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ARTIFICIAL INTELLIGENCE FOR CLINICAL TRIALS

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ABSTRACT:

Artificial Intelligence (AI) in healthcare is the usage of a complex set of algorithms that help to conduct systematic analysis of medical data. AI helps in reducing medical errors, digital acquisition, correcting algorithm mistakes, reading scientific literature and electronic record keeping at its ultra-fast computing speeds plays a major role in the clinical field. AI being a machine simulation of human intelligence processes includes learning, reasoning and self-corrections by using several methods such as machine learning, deep learning and natural language processing while the ultimate goal is to build a smart machine capable of learning and comprehending. Clinical trials are an area with great potential for optimization. Only 12% of drug development programs had success in 2000-2019 study. AI simplifies the lives of patients, doctors and hospital administrations by performing tasks that are typically done by humans but by consuming less time and work. Incomplete medical histories and large caseloads that are not systematically handled can lead to deadly human errors that affect patients. Few causes such as suboptimal patient selection, recruiting techniques, inability to monitor patients effectively during trials are what leads to high trial failure rates. The high failure rates of clinical trials contribute substantially to the inefficiency of the drug development cycle. This article aims at discussing in detail how recent advances in artificial intelligence can be used to reshape key steps of clinical trial design towards increasing trial rates.

INTRODUCTION

The use of plant-derived medications in the treatment and prevention of disease is called phytotherapy which is a science-based medical practice that is distinguished from others and consists of more traditional approaches, such as medical herbalism (1). Generally, a herbalist's approach has not been evaluated in controlled clinical trials or in many rigorous biomedical studies, whereas numerous trials and pharmacological studies of particular phytotherapeutic preparations exist (2,3). The interpretation and acceptance of such evidence for phytotherapeutic practices varies from trial to trial.There are a number of phytotherapeutic preparations in use. Examples include preparations derived from*Caralluma fimbriata* which has antihyperglycemic activity (4,5). It is also known to have cytotoxic activity against human colon cancer cells (6,7).

The most recent advancement of the use of nanotechnology has aided in creating dose-dependant formulations of medicinal compounds in the right amounts for treatment. Few studies conducted such as biosynthesis of zinc oxide nanoparticles using Mangifera indica leaves showed antioxidant and cytotoxic properties in lung cancer cells (8) and another study used Brassica oleracea mediated zinc oxide nanoparticles and showed antibacterial activity against pathogenic bacteria (9,10). Selenium nanoparticles are an emerging field of interest in nanotechnology (11,12). So to eradicate the human errors and introduce a systematic technique to approach such trials, technology has taken a turn toward artificial intelligence (13-15).

The main goal of health related artificial intelligence (AI) applications is to realize relationships between prevention or treatment techniques and patient outcomes. AI basicallyrefers to a simulation of human intelligence inculcated into machines that are programmed to think like humans hence the term is also applied to any machine that exhibits certain traits associated with the human mind processes such as learning and problem-solving (16). The use of AI dates back to the 1970s to provide diagnosis decision support .But the drawback was, once built they were rigid and difficult to update.

AI simplifies the lives of patients, doctors and hospital administrations by performing tasks that are typically done by humans but in less time at a fraction of cost. Incomplete medical histories and large caseloads and data can lead to deadly human errors. Hence, AI can predict and diagnose disease at a faster rate than most medical professionals (17).The two subtypes of AI in medicine are: virtual and physical. The virtual part of AI ranges from applications such as electronic health record keeping systems to neural network-based guidance in making treatment decisions. The physical part of AI mostly deals with robots assisting in performing surgeries, manufacturing intelligent prostheses for handicapped people and elderly care (18).

The basis of such evidence-based medicine is to establish certain clinical correlations whilst developing associations and patterns from the existing insight of the database with information. Traditionally, statistical methods were employed to establish these patterns and associations. Computers are made to learn the art of diagnosing a patient via flowcharts and database approach which are the two broad techniques (19). The flowchart-based approach involves translating the process of history-taking, i.e. a physician will ask a series of questions and then arrive at a probable diagnosis by combining the symptoms that are presented. This requires feeding a large amount of data into the machine-based cloud networks considering the wide range of symptoms and disease processes known in routine medical practice. The outcomes of this approach are limited because the machines will not be able to observe and diagnose cues which can only be observed by a doctor during the patient encounter (20). Although, AI helps in reducing medical errors, digital acquisition, correcting algorithm mistakes, reading scientific literature and electronic record keeping. AI at its ultra-fast computing speeds plays a major role in medical practice by using machines to process huge and massive data sets. While diagnostic skills are functional as well as limited to the computing infrastructure.

DIFFERENT METHODS USED IN AI

Few of the many methods of AI that are most commonly used are discussed as follows. AI being a machine simulation of human intelligence processes includes learning, reasoning and self-corrections (21). The ultimate goal is being able to build machines that can perceive the record and make decisions the same way humans do (22).

Machine Learning (ML)

The scientific study of algorithms that help build a mathematical model out of sample data to make predictions without being explicitly programmed to perform the taste. ML is considered as a branch of AI (23).

Deep Learning (DL)

It is a class of ML methods based on artificial neural networks, capable of information processing and distributed communication nodes in biological systems that use multiple layers In order to extract higher level features from raw input. Hence “deep” in DL means the number of layers through which data is transformed.

Natural Language Processing (NLP)

It is a field of AI that is concerned with the interactions between computer and human (natural language) in specific to show how programmed computers process and analyze such large amounts of natural language data (24).

USES OF ARTIFICIAL INTELLIGENCE

Artificial intelligence is not one technology but a collection of many. In healthcare, the most common application of machine learning (ML) is precision medicine, predicting what treatment protocols are likely to succeed on a patient based on various patient attributes and context of treatment.

Deep learning methods (DL), a more complex ML method is a neural network technology and has a common application that is to recognize potentially cancerous lesions in radiology images. The combination of radionomics and

DL methods promise greater accuracy in diagnoses than the previous generation of image analysis automated tools, also known as computer-aided-detection (CAD) (25).

In healthcare, NLP applications involve creation, understanding and classification of unstructured clinical documentation and help prepare reports while conducting conventional AI. Many recent advances help AI application in fields such as cancer-sub-phenotyping, drug to target interaction and drug repositioning hypothesis.

RECENT ADVANCEMENTS AND APPLICATION

In 2015, misdiagnosis of illness and medical errors accounted for 10% of all US deaths. Hence the following recent advances help in reducing errors and saving lives.

Path AI:

This study was conducted in Cambridge, Massachusetts. It is a developing machine learning technology that helps to assist pathologists in making more accurate cancer diagnosis with AI. The current goal of PATH AI is to reduce error in cancer diagnosis and develop methods for individualized medical treatment (26).

Buoy health:

This study was conducted in Boston, Massachusetts. It is an AI based symptom and cure checker that uses algorithms to diagnose and treat illness. It consists of a chatbot that listens to a patient's symptoms and health concerns and then guides that patient to the right care based on diagnosis (27).

Beth Israel Deaconess Medical Centre:

This study was conducted in Boston, Massachusetts.This helps to diagnose potentially deadly blood diseases at a very early stage. Doctors use these AI enhanced microscopes to scan for harmful bacteria such as *E.coli* and *Staphylococcus* in blood samples at a faster rate than is possible using a manual scanning (28). The machines learned how to identify and predict harmful bacteria in blood with 95% accuracy.

ZEBRA medical vision:

This study was conducted in Shefayim, Israel. It is an AI powered radiology assistant that provides radiologists with assistance by receiving imaging scans and automatically analyses them for various clinical findings it has studied. These findings are then passed on to radiologists who take the assistants report into consideration while making a diagnosis.

BIOXCEL therapeutics:

This study was conducted in New Haven, Connecticut. It uses an AI to identify and develop new medicines in the fields of immune-oncology and neuroscience. Also the drug re-innovation program employs AT to find new applications for existing drugs or identify new patents. This was named as the " most innovative healthcare AI" development of 2019.

CHALLENGES AND DRAWBACKS OF AI

AI techniques have advanced to a maturity that allows them to be employed under real life conditions to assist human decision makers. However, several drawbacks pose as challenges. Moving patients through recruitment timelines is a major challenge and is the number one cause of 86% of all trials delays. The digitalization and accessibility of EMR (Electronic Medical Records) data that are used extensively by AI methods are not trivial. The lack of regulatory frameworks on data collection causes EMR formats to widely differ and become incompatible with each other or not digital at all (29). Also a strongly regulated legal environment strictly limits third party access to patient data and makes it even harder for patients to access their own data. This so-called “EMR Interoperability dilemma’ is the major obstacle towards development of AI technology (30).

FUTURE SCOPE

Although AI has the potential to impact numerous steps of clinical trials design from preparation to execution, data scientists and medical scientists should jointly define achievable application of AT tools to a specific sub task of clinical trial design that promises trial success rates. The AI technology must be tested alongside the existing technology and the added value must be ethically explainable, repeatable to users as well as regulatory bodies. Hence AI may be adopted into the clinical trial design ecosystem step by step and by making trials faster, the failure rates may be lowered (31).

CONCLUSION

The AI techniques discussed in this study offer real life practicability with respect to explain ability and broader inclusion into life science. The opportunity to transform the drug- development cycle through AT must be acknowledged and must qualify the value and reliability of any human innovation. Although AI cannot make success rates of clinical trials sky rocket overnight , they are important building blocks of a much required overhaul of drug development.

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