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Review Article

The Scope of Artificial Intelligence Applications in Medicine: A Review Article

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Abstract

Artificial intelligence (AI) is the high-tech discipline of employing computers to perform or potentially outperform human intelligence. With the deployment of AI systems, the traditional medical environment has already changed. For recent AI developments that have not yet been applied to medicine, as well as potential future developments, to be implementable in medicine, numerous considerations must be taken into account. In this article, we introduce fundamental AI-related concepts for researchers and administrators of healthcare systems. This article also discusses challenges with applications of AI in medicine, potential futures, and preparation strategies for the future of AI-enhanced medicine. In addition, a list of applications of AI in medicine is provided with a categorization that could help medical professionals to understand potential applications of AI systems in their fields of work.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning

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Background

Artificial intelligence (AI) is the ability of a computer system to simulate human behavior (1). At first, it was unclear whether and how computers might replicate human behavior due to the fundamentally incompatible nature of computers. However, recently, software systems emulating a few human behaviors have been developed and are becoming more prevalent in daily life. More well-known systems include autonomous driving systems and chart boxes functioning as preliminary technical support systems.

Since the concept of AI was first introduced, researchers have developed AI-based systems for medical activities (2). New improvements in AI bring the hope of developing medical systems that copy the behaviors of medical experts, such as surgeons, pathologists, radiologists, and emergency ward managers. An advantage of such an AI system is that after inventing a solution for a medical procedure, the solution might be available cheaply and at a low resource cost to everyone as a service. Compared to the current system, which necessitates professionals to spend time and undergo extensive training programs for each unique specialized task, the potential value of this may be recognized.

The basic computer science techniques typically employed in AI systems are not too diverse, essentially. Machine learning (ML) is the field that encompasses all of these methods, and contemporary tools include deep learning (DL) techniques and different variants of neural networks.

On the other hand, medical applications are diverse. Some applications should address well-defined tasks, while others should resolve vague tasks in terms of computer systems. Some applications require analysis of images that could be two-dimensional or three-dimensional. Other applications involve the analysis of natural language texts and human voices. Nevertheless, after preprocessing and understanding the input, there is a prediction task at the heart of all these systems; hence, ML has been developed to address this task.

The purpose of this article is to introduce applications of AI in medicine to medical experts who may already know some applications but have not managed to study the concepts, the extent, and the scope of the applications. In this article, we first defined AI and the concepts linked to it. Then we provided a sample collection of applications of AI in medicine, covering a wide range of medical fields and AI techniques.

AI Concepts: AI, ML, and DL are new information technology (IT)-related concepts in the healthcare sector. In this section, we explain these concepts and their connections in less technical terms.

ML: The task of ML is to find a relation or a rule in the given observed datasets that could be used to predict some desired features of similar samples, which will be given later. Based on this definition, ML has a wide range of applications, from robotics to medicine.

Conceptually, ML is the process of automated extraction of (useful) information from data. The concept of ML is defined by motivation from the ability of human beings to learn general concepts, rules, and relations through explicit observations. To better simulate human learning capacity, several deterministic and heuristic methods are provided and tested on real-world applications. Some statistical methods, such as regression and all its derivatives, which are popular in medical statistical analysis, are classic examples of ML methods (3). The performance and nature of statistical tools are completely known in mathematics. On the other hand, heuristic methods in ML do not have any established, rigorous theoretical guarantees, but they work effectively in real-world applications. A famous heuristic model of ML is artificial neural network (ANN).

ANN: An ANN is a famous model in ML and a mathematical model simulating the brain and its dynamics. Even though they are not fully understood theoretically, ANNs, an old model for ML, perform well in several ML tasks. ANNs consist of nodes representing neurons and their connections to which a strength value is assigned. A mechanism of changing connection strength based on the given dataset is also defined for each ANN, which is called the training mechanism. An initial arrangement of nodes (neurons) and their connections is called the architecture of an ANN, and some have specific names. Multi-layer ANNs, those with neurons clustered in layers with neurons in each layer coupled to neurons in their next and previous layers, perform well in several learning tasks.

DL: Due to the development in computing power, ANNs with increasing numbers of layers were tested on various ML tasks, and the outcome was surprising. ANNs with a high number of layers were able to solve hard tasks like computer vision easily without the need for any preprocessing or human intervention. This observation motivates researchers to provide a name for these ANNs; therefore, the term "Deep Learning" is born to specify ANNs with many layers of neurons. DL is currently a hot topic in ML and shows good performance in several applications, particularly those involving computer vision.

AI: At first, AI was defined as any non-human system that could simulate human intelligence behavior (4). According to its formal definition, AI is a task in ML, but in a general view, ML is considered as merely one instance of human intelligence and as such, a subfield of AI.

Based on the spectrum of their domain, AI systems are categorized into narrow, general, and super intelligence (5). Narrow AI systems are platforms designed for specialized activities, such as diagnosis based on a pathology image, estimating the frequency of hospital visits, or operating a surgical robot. The ability to respond to broad questions distinguishes general AIs from narrow AI systems. A clear example of a general AI would be one that could reason and argue like a human in different areas of human life. On the other hand, a super intelligent AI system would have human abilities and the ability to develop on its own and learn new skills that the human race may not even be aware of. Superintelligence is more of a study area and is outside the focus of this paper.

Explainability: The ethical concerns associated with utilizing ANN-based technologies were taken more seriously as it became increasingly likely that AI would be applied to real-world medical problems. A result that is obtained via a statistical method, e.g., a regression method, is easy to understand because it represents the importance of each feature in the final decision. On the other hand, heuristic methods such as ANN and DL do not provide any explainable model (6). An explainable model could be used by a medical doctor after understanding it. On the other hand, using an unexplainable model with good performance is controversial since it cannot be understood by the human mind.

Applications of AI in Medicine

In many medical domains, several applications of various AI technologies are suggested (Figure 1). Not all applications are equally implementable. In table 1, examples of AI applications are sorted according to the medical fields they belong to. The table contains some applications of artificial intelligence (AI) categorized by medical discipline. While this list is not exclusive to applications, it serves as a typical sample by including a wide range of applications in many fields. A detailed list of proposed methods could be found in a report of Human Behaviour and Machine Intelligence (HUMAINT) project that monitors the development, uptake, and impact of AI for Europe (7).

An AI-based application in medical systems could be divided into three layers: 1) the application level, which solely depends on the application and covers all the details specifically related to the application, 2) the medical task level, which is a semi-general tool that could be used in different applications, and 3) the IT technical level, which includes IT-related details. For instance, the two applications of lymph node metastasis diagnosis from a computed tomography (CT) scan and melanoma detection based on images are distinct applications with different application-level details. However, one may classify both of these two applications as a task of image (two-dimensional array of pixels) feature extraction. The semi-general image feature extraction task is specialized in one application for melanoma detection over images, with image-specific preprocessing and melanoma detection algorithms, and is also specialized in another application for metastasis detection with CT preprocessing algorithms and lymph node cancer detection.

Here, the applications are categorized based on their middle level (medical task level) to provide a broad overview of the applications and their potential. We hope this classification helps medical experts to find novel applications of AI in their field of expertise, either applications that are already ready to be used or applications that need to be developed.

Image-Based Diagnosis: Image processing refers to all activities that include detecting, diagnosing, or interpreting images. Any data representable as an array of pixels that could be analyzed by the human eye is potentially an image processing challenge. The fields of pathology, radiology, cancer diagnosis, and dermatology all involve image-processing activities. In some instances, AI-based methods, including DL, performed as well as the best available experts in studies in different medical areas.

Multi-Aspect Diagnosis: A well-known AI-based task is a task of analyzing a dataset based on different variables or features. Several statistical methods, as well as AI-based methods, are prebuilt for these applications, which could be easily deployed and evaluated for this class of applications, and the main challenges normally are task-specific challenges.

Human-Computer Interaction: In several scenarios, including getting information from patients, the interaction between a computer and a human would be beneficial. To some extent, it could be accomplished via conventional (non-AI-based) software systems. However, to be more human-friendly, they must understand human language and interact with them. The ability to understand natural (human) language is called natural language processing. Although understanding a language is an easy task for humans, this task has been a challenge for AI systems since the introduction of the concept of AI. Another interesting proposed application of human-computer interaction is to build a patient companion device or software system to reassure the patient in stressful circumstances (8).

Managing Processes: In applications like hospital management or management of medical centers, several processes should be done considering their dependencies. Managing the order of tasks and prioritizing them could benefit both patients and medical staff (9, 10). The domains of these tasks vary from detecting high-priority patients in emergency departments (11) to predicting the number of arriving patients (12, 13).

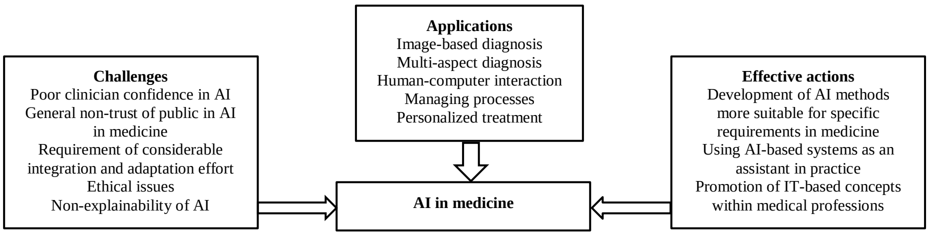

Figure 1. Applications of artificial intelligence (AI), challenges, and effective actions to be taken to get prepared for the future of AI
AI: Artificial intelligence

For all these tasks, AI systems could help the system and decrease the administrative load of medical staff.

Personalized Treatment: Currently, medical advice is provided based on average studies of general populations. Although it is widely accepted that considering ethnic and genetic differences in treatment would be beneficial, it is only used in a small number of fields, such as cancer treatments (14). AI could be used to find the best-personalized treatment based on all the available information from previous studies and treatment results.

Discussion

Are the AI-Based Methods Reliable?

While it has not been widely the case in other areas, in medicine, mistakes might have vital consequences. Therefore, in medicine, it is crucial to consider the reliability of proposed AI systems. Medicine is not the first vital area in which AI system functions may have an impact on human life. Another well-known area that attracts a lot of interest is the topic of autonomous driving systems. Although autonomous driving systems passed the tests that are enough for a human to obtain a driving license, there are still debates about letting computers control such delicate systems. A gold standard for AI methods is to perform like the experts or hopefully outperform them. In several tasks, including cancer detection from pathology slide images or lymph node metastasis detection from CT images, studies show that AI-based systems perform as well as the best experts in the study (15).

Table 1. Applications of artificial intelligence (AI) in different areas of medicine

Items
Cardiology
Predicting instances of acute coronary syndrome based on electronic records (16)
Predicting heart failure based on electronic records (17)
Remote ECG monitoring of ambulatory patients (18)
Detecting ejection fraction based on cardiac MRI (method name: CardioAI) (19)
Pulmonary medicine
Interpreting pulmonary results (20)
Endocrinology
Preventing hypoglycemic episodes in patients with diabetes via continuous monitoring of glucose level (by IBM Watson) (21, 22)
Nephrology
Predicting the decline of glomerular filtration rate based on eGFR values (23)
Predicting progressive IgA nephropathy based on medical laboratory data (24)
Gastroenterology
Diagnosing gastroesophageal reflux disease based on clinical data (25)
Identifying atrophic gastritis based on clinical and biomedical features (26)
Predicting clinical outcome in patients with acute lower-gastrointestinal hemorrhage based on non-endoscopic data (27)
Predicting the survival of patients with esophageal cancer based on a range of patient-related and tumor-related variables (28)
Predicting lymph node metastasis in colorectal cancer from clinicopathological factors (29)
Predicting postoperative distant metastasis for OSCC based on clinicopathological features (20)
Detecting abnormal structures such as colonic polyps based on colonoscopy videos (31)
Neurology
Improving seizure management in patients admitting epilepsy via patient movement monitoring (32, 33)
Assessing gait, posture, and tremor in patients with multiple sclerosis, Parkinson's disease, Parkinsonism, and Huntington's disease (33)
Radiology
Detecting features of tuberculosis on chest radiographs (34)
Quantifying pediatric bone age using hand radiographs (35)
Detecting ulnar and radial wrist fracture based on radiology images (36)
Enhancing brain MRI images (37)
Detecting cancer from lung CT images (38)
Reconstruction of normal MRI images given few samples and with lower acquisition (39)
Ophthalmology
Detecting more than mild DR to be referred to ophthalmology (FDA approved system called IDx-DR) (40)
Identifying urgent cases based on a set of three-dimensional optical coherence tomography scans (41)
Dermatology
Diagnosing skin lesions based on high quality images (incorporating GoogLeNet) (42)
Detecting 12 skin diseases, including common skin cancers (Microsoft ResNet-152) from images (43)
Detecting melanoma early (current methods are not reliable) (44)
Hospital management
Predicting life-threading conditions in triage referee based on vital signals (18)
Detecting presence of ICH from CT images (45)
Detecting presence, location, and chronicity of pulmonary emboli on thoracic CT based on radiology reports (46)
Pathology
Detecting cancer in pathological images (FDA approved AI system, Paige AI) (47)
Detecting lymph node metastasis in breast cancer (48)
Aiding pathologists in lymph node metastasis detection in breast cancer from pathological images (49)
Classifying and identifying adenocarcinoma and SCC in tissue sample slides (48)

OSCC: Oesophageal squamous cell carcinoma; ICH: Intracranial hemorrhage; SCC: Squamous cell carcinoma; ECG: Electrocardiography; CT: Computed tomography; eGFR: Estimated glomerular filtration rate; IgA: Immunoglobulin A; MRI: Magnetic resonance imaging; DR: Diabetic retinopathy; FDA: Food and Drug Administration; AI: Artificial intelligence

Other studies, on the other hand, questioned the results by criticizing the details of their research methods, such as the sparseness of their test samples.

In a general view, for some specific activities, especially those incorporating analysis of images, AI-based methods have already been provided with an accuracy comparable to the best experts in the field. Although the claimed performance of the methods is astonishing, actual use of them requires a more extensive evaluation of the methods on more diverse datasets in practice.

Challenges on the Road: Considering the improvement trends of AI-based systems, we can expect the emergence of AI-based methods that are comparable to those of experts in various fields of medicine. However, what factors slow down the actual deployment of these systems in the real world?

From medical doctors' viewpoints, AI-based techniques are not justifiable, especially in highly specialized domains. Medical doctors are not generally familiar with the actual applications of AI in their field of expertise, and due to the massive amount of fake news in this area, they cannot distinguish between reliable and unreliable methods. On the other hand, those who are in charge of administering medical systems have graduated in medical sciences, and current medical mindsets would make it difficult for AI to be incorporated for actual use.

The actual application of AI in medicine could not be instantaneous, but there is a slow adaptation process between the AI software development systems and the medical staff. This process requires an investment of time and effort from medical staff, those who are required to be motivated via, for example, being convinced about the potential benefits of this process.

It is not surprising that not only physicians but also the general population do not trust AI for medical purposes (50). Obviously, public opinion is influenced by experts, but medical experts have a more significant impact than IT ones.

The ethical implications of employing AI in medicine are up for discussion. For instance, what would the ethical concerns be if an AI system caused a patient to die? To make it more extreme, we can consider a case in which a doctor has prescribed the complete opposite treatment of what the AI system recommends. Since the medical system will not let AI systems take control of patient treatments, such a scenario is very unlikely to happen anytime soon. However, answers to these ethical implications will have an impact on how AI will be used in medicine.

A potential role of AI systems in medicine would be a recommendation system serving medical doctors. Before deciding on a course of therapy, doctors can confirm the AI system's reasoning behind its recommendations and the observations that formed the basis of its suggestions. However, the problem is that not all the leading AI methods provide a reason in addition to diagnostics. This property is called the explainability of AI systems, as it has been already discussed. In order to facilitate the use of AI in medicine, current AI methodologies should be enhanced to provide an explanation for their final decisions or predictions. Explainable AI is a new concept in AI that is especially important for medical sciences, which is young and requires more effort to be useful in practice.

What Are the Next Steps?

What could be done to boost the benefits of medical systems from AI in a reliable and sustainable manner? Different stakeholders are involved in the present and future of AI in medicine, and each will have an impact on the future of the field.

Current AI-based methods and systems do not meet the requirements of a reliable system to be used in practice, including accuracy, general acceptance, and acceptance in the field of medicine. It will take extra effort from computer science researchers to develop reliable AI methods.

An intermediate step would be a scenario where medical systems use AI-based systems as a recommendation system, just like an experimental study. This process might be long and requires constant interaction of the medical staff with the AI development team and the re-installation of new systems. For instance, since the process might be long and not so efficient, to realize its future potential benefits, the administrative level of medical systems might consider providing incentives for those participating in this process.

Integrating AI systems into medicine would be neither instantaneous or fast, and not all medical teams would be involved, at least in the near future. The medical system would, however, be a stronger platform for developing and accepting new AI systems if the medical personnel had greater awareness of the concepts and most recent developments in AI.

Conclusion

The ability of AI systems to replicate human behavior has improved recently, at least in some areas, following recent breakthroughs in AI technologies. This provided computer scientists with the motivation to devise AI-based solutions to handle medical functions. Some methods show good performance in several different medical areas. Currently, some AI-based systems have gained Food and Drug Administration (FDA) certification to be used in practice, and a lot of opportunities are in the field that, at least in research, AI systems have been shown to be beneficial for medical systems. This potential to become actual requires considerations that are discussed in this section.

In the end, it is worth mentioning that analyzing trends in IT, AI, and medicine reveals forces that will determine the future of AI in medicine. The first detrimental force is the improvements in AI that would increase its performance, and it could be imaginable that in the future, even in medicine, some tasks might not be done without AI's assistance. On the other hand, advancements in medicine lead to increasingly complex procedures requiring more and more experts in more medical areas. This will increase the demand for including AI-based systems in medical procedures, at least as assistants. Considering this potential foreseeable future, medical policymakers may consider fundamental changes in the system, including in education systems. In response to the need to prepare future medical leaders for the challenges of AI in medicine, several medical education centers have begun to provide novel medical curricula, including medical-engineering degrees (51). This example may show how deeply the inclusion of AI in medicine may change all aspects of medicine.

Conflict of Interest

The authors declare no conflict of interest in this study.

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