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Review Article

Application of artificial intelligence in medical care: review of current status

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ABSTRACT

Artificial intelligence (AI) has transformed almost all spheres of our life and has the potential to radically alter the field of health care. The increasing availability of healthcare data and rapid development of big data analytic methods has made possible the recent successful applications of AI in healthcare. Guided by relevant clinical questions, powerful AI techniques can unlock clinically relevant information hidden in the massive amount of data, which in turn can assist clinical decision making. To date, many AI systems have been developed in healthcare, but use and adoption in clinical practice has been limited. In this article, we tried to review few of promising AI techniques and tools, which can have a great impact on our health care system and in turn on quality of life**.**

Keywords: Artificial intelligence, Machine learning, Medical care

INTRODUCTION

Artificial intelligence (AI) has grown to be very popular in today's world. It is the simulation of natural intelligence in machines that are programmed to learn and mimic the actions of humans. These machines are able to learn with experience and perform human-like tasks. John McCarthy first coined the term AI in 1956 in a summer workshop called the Dartmouth Summer Research Project on AI.[1] While a number of definitions of AI have surfaced over the last few decades, John McCarthy offered a balanced definition of AI in his paper presented in Stanford University: 'AI is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.[2]

Today, modern dictionary definitions focus on AI being a sub-field of computer science and how machines can imitate human intelligence (being human-like rather than becoming human). The English Oxford Living Dictionary gives this definition: 'The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.

WHAT IS THE PURPOSE OF ARTIFICIAL INTELLIGENCE?

The purpose of AI is to aid human capabilities and help us make advanced decisions with far-reaching consequences - to simplify human effort, and to help us make better decisions. Building an AI system is a careful process of reverse-engineering human traits and capabilities in a machine, and using its computational prowess to surpass what we are capable of.

To understand how AI actually works, one needs to deep dive into the various sub-domains of AI like machine learning (ML), deep learning, natural language processing, computer vision, and cognitive computing (Figure 1).

Machine learning

ML teaches a machine how to make inferences and decisions based on past experience. It identifies patterns, analyses past data to infer the meaning of these data points to reach a possible conclusion without having to involve human experience. This automation to reach conclusions by evaluating data, saves a human time for businesses and helps them make a better decision.

Deep learning

Deep learning is an ML technique. It teaches a machine to process inputs through layers in order to classify, infer and predict the outcome.

Neural networks

Neural networks work on the similar principles as of human neural cells. They are a series of algorithms that captures the relationship between various underlying variables and processes the data as a human brain does.

Natural language processing

Natural language processing (NLP) is a science of reading, understanding, interpreting a language by a machine. Once a machine understands what the user intends to communicate, it responds accordingly.

Computer vision

Computer vision algorithms tries to understand an image by breaking down an image and studying different parts of the objects. This helps the machine classify and learn from a set of images, to make a better output decision based on previous observations.

Cognitive computing

Cognitive computing algorithms try to mimic a human brain by analyzing text/speech/images/objects in a manner that a human does and tries to give the desired output.[3]

AI IN HEALTH CARE

AI is recolonizing all spheres of our life. AI is already a thing of the present, and we are surrounded by it in our daily lives, nearly every part of our day is touched by AI. Few examples of top used AI applications, helping humans to become more productive, live better life are Google's AI-powered predictions (e.g. Google Maps), Ride-sharing applications (e.g. Uber, Lyft), social media feeds, advertisements, music and video streaming, smart home, Finance services, AI autopilot in commercial flights, spam filters on e-mails, plagiarism checkers and tools, facial recognition, search recommendations, voice-to-text features, smart personal assistants (e.g. Siri, Alexa), fraud protection and prevention. Healthcare systems, on the other hand, have been very slow in adopting these advancements despite more than a decade of significant focus. The use of AI in clinical practice still remains limited, with many AI tools for health care still at design and development stage. Satya Nadella, chief executive officer, Microsoft once said - 'AI is perhaps the most transformational technology of our time, and healthcare is perhaps AI's most pressing application.' In this article, we tried to review few of promising AI techniques and tools, which can have a great impact on our health care system and in turn on quality of life.

Before deploying any AI system in health care areas, it needs to be fed and trained with data. Health care data is generated mainly from clinical activities like screening, diagnosis and treatment, follow up and it is in the form of demographics, clinical notes, physical examination, laboratory investigations and radiological images. Much of this data is in the form of unstructured narrative texts, that is not directly analyzed. They have to be first converted to machine understandable electronic medical record (EMR) through relevant AI applications. So based on data category, AI devices mainly fall into two categories. In first category, ML techniques analyze structured data such as genetic and electrophysiological data and then try to cluster patients' traits or infer the probabilities of the disease outcomes.[4] The second category includes NLP processes that extract information from unstructured data, which can be further analyzed by ML techniques.[5] So, AI devices and applications work from clinical data generation through NLP data enrichment and ML data analysis to clinical decision making.[6] The key areas of health care in focus for AI interventions till now are precision diagnostics, treatment recommendations, prediction of outcome and prognosis, patient education and adherence and administrative activities.

AI IN PRECISION DIAGNOSTICS

Diagnosis and treatment of disease remained as important focus area for AI since decades. Many previous research had shown promise for accurate diagnosis of diseases, but could not get acceptance in clinical practice as not found to be substantially better than human efforts. Many AI application and devices have received considerable attention in recent past.

Radiomics

The automated classification of medical images is the leading AI application today. A recent review of AI/ML-based medical devices approved in the USA and Europe from 2015–2020 found that more than half (129 (58%) devices in the USA and 126 (53%) devices in Europe) were approved or CE marked for radiological use.[7]

The term "radiomics" was coined by Lambin et al to describe automatic identification of unique prognostic and diagnostic features in cancer imaging data. The four main processes of radiomics include; imaging, segmentation, feature extraction and analysis.[8] Radiomics are the features that are extracted from medical images, these features can then be compared to end point data such as 2-year survival for improved prediction. The ultimate goal of radiomics is to provide a decision support system (DSS), that aids clinical decision making by providing accurate diagnosis that enables personalized radiotherapy, hopefully leading to improved treatment outcomes.[9]

Ophthalmology

DL has been applied to ocular imaging, principally fundus photographs and optical coherence tomography (OCT). Major ophthalmic diseases which DL techniques have been used for include diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD) and retinopathy of prematurity (ROP).[10] Diabetic retinopathy is a major end-organ manifestation of diabetes. AI technology using DLS has been shown to be as effective as human graders in screening for diabetic retinopathy. Over the past few years, DL has revolutionized the diagnostic performance in detecting DR. Using this technique, many groups have shown excellent diagnostic performance. More recently, Gulshan and colleagues from Google AI Healthcare reported another DL system with excellent diagnostic performance. The DL system was developed using 128 175 retinal images, graded between 3 and 7 times for DR and DMO by a panel of 54 US licensed ophthalmologists and ophthalmology residents between May and December 2015. The test set consisted of approximately 10 000 images retrieved from two publicly available databases (EyePACS-1 and Messidor-2), graded by at least seven US board-certified ophthalmologists with high intragrader consistency. The AUC was 0.991 and 0.990 for EyePACS-1 and Messidor-2, respectively.[11]

Although a number of groups have demonstrated good results using DL systems on publicly available data sets, the DL systems were not tested in real-world DR screening programs. In addition, the generalizability of a DL system to populations of different ethnicities, and retinal images captured using different cameras, still remains uncertain. Ting et al reported a clinically acceptable diagnostic performance of a DL system, developed and tested using the Singapore integrated diabetic retinopathy program over a 5-year period, and external data sets recruited from 6 different countries, including Singapore, China, Hong Kong, Mexico, USA and Australia. The DL system, developed using the DL architecture VGG-19, was reported to have AUC, sensitivity and specificity of 0.936, 90.5% and 91.6% in detecting referable DR. For vision-threatening DR, the corresponding statistics were 0.958, 100% and 91.1%. The AUC ranged from 0.889 to 0.983 for the 10 external data sets (n=40 752 images).[12] More recently, the DL system, developed by Abramoff et al has obtained a US Food and Drug Administration approval for the diagnosis of DR. It was evaluated in a prospective, although observational setting, achieving 87.2% sensitivity and 90.7% specificity.[13]

Dermatology

Skin cancer, one of the most common human malignancies, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. Deep convolutional neural networks (CNNs) show potential for general and highly variable tasks across many fine-grained object categories. Esteva A et al had demonstrated classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. They trained a CNN using a dataset of 129,450 clinical images, consisting of 2,032 different diseases. Then they tested its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer. The CNN achieves performance on par with all tested experts across both tasks, demonstrating an AI capable of classifying skin cancer with a level of competence comparable to dermatologists.[14]

Fiszman et al were among the first few researchers to evaluate the performance of a natural language processing system in medical diagnostic. They showed that in extracting pneumonia related concepts from chest X-ray reports, the performance of the natural language processing system was similar to that of physicians and better than that of lay persons and keyword searches.[15]

AI IN STROKE DIAGNOSIS

For diagnosis of stroke, neuroimaging techniques, including magnetic resonance imaging (MRI) and computed tomography (CT), are important for disease evaluation. Some studies have tried to apply ML methods to neuroimaging data to assist with stroke diagnosis. Rehme et al used SVM in resting-state functional MRI data, by which endophenotypes of motor disability after stroke were identified and classified. SVM can correctly classify patients with stroke with 87.6% accuracy.16 Griffis et al tried naïve Bayes classification to identify stroke lesion in T1-weighted MRI. The result was comparable with human expert manual lesion delineation.[17] Kamnitsas et al tried three-dimensional CNN (3D CNN) for lesion segmentation in multi-model brain MRI. They also used fully connected conditional random field model for final postprocessing of the CNN's soft segmentation maps.[18] Rondina et al analysed stroke anatomical MRI images using Gaussian process regression, and found that the patterns of voxels performed better than lesion load per region as the predicting features.[19]

Arterys's medical imaging platform has been approved to be put into use to help doctors diagnose heart problems. It uses a self-teaching artificial neural network which has learned from the clinical cases added, ongoing process. It is a cloud-based, self-teaching neural network. The software can produce editable automated contours, enabling healthcare practitioners to see ventricular function within seconds. A similar feature is comprehensive anatomy as well as visualization and quantification of blood flow around the heart.[20]

AI IN PRECISION THERAPEUTICS

Precision medicine is an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person. This approach will allow doctors and researchers to predict more accurately which treatment and prevention strategies for a particular disease will work in which groups of people. It is in contrast to a one-size-fits-all approach, in which disease treatment and prevention strategies are developed for the average person, with less consideration for the differences between individuals.[21]

IBM's Watson

In recent years, IBM's Watson has received considerable attention in the media for its focus on precision medicine, particularly cancer diagnosis and treatment. Watson employs a combination of machine learning and NLP capabilities. Watson is not a single product but a set of 'cognitive services' provided through application programming interfaces (APIs), including speech and language, vision, and machine learning-based data-analysis programs.[22] In one cancer research, 99% of the treatment recommendations from Watson are coherent with the physician decisions.[23]

In addition, the system started to make impact on actual clinical practices. For example, through analysing genetic data, Watson successfully identified the rare secondary leukaemia caused by myelodysplastic syndromes in Japan.[24] However, early enthusiasm for this application of the technology has faded as customers realized the difficulty of teaching Watson how to address particular types of cancer and of integrating Watson into care processes and systems.[25] Most observers feel that the Watson APIs are technically capable, but taking on cancer treatment was an overly ambitious objective.

Diabetes management

AI seems promising to cause a paradigm shift in diabetic management through data-driven precision care. In fact, ML/AI is already being used to predict risk of diabetes based on genomic data, diagnosis of diabetes based on EHR data, to predict risk of complications such as nephropathy and retinopathy, and also in diagnosis of diabetic retinopathy.[26]

Type I DM

There is a huge amount of literature on AI/ML approach being used in type 1 diabetes. There are algorithms that have been used to detect composition of food based on images of food thereby helping in carb counting.[27] Prediction of future blood glucose values and anticipating impending hypoglycemic or hyperglycemic event has been the focus of research in numerous publications.[28] Wearable continuous glucose monitoring (CGM) sensors are revolutionizing the treatment of type 1 diabetes (T1D). The current research in diabetes technology is putting considerable effort into developing decision support systems for patient use, which automatically analyze the patient's data collected by CGM sensors and other portable devices, as well as providing personalized recommendations about therapy adjustments to patients.[29] Another major work is also being done on developing bolus calculators to automate the process of calculating premeal insulin dose prediction.[30] AI allows patients with diabetes to take daily decisions for diet and activity. Apps have been used to allow patients to assess the quality and calorie value of food intake. Accountability for diabetes care is enhanced when patients capture a picture of their own food and assess what they eat.[31]

Type 2 DM

Published literature on studies trying to decide, optimize or automate therapy for type 2 DM using machine learning algorithms at the patient level, on their routine visit is scant at the global level and is almost non-existent at the national level. Mei et al have shown successful use of hierarchial recurrent neural network (HRNN) to provide personalized hypoglycemic medication prediction for diabetic patients by using data source of 21796 patients from a HER repository of a city of China, but clinical benefits were not elaborated in the study.[32] Aileen et al tried to identify temporal relationships between medications and accurately predicting the next medication likely to be prescribed for a diabetic patient by using constrained sequential pattern discovery approach. Authors were able to predict the medication prescribed for 90.0% of patients when making predictions by drug class, and for 64.1% when making predictions at the generic drug level with three attempts.[33] A group from the center for chronic disease control (CCDC) and AIIMS, implemented a decision support system on a mobile platform to help primary care physicians in making better choices for selecting diabetes management strategy.[34] However, the intervention failed to show any improvement in glycemic control.[35]

Stroke treatment

AI/ML has been tried to be applied for better stroke management strategies, especially in field of predicting and analyzing the performance of stroke treatment.[36] As a critical step of emergency measure, the outcome of intravenous thrombolysis (tPA) has strong relationship with the prognosis and survival rate. Bentley et al used SVM to predict whether patients with tPA treatment would develop symptomatic intracranial hemorrhage by CT scan. They used whole-brain images as the input into the support vector machine (SVM), which performed better than conventional radiology-based methods.[37]

To improve the clinical decision-making process of tPA treatment, Love et al proposed a stroke treatment model by analyzing practice guidelines, meta-analyses and clinical trials using Bayesian belief network. The model consisted of 56 different variables and three decisions for analyzing the procedure of diagnosis, treatment and outcome prediction.[38] Ye et al used interaction trees and subgroup analysis to explore appropriate tPA dosage based on patient characteristics, taking into account both the risk of bleeding and the treatment efficacy.[39]

AI IN OUTCOME PREDICTION AND PROGNOSIS EVALUATION

Compared with conventional methods, AI/ML methods have advantages in improving outcome and prognosis prediction performance. Such data driven AI health care approach can assist physicians in selecting the best evidence-based treatment options, save patients' time, reduce treatment costs and improve the quality of treatment overall by reducing the amount of trial-and-error in the treatment process.

Stroke

Asadi et al compiled a database of clinical information of 107 patients with acute anterior or posterior circulation stroke who underwent intra-arterial therapy. The authors analysed the data via artificial neural network and SVM, and obtained prediction accuracy above 70%.[40] They also used ML techniques to identify factors influencing outcome in brain arteriovenous malformation treated with endovascular embolisation. While standard regression analysis model could only achieve a 43% accuracy rate, their methods worked much better with 97.5% accuracy.[41] Birkner et al used an optimal algorithm to predict 30-day mortality and obtained more accurate prediction than existing methods.[42] Brain images have been analysed to predict the outcome of stroke treatment. Chen et al analysed CT scan data via ML for evaluating the cerebral oedema following hemispheric infarction. They built random forest to automatically identify cerebrospinal fluid and analyse the shifts on CT scan, which is more efficient and accurate than conventional methods.[43] Siegel et al extracted functional connectivity from MRI and functional MRI data, and used ridge regression and multitask learning for cognitive deficiency prediction after stroke.[44]

Diabetes mellitus

Principles of machine learning have been used to build algorithms to support predictive models for the risk of developing diabetes or its consequent complications. Screening entire populations for diabetes detection is not cost-effective, and screening should therefore be restricted to groups that are at high risk for diabetes. Models predicting who are at risk for diabetes or for developing diabetes in the near future are of interest in the medical fraternity. Most models are variants of multivariable linear regression models; and most use anthropometric, anamnestic, and demographic information as predictors. Many predicting models are also presented for long term and short-term complications of diabetes. However, although the number of prediction models developed is large, only very few end up being used in clinical practice.[45]

Skin conditions

Dermatology is at a particular advantage in the implementation of machine learning due to the availability of large clinical image databases that can be used for machine training and interpretation. While numerous studies have implemented machine learning in the diagnostic aspect of dermatology, less research has been conducted on the use of machine learning in predicting long-term outcomes in skin disease, with only a few studies published to date.

Wang et al and Roffman et al used convolutional neural networks (CNN) and artificial neural networks (ANN), respectively, to delineate the risk of developing non-melanoma skin cancer.[46,47] Both approaches are branches of deep learning and make use of the algorithm's ability to extract important classifying information at each node of a network of data. Both studies included data from non-melanoma skin cancer patients as well as an abundance of data from non-cancer patients. The system by Wang et al analyzed data from a total of 9,494 patients, using 20 clinically relevant features per patient, and reported higher outcomes (AUC=0.89, sensitivity 83.1%, specificity 82.3%). Emam et al considered seven different modeling techniques in evaluating a dataset of 681 psoriasis patients to determine which learner performed best in terms of accuracy, interpretability and runtime to predict risk of biologic discontinuation. Thirteen clinically relevant features per patient were analyzed. The generalized linear model (GLM) outperformed the six other models that were tested.[48]

AI IN HEALTH EDUCATION AND PATIENT SELF-MANAGEMENT AND ADHERENCE

Patient engagement and adherence along with lack of awareness about their illness has long been seen as the ‘last mile’ problem of healthcare – the final barrier between ineffective and good health outcomes. The more patients proactively participate in their own well-being and care, the better are the outcomes. AI-based capabilities can be effective in personalizing and contextualizing care. The most opted example is AI guided self-management tools in diabetes.

Diabetes mellitus

Self-management is the key to the treatment of diabetes. With the introduction of AI, patients are empowered to manage their own diabetes, based on timely advice, by generating data for their own parameters, and be their own experts for health. Digital platforms allow a targeted education of patients with diabetes. Online diabetes communities and support groups offer a chance for patients to connect and learn from the experience of others. This collaborative method of learning more about the various aspects of the disease is engaging for patients and caregivers and has a positive impact on desired outcomes and well-being of patients.[49]

AI allows patients with diabetes to take daily decisions for diet and activity. Various apps have been designed and in use that allow patients to assess the quality and calorie value of food intake, to provide customized dietary plans and schedules and to suggest alterations in food intake to suit an individual's lifestyle. Daily activity levels can be tracked by wearables that record step counts and time and intensity of other activities. In a 12-week interventional study conducted by Berman et al, 118 adults with type 2 diabetes mellitus received a digital intervention (FareWell) via an app and a digitally delivered specialized human support in the form of coaching every 2 weeks via telephone. All patients had HbA1c >6.5% at baseline and 28% patients achieved HbA1c <6.5% at the end of the study. At 12 weeks, >86% participants were still using the app, and a total of 57% achieved a composite outcome of reducing HbA1c, reducing diabetic medication use, or both.[50] Telemedicine/telehealth can revolutionize the management of diabetes. Remote monitoring reduces the time spent in follow-up visits and allows a more real-time monitoring of the glycemic status as well as the overall health of the patient. AI has the ability to replace 50-70% of routine follow-up clinical consultations with virtual engagements and remote monitoring.[51]

AI ADMINISTRATIVE APPLICATIONS

There are many administrative applications in healthcare already in use. The use of AI is somewhat less potentially revolutionary in this domain as compared to patient care, but it can provide substantial efficiencies in claims processing, clinical documentation, revenue cycle management and medical records management.

LIMITATIONS

Application of AI truly has the potential to transform many aspects of health care. Yet there are significant challenges related to the wider adoption and deployment of AI into healthcare systems. These challenges include, but are not limited to, data quality and access, technical infrastructure, organizational capacity, acceptability by clinicians and ethical and responsible practices in addition to aspects related to safety and regulation.[52]

Data access, quality and integration issues

The performance of AI algorithms is contingent on the quality of data available. Thus, the first barrier to build AI based health system is poor quality of data and limited access to data. Medical data is often difficult to collect and difficult to access. Medical professionals often resent the data collection process when it interrupts their workflow, and the collected data is often incomplete. It is also difficult to pool such data across hospitals or across health care providers. EHR systems are largely not compatible across government-certified providers that service different hospitals and health care facilities.[53]

The result is data collection that is localized rather than integrated to document a patient's medical history across his health care providers. Without large, high-quality data sets, it can be difficult to build useful AIs. Another hurdle is data exchange. Continuation of the data supply becomes a crucial issue for further development and improvement of the system as current healthcare environment does not provide incentives for sharing data on the system.

Algorithmic limitations

When neural networks are used, it is often difficult to understand how a specific prediction was generated, there is a substantial risk that the AI will generate solutions with flaws only discoverable after they have been deployed. This lack of transparency can reduce trust in AI and reduce adoption by health care providers, especially considering that doctors and hospitals will likely be held accountable for decisions that involve AI.

Limitations of design

Most of the current models and applications of AI in health care have been validated using retrospective data sets. Prospective validation of these technical advances holds promise for automating medical care.[9] Endpoints in clinical studies will also need to be redefined to include the digital biomarkers and data from apps and monitors and activity trackers.

Integration issues in medical care

AI-based diagnosis and treatment recommendations are sometimes challenging to embed in clinical workflows and EHR systems. Such integration issues have probably been a greater barrier to broad implementation of AI than any inability to provide accurate and effective recommendations; and many AI-based capabilities for diagnosis and treatment from tech firms are standalone in nature or address only a single aspect of care.

Regulatory barriers

Some of the algorithmic and data issues derive from underlying regulatory barriers and privacy laws of various countries. Privacy regulations can make it difficult to collect and pool health care data. With especially strong privacy concerns in health care, it may be too difficult to use real health data to train AI models as quickly or effectively as in other industries. Second, the regulatory approval process for a new medical technology takes time, and the technology receives substantial scrutiny. Innovations can take years to navigate the approval process. Liability concerns may also provide a barrier as health care providers may hesitate to adopt a new technology for fear of tort law implications. Lastly, substantial changes will be required in medical regulation and health insurance for AI based diagnosis and treatment recommendations to take off.

Ethical implications

Finally, there are also a variety of ethical implications around the use of AI in healthcare. Healthcare decisions have been made almost exclusively by humans till now, and the use of smart machines to make or assist with them raises issues of accountability, transparency, permission and privacy. Many AI algorithms – particularly deep learning algorithms used for image analysis – are virtually impossible to interpret or explain. If mistakes are made by AI systems in patient diagnosis and treatment and it may be difficult to establish accountability for them. Machine learning systems in healthcare may also be subject to algorithmic bias, perhaps predicting greater likelihood of disease on the basis of gender or race when those are not actually causal factors.[54]

CONCLUSION

AI advances have the fundamental potential to transform many aspects of healthcare, might enable to provide more personalized, precise, predictive and comprehensive medical care in near future. At present, key categories of AI applications involve diagnosis and treatment recommendations that can definitely assist physicians to make better clinical decisions or even replace human judgement in certain functional areas. The greatest challenge to AI in healthcare is not whether the technologies will be capable enough to be useful, but rather ensuring their adoption in daily clinical practice.

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