining, pattern recognition, and natural language processing.[85] It can be used for the purpose of helping physicians to plan personalized patient treatment plans[86] by synthesizing vast amounts of information and integrating it into decision-making more quickly than humans. Cognitive computing combines patient information with research publications, ongoing research discoveries, clinical guidelines,[87] evidence-based literature,[88] and ongoing clinical trials[89] into a single large database. This may help physicians to stay abreast of scientific literature, which according to current estimates would require 29 hours per working day.[87] Cognitive computing is not exclusive to oncology and is being explored across other clinical specialties to assist clinicians in managing challenging workloads;[90] expanding treatment options for patients;[91] enhancing the speed and accuracy of diagnosis;[84] improving treatment decisions;[88] and assisting in the delivery of personalized, evidence-based treatment options.[87] A study on one such device reported that it was in agreement with recommendations made by physicians 93% of the time for patients with rectal cancer and 81% of the time for patients with colon cancer, while providing them with more data to support their findings.[86] Cancer-oriented cognitive computer systems may be of relevance to patients in rural and remote settings where cancer expertise is limited.[88]

Other potential future applications of AI in cancer may relate to the enhancement of cancer research through the development of cancer networks and registries and the identification of cost-efficiencies. As well, AI may provide new insight on the collection of data, particularly as it relates to epidemiologic trends, therapies for rare cancers, treatment pathways, cancer etiologies, new associations with particular cancers, and therapeutic results and prognosis.[88]

Neurology

Many AI algorithms for neurology have been developed to predict the development of disease using neuroimaging[56] and these developments have been alluded to in the Radiology section of this report. Beyond neuroimaging, it is anticipated that machine learning holds promise in advancing the field of neuroscience. It has been suggested that AI applications in neuroscience may have the potential to support large-scale hypothesis generation, as well as provide insight on interactions, structure, and mechanisms of the brain and behaviour.[92]

In the area of stroke, the incorporation of AI algorithms that recognize the early warning signs of stroke through movement detection devices that can discriminate between normal resting and stroke-related paralysis are being used for early stroke prediction.[93,94] As well, machine learning can be used to predict three-month outcomes in patients with acute ischemic stroke by examining correlations between physiological parameters of patients during the first 48 hours after stroke onset, which may play an important role in the early clinical treatment of patients.[95]

Researchers have demonstrated how a machine learning algorithm can be used to assess the extent of severity of Parkinson's disease by developing a tool that can be used with a smartphone, to generate a Parkinson's disease score that is intended to objectively weigh measures of disease severity. The score is used as an adjunct to standard Parkinson's disease measures and can provide frequent and objective assessments in the real-world setting that could be used to improve clinical care and evaluate the effectiveness of novel therapeutics.[96]

AI is also being used in patients with spinal cord injury to provide prognostic evaluation and predict outcomes. An algorithm has been developed that provides data on patient-specific motor defects that can be used with a robot-assistive rehabilitation harness to assist people in learning to walk again.[97] It has also been used in conjunction with electrical stimulation systems in quadriplegic patients to restore some movement.[98]

Mental Health

The Government of Canada has identified access to timely and appropriate mental health care as essential for Canadians living with mental illness.[99] Strategies for improving and managing mental health may be more effective when the person receiving care interacts with a health care provider.[100] Applications that use NLP coupled with machine learning algorithms that gather and adapt to new information may help simulate participant-clinician interactions.[100-103] Called chatbots, or conversational agents, these programs mimic conversation using text or voice and may also include a virtual, human-like, presence (an embodied conversational agent).[100-102]

Mental health research has explored using conversational agents to enhance the searchability of online support communities,[101] to diagnose major depressive disorder,[103] and to deliver cognitive behaviour therapy to people with depression and anxiety.[102] A 2017 scoping review100 also identified conversational agents used for autism spectrum disorder and post-traumatic stress disorder.

AI has also been explored as a support or supplement for moderators of an online community for youth mental health.[101] When human moderators were not available, programs that assess the sentiment, emotion, and keywords of participant posts were used to recommend appropriate steps and actions.[101]

In 2018 the Public Health Agency of Canada began exploring the use of AI to help identify communities at increased risk of suicide. AI was used to analyze data from social media posts for suicide-related content to assist in the targeted deployment of mental health resources.[104] Similarly, a user reporting system, developed by Facebook, uses AI to automatically alert emergency responders.[104] Prediction of suicide and accidental death following hospital discharge using NLP to analyze electronic health records has also been studied in the US.[105]

Looking into the future, devices that observe, capture, and analyze behaviour in the real world, outside of a clinician's office, may offer new ways to personalize care.[106]

Diabetes Care

Because of its disease prevalence combined with large amounts of readily available data about blood sugar levels and trends, the care of people living with type 1 and type 2 diabetes is emerging as an area of interest for AI researchers.

Artificial neural networks and support vector machine methods have been explored in the development of a screening tool for pre-diabetes.[107] The tool used data from a Korean national health survey including nine variables previously used to predict diabetes such as family history, waist circumference, and physical activity. An artificial neural network approach was selected because of its ability to detect complex non-linear relationships.

In the development of artificial pancreas systems,[108] a key component is the computer program that connects the readings taken by the continuous glucose monitor to the insulin administered through the insulin pump.[109] Researchers have explored the role of AI in supporting these computer programs in personalizing insulin delivery, because of its ability to learn from data in uncertain environments.[109]

Complications from diabetes are responsible for much of the direct and indirect costs of the disease.[110] Researchers in Australia used an artificial neural network to predict these complications while still treatable.[110] The artificial neural network models were developed using data from existing surveys that assessed the relationship between risk factors such as hemoglobin A1C and three complication outcomes.

Diabetes is also an area of active machine learning research.[111] A 2017 review of biomedical and computer science publications found research on biomarkers for and prediction of future risk of diabetes, diabetes complications, treatment and drug development, genetics, and health systems management.[111]

Eye Care

As in radiology, specialized vision care relies on the collection and analysis of images.[112] In ophthalmology, advances in AI have the potential to disrupt existing vision screening programs and allow for point-of-care diagnosis of patients.[112] The use of AI to screen people living with diabetes for diabetic retinopathy has emerged as an area of particular interest.[112-116] In April 2018 the FDA approved its first AI enabled device to detect "more than mild" diabetic retinopathy and recommend referral to eye care professionals for appropriate patients.[117]

Other areas being explored include using deep learning to differentiate healthy eyes from eyes with age-related macular degeneration[112] and to predict cardiovascular disease from retinal fundus images,[118] as well as using neural networks to automate grading of age-related macular degeneration,[119] screening for glaucoma,[112] and diagnosis of cataracts.[112]

Critical Care

Critical care is another clinical specialty that may benefit from AI, particularly since it is an environment that requires clinicians to synthesize data quickly from multiple sources[120] in a setting where there is a high degree of stress and uncertainty.[121] Numerous organizations are currently developing tools that leverage machine learning algorithms to predict, for example, the mortality of patients,[122] the early onset of sepsis,[123] the optimal use of mechanical ventilators,[124] and appropriate intravenous fluid requirements.[124] It is anticipated that AI may play a role in reducing the average length of stay in an intensive care unit by reducing the time it takes to diagnose and treat patients.[125]

Population and Public Health

Disease surveillance is an area of interest for AI research because of the availability of text data and information sources already used for traditional monitoring of outbreaks.[126-128] Automating the collection, sorting, and analysis of indicators such as country reports, social media posts, and emergency room data for patterns using AI requires less human effort than traditional monitoring and could potentially reduce the time needed to detect an outbreak.[126,127] The Public Health Agency of Canada's Global Public Health Intelligence Network is an example of an early (and still evolving) AI-based surveillance system that has detected early signals for severe acute respiratory syndrome in 2003 and Middle East respiratory syndrome coronavirus in 2012, as just two examples of its successes.[129] Using AI to expand the sources of information used for influenza surveillance to include social media posts or Internet searches has also been proposed.[127] AI may also help identify populations or areas at risk of diseases such as diabetes or heart disease thereby assisting public health programs to more effectively target education programs.[130]

Non-Clinical Health-Related Applications

In addition to applications in clinical settings, research into how AI may support or advance non-clinical work in health care is also taking place in areas such as health research and drug discovery and development.

Health Research

The use of machine learning to advance understanding of the processes that underlie disease is being explored in areas such as genomics and other "omics," which depend on large volumes of data.[1]

Machine learning is also being used to discover biomarkers for conditions such as schizophrenia, bipolar disorder, and depression with the hope of improving diagnosis[131] or generating hypotheses for future research.[132]

AI may also impact methods of knowledge synthesis such as systematic reviews and health technology assessments with tasks such as data extraction and searching becoming automated.[133,134]

Drug Discovery and Development

AI may help assist researchers to identify genetic mutations that cause disease and help predict the effects of treatments.[111,135] Applying machine learning to drug development and finding new uses for existing drugs are also being explored.[1]

Implementation Issues

The success of AI in health care depends on a number of factors, including the public's acceptance of AI playing a role in their treatment, the use of patient data, the health care system's ability to deploy new technology that uses AI, and staff training on how to use the technology.[54] While there is great enthusiasm for the improvements that AI is expected to bring to the health care system, there is a need for pragmatic consideration of potential challenges and enablers of optimal AI integration.[6] Topics such as cost, data reliance, training requirements, effects on clinicians, clinician-patient relationships, decision transparency, hardware limitations and scaling, and ethical, social, and privacy concerns are addressed below.

Costs

Implementation of AI requires resources for hardware and software.[2] Recent advances and acceleration of machine learning, and particularly deep learning, make use of computer chips called graphics processing units (GPUs) to rapidly perform required calculations.[5,136] GPUs are relatively inexpensive (about US$1,000) and can be added to most computer systems. Thus, a single card can potentially process hundreds of millions of images a day.[5] Cloud-based computing services, which provide increased access to low-cost computing power, are also driving advances in AI while lowering costs for organizations.[137-140]

AI may play a role in the sustainability of a publicly funded health care system by detecting disease earlier[141] and providing a more accurate diagnosis.[142] The impact of machine learning algorithms that can read and interpret imaging exams has the potential to reduce the cost of analyzing imaging exams and increase the speed in which it takes to review them, allowing far more to be taken over the course of a treatment, wait times permitting.[143]

AI may bring about improvements in patients outcomes because it supports clinical decision-making and ensures that interventions and treatments are personalized to each patient. This may eradicate costs associated with post-treatment complications.[142]

Cost savings have been associated with AI applications involving robot-assisted surgery and virtual nursing assistants.[144]

Misdiagnoses are the leading cause of malpractice claims in Canada. Machine learning may help to reduce health care and legal costs by improving diagnostic accuracy[145] and reducing therapeutic errors that occur in the human practice of medicine.[8] Conversely, AI technologies may also contribute to misdiagnosis if the performance of the underlying algorithms is not adequate to fulfill the diagnostic task it is assigned.[146,147]

Data Reliance and Training Requirements

AI systems require large amounts of high-quality data to learn.[8,148,149] While it is difficult to determine how much data and training a neural network needs, it is agreed that large datasets are required in order to reach acceptable levels of accuracy and performance.[9,40,150] In radiology, for example, machine learning algorithms should be fed by thousands to millions of images.[40] As well, algorithms must be trained separately for each condition and disease.[40,151] Since the performance of AI systems is dependent on the data used to train them, access to high-quality data is critical. In some instances, clinically relevant datasets may be too small for effective training.[149] Additionally, building datasets that are useful for training AI systems often requires skilled experts to accurately label images or other information sources, a time-consuming process that may ultimately limit their availability.[17,149]

The Centre for International Governance Innovation paper on key elements and policy considerations for a national data strategy in Canada discusses the need for open-structured and secured data sharing, that enables research and development initiatives to utilize the growing amount of digital health information instead of traditional reliance on constrained data capture.[152]

Data Bias

AI systems have the potential to remove human bias in decision-making, but there remains the risk that, depending on the data used for training algorithms, some models incorporate and reinforce biases from the demographics of the population used for their training.[17,153] This bias can be challenging to detect and can unintentionally be incorporated into the logic systems of machine learning products.[17,154] The data may not be representative of the target population in which it is being applied which could result in discrimination of legally protected groups in ways hidden from those tasked with making decisions from AI outputs.[17] For example, an algorithm may work well in an academic or limited clinical setting, but may not be scalable to a real-world setting, and consequently has the potential to lead to misdiagnosis and harm to patients.[153,155] This was demonstrated recently with machine learning software developed for stratifying cancer risk in pulmonary nodules detected with CT imaging. The software attained high performance on the training data set based on patients from the US National Lung Screening Trial but achieved lower performance when applied to patients at Oxford University Hospitals.[24]

Effects on Clinicians

It has been argued that as machine learning systems evolve, clinicians may become over-reliant on their use and may lose the ability to make informed opinions in their absence.[156] While this concern may be valid, it may not differ from the process of adopting any new technology.[157]

Clinician acceptance of AI and consideration of their experiences and perspectives will be critical for the widespread adoption and implementation of AI in the health care system.[6,158,159] Health care providers may perceive that AI reduces their authority and autonomy.[17] Introduction of AI systems could also lead to new or changing skill sets as AI systems automate some historically human-centered tasks and incorporate increasingly complex data into patient care.[17,160] It is also possible that as more tasks are handed over to AI systems that fewer health care professionals will be needed.[6]

As the influence and uses of AI expand, a deeper knowledge of health informatics may prove an important skill for health professionals' understanding of increasingly data-reliant health systems.[160]

Clinician-Patient Relationships

There is concern that some AI applications, such as those that monitor speech or behaviour could change the relationship between patient and clinicians by generating fear that all the data collected could be used and scrutinized for health care decisions.[161] Conversely, patient and physician communication may be facilitated with the use of AI by minimizing processing times and in so doing, improving the quality of patient care.[6,162] Another consideration is whether AI applications may circumvent or minimize traditional face-to-face patient-clinician interactions.[163] Responsibility and liability for misdiagnosis or treatment and its impact on care decisions is a topic of debate.[145,146]

Decision Transparency

Before deep learning, using computers to predict outcomes relied on programs in which human experts determined the features to look for and the rules by which these features were to be analyzed.[4] Deep learning prediction capabilities are often described as a "black box." This is because data are processed through hidden layers of decision-making that are often viewed as opaque, with only the output available to the interpreter.[2,4,9,150,164]

Programs supported by deep learning cannot express reasons why a particular conclusion was made and clinicians cannot tell what inputs were used to come to a decision.[4,164] Achieving insight on how decisions are reached is a challenge, not only for clinicians but also for developers of AI systems.[165] AI that uses machine learning algorithms based on artificial neural networks may be almost impossible to understand as far as why or how algorithms reach conclusions. Machine learning based on decision trees or Bayesian networks are more transparent to inspection.[166] Within a health care context, AI tools must be able to provide evidence as to how they arrive at specific conclusions, allowing physicians to confirm that the conclusion makes sense and course correct if necessary.[155] Abstract, hidden layers may also create challenges in comparing and assessing the performance of different AI systems.[148]

In Europe, the General Data Protection Regulation[167] provides individuals with the "right not to be subject to a decision based solely on automated means."[168] The regulation also specifies that individuals should also be provided with meaningful information about how automated systems make their decisions.[167]

Hardware Limitations and Scaling

Although improvements in computing technology, particularly graphic processing units, have been essential for the expansion of AI applications and research, there are questions about whether hardware improvements will continue at the rate needed to process an ever-expanding volume of health data.[1]

The standardized nature of AI systems means they can be replicated and scaled and, once trained, a program can be readily deployed across many locations.[5] However, there are considerations such as the portability of programs across different systems, scanning machines or acquisition techniques, or the use of different software that may impact how readily and successfully an AI system can be deployed.[169,170]

Privacy, Social, and Ethical Considerations

In computer science, collaboration and exchange of data sets to improve AI programs are common.[24] Making the most of AI in health care may mean clinicians, administrators, and patients shift their expectations regarding control over personal information.[24] Backlash against AI is anticipated if the public's best interest is not considered when these technologies are being developed.[17] Maintaining public trust over the use of personal data in a safe and secure way is important for the successful widespread adoption of AI.[54] New approaches may be required to assess the ethical acceptability and legitimacy of data science,[24] and to develop best practices for data management in AI, including ways of anonymizing data.[24]

Data Privacy and Security

One challenge is ensuring AI developers working with health care organizations and patient data meet security, data compliance, and audit requirements.[171] Possible solutions include having usage agreements and permissions in place for the data being analyzed and commitments to patient data privacy and security.[171] There are circumstances where machine learning could inadvertently "leak" private information which could hinder further adoption of AI.[171] The Office of the Privacy Commissioner of Canada has issued guidance on obtaining meaningful consent[172] and inappropriate data practices[173] to support compliance with the *Personal Information Protection and Electronics Documents Act* (PIPEDA) in the digital age.

Legal and Social Issues

Medicolegal concerns around civil and criminal liability and medical malpractice — for instance, if an AI system misdiagnoses a patient, or if a clinician fails to use an AI system — have also been raised but are as yet unresolved.[154]

There are concerns that not all parts of the population will benefit equally from AI systems.[17] For example, where there is limited data about populations, such as people living with rare diseases or people underrepresented in clinical trials, it may be difficult to collect and consider in a data set.[17] At the same time, people living in rural and remote settings may benefit from AI through the use of remote diagnostic applications that can provide real-time prediction of diagnoses and treatments, saving patients from travelling great distances to seek medical advice.[174]

Ethical Issues

Ethical questions have been raised around the potential effects of AI on patients.[17] While AI applications have the potential to empower people to assess symptoms and provide self-care where appropriate, there are concerns that it could lead to the social isolation of people who would otherwise seek advice from care providers and assistance from family and friends.[17] As well, there are concerns around whether AI devices will ensure the dignity, autonomy, and self-determination of users. For example, if an AI tool creates a treatment plan recommending a course of action that a health care provider is unable to explain the logic behind, this may be regarded as an infringement of the patient's freedom to make informed decisions about their health.[17] As well, AI applications that are designed to provide remote care to patients in their homes could lead to confusion by the user around whether they are communicating with a real person or an AI device, which may be perceived as a type of deception or fraud.[17]

Ethical concerns also relate to the safety of these systems. Currently, industry standards for testing the safety and reliability of AI are not in place in many countries.[175] Consequently, there is potential for patient harm if errors are not detected and corrected before diffusion of these technologies.[17]

Questions have also been raised around the malicious use of AI, particularly its use in covert surveillance or screening,[17,176] which could reveal information about a person's health, without their knowledge, that could potentially be used against them.[17]

Final Remarks

Beyond the potential value and implementation prospects of technological innovations, there are unresolved areas of inquiry regarding the ethical, social, and political challenges with AI. The Wellcome Trust has outlined several areas for future research including the issues of consent, fairness, and rights.[6] There is interest in improving understanding of the effect of AI in health care on human relationships, management of data, transparency in decision-making, inequalities, patient preferences, regulation, appropriate use, trust, and the relationship between the private and public sectors involved in the delivery of health care.

Adopting AI into health care will come with challenges, but some promising work has already occurred. To advance innovation and integration of AI in Canada, the Standing Committee on Social Affairs, Science and Technology recommended convening a national conference to bring together government decision-makers with stakeholders.[3]

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