JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

EMERGING AND EFFICACY BASED ARTIFICIAL INTELLIGENCE TOOLS EMPLOYING IN THE PROGRESSION OF HEALTH CARE SYSTEMS IN THE CURRENT SCENARIO

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Abstract

As healthcare becomes more complex and has more data, artificial intelligence (AI) will become increasingly relevant. Some types of AI are already in use by payers, providers of care, and life sciences companies. Among the key application categories are diagnosis and treatment recommendations, patient engagement and adherence, and administrative functions. It is true that AI can perform healthcare tasks as well as humans in many cases, but implementation factors will prevent large-scale automation of healthcare professional jobs for some time. The application of AI to healthcare is also discussed in terms of ethical issues.

Keywords: Systems for Electronic Health Records, Artificial Intelligence, and Clinical Decision Support

Introduction

Technology such as artificial intelligence (AI) and related technologies are becoming increasingly prevalent in society and business. These technologies have the potential to transform industries like healthcare. There are already a number of research studies that suggest that a number of aspects of patient care, as well as administrative processes within providers, payers, and pharmaceutical companies, have been impacted. Algorithms are already outperforming radiologists at detecting malignant tumours and can perform as well as or better than humans in key healthcare tasks, such as diagnosing diseases. Developing cohorts for expensive clinical trials. However, we believe that it will be many years before AI replaces humans for broad medical processes for a variety of reasons. Here we describe the potential of artificial intelligence for automating healthcare aspects, as well as some of the barriers to its rapid implementation. Unless you are a healthcare professional, in which case you have already been replaced by a robot - don't worry, you won't be replaced anytime soon by a robot!

1. Types of AI of Relevance to Healthcare

In healthcare, artificial intelligence is more than one technology; it is a collection of technologies. Most of these technologies have immediate relevance, but their specific processes and tasks vary greatly. Following is a description of some of the most significant AI technologies in healthcare.

Machine Learning – Neural Networks and Deep Learning

Models are fitted to data using machine learning, which then learns by training them with the data. One of the most common forms of artificial intelligence is machine learning; according to IBM survey of US managers whose organizations were already pursuing AI, 69% of companies surveyed were using AI whereas machine learning using 56%. It is a broad technique at the core of many approaches toAI, and it is available in many versions [1].

Predicting what treatment protocols will succeed on a patient based on various patient attributes and the treatment context is the most common application of traditional machine learning in healthcare. There are several types of machine learning and precision medicine applications [2], but most of them require training datasets for which outcome variables (such as disease onset) are known; this is called supervised learning.

It has been well established in healthcare research for several decades that neural networks are a more complex form of machine learning. They have been available since the 1960s and have been used for categorisation applications such as predicting the likelihood that a patient will contract a disease for decades [3]. Problems are viewed in terms of inputs, outputs, and weights associated with variables or 'features' that connect inputs with outputs. It has been likened to the way neurons process signals, but theanalogy is weaker.

With many levels of features or variables that predict outcomes, deep learning and neural network models are the most complex forms of machine learning. Using today's graphics processing units and cloud architectures, thousands of hidden features are uncovered in such models. The detection of cancerous lesions in radiology images is one of the most common uses of deep learning in healthcare. Radiology, which involves detecting clinically relevant features in imaging data beyond what the human eye can see, is increasingly being applied to deep learning [4]. In oncology-oriented image analysis, radiomics and deep learning are most commonly employed [5]. Combining them seems to offer greater accuracy than computer-aided detection, or CAD, the previous generation of automated tools for image analysis. As part of natural language processing (NLP), deep learning is also increasingly being used for speech recognition. An observer of a deep learning model is typically unable to understand the meaning of a particular feature. As a result, the explanation of the model's outcomes may be almost impossible.

Natural Language Processing

The goal of AI researchers has been to understand human language since the 1950s. It includes applications such as speech recognition, text analysis, translation and other language-related tasks. A statistical NLP approach and a semantic NLP approach are both basic approaches. Machine learning (deep learning neural networks in particular) is the basis of statistical NLP, which has recently contributed to an increase in recognition accuracy. In order to learn a language, you must have access to a large body of material.

Among the most common applications of NLP in healthcare are the creation, understanding, and classification of clinical documentation and publications. Using NLP, clinical notes can be analysed, reports can be prepared (for radiology examinations), patient interactions can be transcribed, and engage in conversational AI.

Rule-based Expert Systems

AI was dominated by expert systems based on collections of if-then rules in the 1980s, and they were widely used commercially during that period. Over the past few decades, they have been widely used for clinical decision support in healthcare, and they remain widely used today [5]. Electronic health record (EHR) providers provide a set of rules with their systems today.

Generally, expert systems require human experts or knowledge engineers to construct a series of rules in a particular domain. The rules tend to break down when there are a great deal of rules (usually over several thousand) and the rules conflict with each other. Furthermore, if the knowledge domain changes, the rules are likely to change as well. As algorithms based on machine learning and data become more prevalent in healthcare, rules become increasingly difficult and time-consuming.

Physical Robots

Approximately 517,000 industrial robots are installed around the world till last year 2022, performing predefined tasks like lifting, repositioning, etc. In factories and warehouses, they weld or assemble objects and deliver supplies to hospitals. A growing number of robots now collaborate with humans and can be trained more easily by moving them through certain tasks. As other AI capabilities are embedded in their ‘brains’ (really their operating systems), they are also becoming more intelligent. We may see the same improvements in intelligence as we have in other areas of artificial intelligence inthe future. Robots that are physically incorporated.

As of 2000, surgical robots were approved in the USA. They give surgeons ‘superpowers’, such as seeing, creating precise incisions, stitching wounds, etc. [6] However, six important decisions remain the responsibility of human surgeons. A common surgical procedure that uses robotic surgery is gynaecologic surgery, prostate surgery, and head and neck surgery.

Robotic Process Automation

As if a human user were following a script or rules, this technology performs structured digital tasks for administrative purposes, such as those involving information systems. They are inexpensive, easy to program, and transparent in their actions, as opposed to other forms of AI. The only thing involved in robotic process automation (RPA) is computer programs on servers, not robots. It relies on a combination of workflow, business rules and 'presentation layer' integration with information systems to act as a semi-intelligent user of the systems. Prior authorisation, updating patient records, and billing are among the repetitive tasks they are used for in healthcare. Combined with other technologies such as image recognition, they can be used to extract data from faxed images and input it into transactional systems, for instance [7].

Despite describing these technologies individually, they are increasingly being combined and integrated into one another; robots are getting AI-powered 'brains', and image recognition is being integrated with robotic process automation. It is possible that these technologies will become so intertwined that composite solutions will become more feasible or likely in the future.

2. Diagnosis and Treatment Applications

At Stanford, MYCIN was developed for diagnosing blood-borne bacterial infections in the 1970s, paving the way for AI applications in disease diagnosis and treatment. [8] This and other early AI applications have been a focus of AI since at least the 1970s. Despite showing promise for accurately diagnosing and treating disease, rule-based systems weren't adopted into clinical practice. They were not substantially better than human diagnosticians, and they did not improve treatment outcomes. Clinical workflows and medical record systems were poorly integrated.

Recently, IBM's Watson has received considerable attention from the media for its focus on precision medicine, particularly cancer diagnosis and treatment. Watson uses a combination of machine learning and Natural Language Processing. When customers realized it was difficult to teach Watson how to deal with particular types of cancer [9] and integrate Watson into care processes and systems, their enthusiasm for this application of the technology faded. In Watson, 'cognitive services' are provided through application programming interfaces (APIs), including speech and language interpretation, vision analysis, and machine learning [10].

Implementation issues with AI bedevil many healthcare organisations. Although rule-based systems incorporated within EHR systems are widely used, including at the NHS,[11] they lack the precision of more algorithmic systems based on machine learning. As medical knowledge changes, these rule-based clinical decision support systems are difficult to maintain. Additionally, they are often unable to handle the explosion of genomic information and data. Care based on proteomics, metabolic analysis, and other 'omic-based' approaches.

In terms of clinical practice, this situation is beginning to change, but it is more prevalent in research labs and tech firms. Almost every week, a new research lab claims to have developed a method for diagnosing and treating diseases using artificial intelligence or big data that is as accurate as human clinicians. Radiological image analysis [12] is a common source of these findings, but other types of images, such as retinal scanning [13], and genomic-based precision medicine, are also used. By using statistically-based machine learning models, [14] these findings are paving the way for evidence- and probability-based medicine, which is generally regarded as a good thing but poses many ethical concerns and challenges to patient/ clinician relationships [15]

Start-ups and tech firms are also working on the same issues. Google, for example, is collaborating with health delivery networks to build prediction models for health outcomes. It provides a 'clinical' interpretation of images for clinicians of high-risk conditions, such as sepsis and heart failure. Google, Enclitic, and a variety of other start-ups are developing AI-derived image interpretation algorithms [16]. Using a 'success machine', clinicians would be able to identify risky patients and those most likely to respond to treatment protocols. These tools could assist clinicians in finding the most effective treatment. Treatment and diagnosis of patients. Some firms specialize in diagnosing and treating cancers based on the genetic profile of the patients. Human clinicians have found it increasingly complex to understand all genetic variants of cancer, as well as how they respond to new drugs and protocols, since many cancers have a genetic basis. This approach is specialized in firms such as Foundation Medicine and Flatiron Health, both now owned by Roche.

Providers and payers for care are also using 'population health' machine learning models to predict whether populations are at risk for certain diseases [17] or accidents [18], as well as to predict hospital readmissions. In spite of sometimes lacking the necessary data, such as patient socioeconomic status, these models can be effective at predicting. Even so, embedding AI-based diagnosis and treatment recommendations in clinical workflows and EHR systems can sometimes be challenging, regardless of whether they are rules-based or algorithmic in nature [19]. There are likely to have been more integration problems with AI implementation than any inability to provide accurate and effective recommendations, and many AI-based diagnostic and treatment capabilities from tech firms are standalone in nature or only address one aspect of care. AI has been embedded into some EHRs (beyond rule-based clinical decision support), 20 but this is still an early stage. Either providers will need to undertake substantial integration projects themselves or wait for EHR vendors to add more AI capabilities.

In healthcare, patient engagement and adherence have long been considered the last mile problem - the final obstacle between ineffective care and good health. Patients who actively engage in their own well-being and care are more likely to achieve better results, including utilisation, financial outcomes, and member experiences [20]. Big data and AI are addressing these factors more and more. Clinical expertise is often used by providers and hospitals to develop care plans that improve the health of chronic or acute patients. However, it doesn't matter if the patient fails to make the necessary behavioural adjustments, e.g., losing weight, scheduling a follow-up visit, filling prescriptions, or following the treatment plan.

3. Patient Engagement and Adherence Applications

Patients who do not follow a treatment plan or take prescribed medications as directed are at risk of noncompliance. More than 70% of respondents in a survey of more than 300 clinical leaders and healthcare executives said that less than 50% of their patients were highly engaged, while 42% said less than 25% of patients were highly engaged. Can AI-based capabilities be effective in personalizing and contextualizing care if deeper patient involvement results in better health outcomes? In order to drive nuanced interventions along the care continuum, machine learning and business rules engines are being increasingly used [21]. Research in messaging alerts and relevant, targeted content that prompts action at the right moments is promising [22].

In healthcare, another important focus is on designing 'choice architectures' based on real-world evidence to influence patient behavior. By comparing patient data with other effective treatment pathways for similar cohorts using information provided by provider EHR systems, biosensors, watches, smartphones, and conversational interfaces, the software can tailor recommendations. Depending on the situation, providers, patients, nurses, call centers, or care coordinators may receive recommendations.

4. Administrative Applications

As well as patient care, AI can also be used extensively in administrative functions in healthcare. The use of AI is somewhat less revolutionary in this domain than in patient care, but it can still provide significant efficiencies.

Healthcare needs these because, for example, the average US nurse spends 25% of their time with regulatory and administrative duties. RPA is the technology most likely to be relevant to this objective. Among its many applications in healthcare are claims processing, clinical documentation, revenue cycle management, and medical records management [23]. Several healthcare organizations have also explored the use of chatbots for patient interaction, mental health, and telehealth. These NLP- based applications may be useful for making appointments or refilling prescriptions [24]. According to a survey of 500 US patients using the top five healthcare chatbots, patients expressed concerns about revealing confidential information, discussing complex health conditions, and poor usability [25].

Using machine learning for probabilistic data matching across a range of databases is another AI technology relevant to claims and payment administration. Insurers have a duty to verify the accuracy of millions of claims. Identification, analysis, and correction of coding issues and inaccurate claims can save time, money, and effort for all stakeholders – health insurers, governments, and providers. With data-matching and claims audits, it is possible to uncover significant financial potential hidden behind incorrect claims.

5. Implications for the Healthcare Workforce

There has been considerable attention to the concern that AI will result in the automation of jobs and substantial displacement of the workforce. A Deloitte collaboration with the Oxford Martin Institute 26 suggested that 35% of UK jobs could be automated out of existence by artificial intelligence within 10 to 20 years.

Although some jobs can be automated, a number of external factors, other than technology, may limit job losses, including costs of automation technologies and labor availability. Growth and cost of the market, the benefits of automation beyond simple labour substitution, and the regulatory and social acceptance of automation [26].

-To our knowledge, AI has not eliminated any jobs in the health care industry. These factors may limit actual job losses to 5% or less [27]. AI has only entered the industry in limited numbers so far, and the difficulty of integrating AI into clinical workflows and EHR systems has contributed to the lack of job impact. Healthcare jobs that deal with digital information, such as radiology and pathology, seem more likely to be automated than those that deal with patients directly. Even so, the penetration of AI into jobs like radiologists and pathologists is unlikely to be as fast as it should be [28]. Despite the fact that deep learning technologies are making inroads into diagnosing and categorising images, there are several reasons why radiology jobs won't disappear anytime soon, for example [29].

It is important to note that radiologists perform more than just reading and interpreting images. In research labs and start-ups, deep learning models are trained to recognize specific types of images (like nodules in chest computed tomography or haemorrhage in brain magnetic resonance imaging). AI can only perform a few of these narrow detection tasks today, but thousands of these are needed to identify all potential findings in medical images. The role of radiologists also extends to the diagnosis and treatment of diseases (for example, performing local ablative therapies) as well as image-guided interventions such as vascular stents and cancer biopsies (interventional radiology). Define the technical parameters of the imaging examinations to be performed (tailored to the patient's condition), relate findings from images to other medical records and test results, and discuss procedures and results with patients.

Additionally, AI-based image work is far from being ready for use on a daily basis in clinical settings. Deep learning algorithms and imaging technology vendors have different foci: the likelihood of a lesion, cancer, the location or feature of a nodule. Deep learning systems would be difficult to integrate into clinical practice because of these distinct foci. Lastly, deep learning algorithms for image recognition require labelled data, meaning millions of images from patients who have been diagnosed with cancer, broken bones, or other diseases. However, there is no aggregated repository of radiology images, either labelled or unlabeled. In order for automated image analysis to really take off, significant changes in medical regulation and health insurance will be required.

In pathology and other digitally oriented areas of medicine, similar factors exist. Consequently, over the next 20 years or so, there is unlikely to be a substantial change in healthcare employment as a result of artificial intelligence. AI technologies may also result in the creation of new jobs. As a result, AI technologies are unlikely to substantially reduce medical treatment and diagnosis costs over the nextdecade or two due to static or rising employment levels.

6. Ethical Implications

Furthermore, the use of AI in healthcare has many ethical implications. In the past, healthcare decisions were made almost exclusively by humans, and the use of smart machines to make or assist with them raises questions about accountability, transparency, permission and privacy. With today's technology, transparency is perhaps the most challenging issue to resolve. Many AI algorithms – particularly deep learning algorithms used for image analysis – are virtually impossible to interpret. When a patient is informed that an image led to a cancer diagnosis, he or she probably wants to know why. Medical professionals who are generally familiar with deep learning algorithms may not be able to explain their operation.

There is no doubt that AI systems will make mistakes when diagnosing and treating patients, and it may be difficult to hold them accountable. Moreover, AI systems are likely to provide medical information to patients they would prefer to receive from an empathetic clinician in some instances. Similarly, machine learning systems in healthcare may be subject to algorithmic bias, predicting disease more often based on gender or race than is actually the case.

Artificial intelligence in healthcare is likely to result in many ethical, medical, occupational, and technological changes. To limit negative consequences, healthcare institutions, as well as governments and regulatory bodies, must establish structures to monitor key issues, respond responsibly, and establish governance mechanisms. For many years to come, this will require continuous attention and thoughtful policy because it is one of the most powerful and consequential technologies to impact human societies [30].

With AI in healthcare, we will likely see a number of changes in ethics, medicine, occupational safety, and technology. Health care institutions and government and regulatory bodies need to establish structures to monitor key issues, respond in a responsible manner, and implement governance mechanisms to limit negative effects. For many years to come, this technology will require continuous attention and thoughtful policy.

7. The Future of AI in Healthcare

AI will play a major role in the future of healthcare, according to us. Precision medicine is a widely acknowledged advance in care that is primarily driven by machine learning, the primary capability behind it. Although early efforts at providing diagnosis and treatment recommendations have proved challenging, we expect AI to ultimately master that domain too. A machine seems likely to analyze most radiology and pathology images at some point given the rapid advances in AI for imaging analysis. For example, speech and text recognition are already used for patient communication and clinical notes, their usage will increase as well.

The greatest challenge for AI in these healthcare domains is not whether the technologies will be capable enough to be useful, but rather ensuring that they are adopted into daily clinical practice. In order to be widely adopted, AI systems need to be approved by regulators, integrated with EHR systems, standardized in a way that similar products operate similarly, taught to clinicians, paid for by public or private payers, and updated over time. The challenges will ultimately be overcome, but it will take much longer than the technologies themselves to mature. As a result, we expect to see limited AI use in clinical practice within 5 years and more extensive use within ten.

Human clinicians will not be replaced on a large scale by AI systems, but rather they will be enhanced in their efforts to care for patients in the future. In the future, human clinicians may be able to design tasks and jobs that utilize empathy, persuasion, and big-picture thinking. Healthcare providers who refuse to work alongside artificial intelligence may be the only ones to lose their jobs over time.

Conclusion:

There are many more benefits of Artificial Intelligence that span from space exploration to advancements in defence systems and more. Technology is constantly changing, and it has the potential to become more intelligent than ever. The future of AI is uncertain as there is no sure-fire way of predicting the exact future of the technology, but it is certain that it will continue to benefit both businesses and end users in their everyday lives for a long time to come.

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