Asian Journal of Research in Computer Science

Volume 15, Issue 4, Page 1-14, 2023; Article no.AJRCOS.98566
ISSN: 2581-8260

Artificial Intelligence in Health Sector: Current Status and Future Perspectives

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJRCOS/2023/v15i4325

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/98566

Review Article

Received: 08/02/2023
Accepted: 10/04/2023
Published: 15/04/2023

ABSTRACT

The developing fields of artificial intelligence (AI)/ machine learning (ML) offer a significant potential to improve healthcare services. Many areas of clinical practice, scientific research, and healthcare management have included AI/ML techniques. Screening and daily fitness monitoring, diagnostic services in gastroenterology, pathology, and radiology, as well as support for clinical decision-making and palliative care, are the main categories involved. However, there are significant obstacles to the widespread use of AI/ML in healthcare, including higher installation and maintenance costs, potentially harmful medical mistakes, a lack of ethical frameworks for AI, unemployment, and reduced capacity building within the human workforce. Many business initiatives have now been created in the field of healthcare AI/ML innovation. They offer everything from advanced diagnostics to vitals monitoring in their products and services. In short, AI/ML may be extremely important in addressing the difficulties with complexity and the explosion of data in the healthcare system. AI/ML is a component of contemporary healthcare, and its further adoption is contingent on thoroughly addressing pertinent issues.

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Keywords: Machine learning; artificial intelligence; health; medical; supervised machine learning; unsupervised.

1. INTRODUCTION

Several statistical methods that enable computers to learn from experience without being explicitly programmed are together referred to as "machine learning" (ML) [1]. “Usually, an algorithm's operation is changed as a result of this learning. A machine learning system may be able to recognize faces if it is shown a number of photographs that contain a variety of different people” [2,3]. “The two main subfields of ML are unsupervised learning and supervised learning. One of the biggest industries in the world that may profit from this technology is healthcare” [4]. “The healthcare industry has always been one of the most vocal supporters of cutting-edge technologies. AI and ML have many applications in healthcare, just as they do in the commercial and e-commerce worlds” [5,6]. “The scope of what can be achieved with this technology is practically limitless. The healthcare industry is benefiting from ML's innovative applications, which are helping to enhance patient outcomes. Healthcare systems have already used big data technologies for next-generation data analytics for electronic medical records as a result of mandatory procedures like electronic health records (EMR). The use of ML technologies is anticipated to significantly improve this procedure. ML has the potential to improve automation and intelligent decision-making in primary/tertiary patient care and public healthcare systems. This may be the most consequential impact of ML methods, since ML can improve the lives of billions of people throughout the world” [7-9].

“There are many different applications for machine learning technology that may be used to improve clinical trial research” [10]. By applying sophisticated predictive analytics to individuals interested in participating in clinical trials, medical professionals would be able to evaluate a greater variety of data, hence reducing the cost of essential medical tests and the amount of time they take to complete. Using electronic health records and a variety of ML applications, researchers will be able to establish the optimal sample sizes for clinical trials, which will increase the effectiveness of the studies and reduce the chance of data mistakes (EHRs) [11]. This approach seeks to alleviate a critical issue in the healthcare sector worldwide: the shortage of highly skilled radiologists [12]. ML in healthcare can give more dynamic and effective personalized treatments by combining personal health with predictive analytics. Many applications for ML exist in scientific and medical investigations [13]. “Researchers can move with a supply from numerous data sources, such as prior doctor visits, social media, etc., by using ML-based predictive research to discover latent clinical trial participants. Additionally, ML maintains the trial associations and guarantees that data is obtained in real-time, enabling the most suitable sample size to be studied and utilizing the power of electronics work, both which contribute to the decrease in data-based errors” [14].

“Medical imaging data that has been electronically stored is widely available, and several algorithms can be used to search through this collection for patterns and anomalies. Similar to a highly trained radiologist, machine learning algorithms can analyze imaging data and identify suspicious skin patches, lesions, tumors, and brain hemorrhages. The usage of these platforms to assist radiologists is therefore anticipated to increase dramatically” [15]. “Several studies have already shown that AI is capable of doing important healthcare jobs including disease diagnosis equivalent to or better than humans” [16-18]. Though machine and human errors are possible, applying the combined knowledge from AI and humans may likelihood the likely of medical errors while increase the quality of healthcare. “Today, algorithms already surpass radiologists in identifying cancerous tumors and advising researchers on how to create cohorts for expensive clinical trials. Nonetheless, it may be a long time before AI completely replaces humans in large medical process domains for a variety of reasons” [19].

1.1 Why ML In Health Care Sector?

“Healthcare services are getting better all the time, and there are better treatment approaches to complicated conditions. The dosage and duration of medicines depending on patient characteristics or for patient groups with marginal clinical research, including for children, remain major issues, though” [20]. “Hence, ML has been successfully included inpediatric care in recent years to foretell the finest and most individualized treatments for children” [21]. “Since the COVID-19 pandemic's emergence, ML has come into the public eye. Organizations are using ML to boost

Research and Development (R&D), streamline operations, and gain an advantage in an often chaotic and unpredictable work environment. Hospitals and healthcare systems have used ML to overcome specific difficulties" [22,23]. Several companies are making efforts to benefit from machine learning, one of the most fascinating branches of artificial intelligence. Machine learning (ML) is a rapidly developing field that employs algorithms to facilitate data-driven learning and has many potential applications in fields as diverse as business and healthcare. The healthcare industry is ever-evolving due to the constant influx of new ideas and innovations. ML has the potential to aid medical professionals in these unusual scenarios. Unstructured text, which was previously impossible to generate and utilise widely, may now give useful insights with the assistance of current technologies. This new wealth of ML-derived knowledge can help doctors and executives make better, faster decisions regarding patient care and operational software that might have an enormous influence on the lives of millions of people [24-26].

Machine learning (ML) is increasingly employed in the real world, and its applications are ubiquitous. In healthcare, it is especially important for protecting sensitive patient information. Machine learning is used to examine patient information and make illness predictions [27,28].

2. TYPES OF MACHINE LEARNING IN HEALTH CARE SECTOR

Artificial intelligence and machine learning, when combined with IoT-enabled WSNs, can significantly improve the healthcare system in terms of disease prevention, early disease diagnosis, and therapeutic decision-making. Future medical care can be more superior and individualized. Machine learning is a crucial part of artificial intelligence. Models are developed by the use of complex algorithms and pattern recognition on massive amounts of sample data. Once refined, these models can be used in previously unexplored regions [29-31].

Supervised learning, unsupervised learning, and reinforcement learning all have quite distinct approaches to learning. Many methods and approaches are used to accommodate each of the three distinct styles of learning. Recently, deep learning's ability to recognize subtle patterns in large amounts of data has increased its relevance here [32-34].

2.1 Supervised ML

"With supervised machine learning, programmers give the algorithms a ready-made dataset to use as training material. The algorithms' only duty is to identify the pattern: Why does this data belong in category A rather than category B? Such algorithms are used to categorize natural data using supervised learning (photos, handwriting, language, etc.). Moreover, one prominent area of application for supervised learning is regression problems. Based on particular habits, computers should be able to forecast things like consumer health" [35-37].

"Assume for the moment that someone wants to train algorithms to distinguish l cancerous tumors from non-cancerous ones. Then, the programmers would create a sizable data collection for this. This might include scans that have all been tagged or are in a specific category. Think of three categories: malignant, non-cancerous, and other. The data collection must display the most variance possible. Simply said, the algorithm will assume that all tumors are malignant if the training set solely contains scans of benign tumors. Hence, the data set should attempt to map the real range of variations" [38-40].

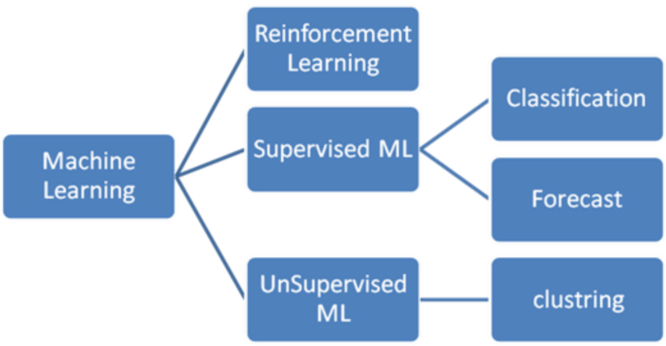

Fig. 1. Machine learning

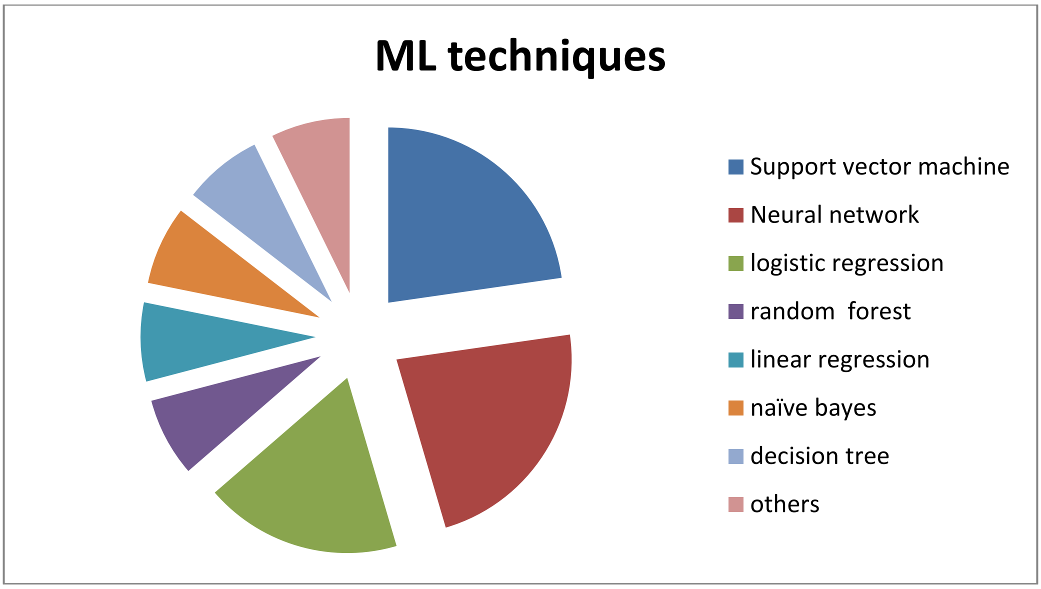

Fig. 2. Most common ML techniques in healthcare sector

"When training, the algorithm first gets the content (unsorted), makes a decision on its own and then compares the result to the output that the developers have provided. The system compares its own result to the correct one and makes inferences based on this that have an impact on the next assessments throughout the training. Unless the computer and its judgements are sufficiently close to the right outcomes, more training is required" [41,42].

The training technique relies heavily on the tasks performed by the algorithms in their late stages. When it comes to solving classification and regression problems, supervised learning is superior to unsupervised methods [43-45]. Algorithms can be trained using supervised learning to ensure they are optimally prepared for their intended usage. You have complete control over the training data, so all you need is enough time and input to calibrate the algorithms properly. Large-scale input should be the primary emphasis of the compilation process. It's a lot of effort for programmers and scientists to apply supervised learning since everything needs a label. There is a lot of work to be done, but the process may be easily understood. Supervised learning clearly states what the computer will do, but unsupervised learning leaves open questions since the algorithms function autonomously without genuine supervision. The disadvantage of this is that the trained algorithms are limited by the parameters with which they are provided. It might be challenging to anticipate creative responses [46].

2.2 Unsupervised ML

To put it more succinctly, this method of learning makes use of an artificial neural network to investigate a large amount of data in order to recognize contexts, patterns, and similarities among data. This approach is comprised of a number of distinct stages. One of the approaches that may be applied in this type of education is known as group analysis or clustering. Before eventually allocating the groups to the data, the algorithms in this scenario are the ones in charge of generating them on their own. During the unsupervised analysis, the software may, for instance, place all of the photographs of malignant and non-cancerous tumors into one group, and then place all of the images of non-cancerous tumors into another group. In contrast to supervised learning, unsupervised learning does not have any preset categories. In unsupervised learning, computers come to these conclusions on their own based on the similarities and differences in the photos. In this particular scenario, the algorithm combines the data before sorting it based on the features they have in common. Mapping is another approach. Discovering linkages between things in this way is the job of the algorithms, and it does not even need there to be any resemblance between them [47-51].

"Machine learning is not only used to progress technology, but it also makes many elements of everyday life easier while simultaneously improving business, research, and daily life. In contrast to the other two learning procedures (monitored and reinforced) developers are not involved in the actual training process. This may save time, but it also has additional benefit that makes it simpler to spot patterns that were previously unseen. Because of this, it is possible for algorithms to come up with unique concepts through unsupervised machine learning” [52-54].

2.3 Reinforcement ML

In contrast to the other two methods, reinforcement learning does not require the prerequisite data in order to function properly. Instead, they are constructed and tagged in a simulation environment over the process of training, which takes place over the course of several runs. Artificial intelligence can now solve complex control problems thanks to a technique called reinforcement learning, which eliminates the requirement for prior human experience [55-57]. When compared to conventional engineering, this type of problem may be handled far more quickly, with greater efficiency, and in an ideal scenario, even more successfully and ideally. Leading experts in artificial intelligence research have pointed to a technique known as reinforcement learning (RL) as a method that shows potential for developing AI. Reinforced learning is primarily focused on acquiring knowledge by participation in various activities that include contact with one's surroundings. The solution to any difficulties involving reinforcement lies on determining the most helpful guidelines or value functions. The problem that has to be solved has direct repercussions for the representation of a policy as well as the technique of reinforcement learning that is going to be implemented [58].

Reinforcement learning may be used to teach a software agent how to autonomously learn a strategy using a variety of different methods.

The goal of the learning process is to achieve one's full potential within a setting that is representative of the real world. Once a new time step is reached in the training process, the agent will do activities inside this environment and will get feedback on those actions. The software agent does not know in advance which line of action will be the most effective response to any given set of circumstances. Instead, the agent is compensated at predetermined intervals during the process. During training in the simulated world, the agent develops the capacity to evaluate the impact of actions given certain situations. On the basis of this information, the agent can devise a long-term strategy to maximize the payout [59,60].

3. HEALTHCARE APPLICATIONS OF AI AND MACHINE LEARNING

“Using wearables and mobile apps, an increasing number of individuals are keeping track of their own health information. Using this data and running it through an AI system can be highly advantageous. Scientists and practicing physicians are investigating rare inherited diseases and previously undiagnosed medical disorders with the aid of data science, as well as creating novel prevention strategies” [61,62]. “Without intricate data analysis, new diagnostic techniques for tailored therapy are typically not feasible. These algorithms can be used by medical experts and support experts to make the images from radiographs, nuclear medicine procedures, magnetic resonance tomography scans, or ultrasound of organ systems (brain, lungs, skin, fundus, etc.) even more precise, quick, and reliable to analyze” [63]. “Medical procedures for diagnostic imaging are already benefiting from AI algorithms today. AI-based solutions for patients may also provide them with more autonomy. Wearables give kids the ability to create their own health goals, track them, and use them as a foundation for a healthier way of life. With direct access to personal information, the person has more information at their disposal to assess therapeutic alternatives or perhaps even do a preliminary self-examination. Long-term, AI holds the potential toeffectively analyzing vast volumes of data and producing new ones that produce knowledge, such as in epidemiology, the study of the relationships and distributions of diseases and risk factors in the population. There are also new possibilities for the early diagnosis of diseases by looking at an organism's phenotypic, proteome, genome, or genetic makeup of its cells or microbes (microbiome). Vital indicators like blood pressure and blood sugar are also easier to monitor and manage” [64-67].

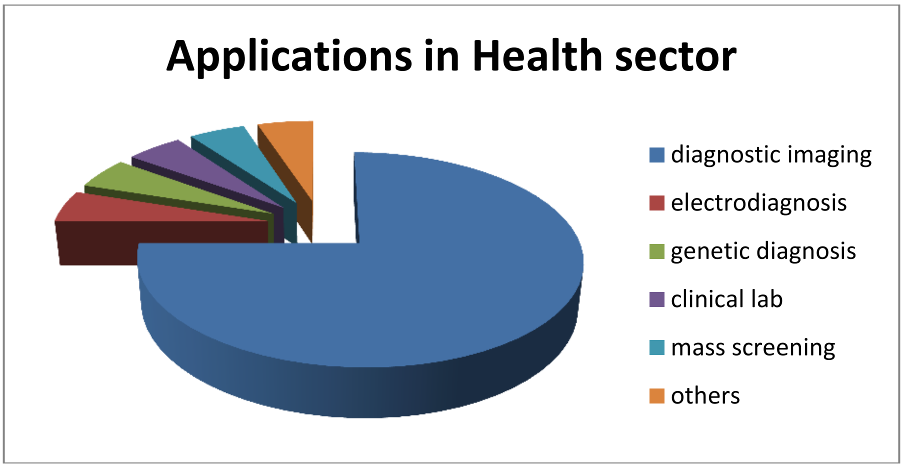

Fig. 3. Some applications of AL in the health sector

Table 1. ML teachnques and application in the health sector

ML techniques	Application	References
Convolutional neural networks (CNN)	Medical imaging data analysis and Medical images clinical variables analysis	[70]
Artificial neural network (ANN)	Speech recognition, clinical diagnosis, cancer prediction, and duration of stay prediction	[71,72]
Logistic regression	Diagnosing heart disease	[73]
Deep neural network (DNN)	Medication adherence predictor in heart failure	[74,75]
Decision tree	Predict the likelihood of a patient's readmission	[75]
Recurrent neural network (RNN)	classification of Medical data	[76]
K-nearest neighbor (KNN)	Sentimental analysis for positive and negative reviews of the patients	[77]

"Instead of offering a simple black-or-white choice, AI systems evaluate the likelihood of an event occurring based on a model of reality. Even well-trained models, nevertheless, can only accurately represent reality to a certain extent. As a result, an AI algorithm is unable to make an independent judgment. The outcome shows that the necessary steps must be taken by the medical and nursing staff. The advantages of AI for healthy people as well as for various sick groups are demonstrated by the examples below. The distinctions between the categories are illegible. A patient may occasionally fall under more than one category.For instance, a stroke is an acute sickness although it typically develops as a result of chronic symptoms. AI has the ability to identify diseases at an early stage, minimizing negative patient outcomes. Machine learning might offer fresh perspectives on health data. The artificial intelligence discovers connections and patterns in the data. The database grows the amount of data that is available for machine learning as soon as it does. This could help patients determine their risk of developing future illnesses and, if necessary, alter their health-related behaviors" [68,69].

3.1 Health Monitoring and Prognosis

It is projected that artificial intelligence technologies would be utilized more frequently in preventative medical tests in order to assess health data and indicate potential concerns. This would make the identification of risk groups for certain diseases as well as focused testing and screening possible much more quickly. Examinations by the physician are probably going to be the best course of action in this particular scenario. Particularly helpful for the early detection of disorders is AI. In point of fact, it may be difficult to identify uncommon diseases in their early stages due to the minor symptoms they present with [78]. “A smart phone app was recently created by researchers working on the EU project I-PROGNOSIS to enable the early diagnosis of Parkinson's disease. They are currently gathering data from both healthy and ill study participants as part of the research study; routine activities like holding a smartphone, making calls, and taking photos are recorded as data in a Cloud. The behavior is examined using machine learning techniques, and the user is urged to see a doctor if there are any anomalies” [79].

Individual recommendations for a patient's lifestyle adjustments might be made through learning systems, which would also assist the patient in self-management. Wearables are anticipated to play a significant part in this and pose new concerns regarding how people and technology interact. Wearables can offer continuing risk assessments, assist in establishing objectives for a healthier way of life, and help develop training programs. Global models could be trained using the local data gathered from end devices. Afterward, recommendations can be produced for taking action on several levels (e.g., individually, regionally, and globally). Distributed machine learning, in which various computers share their artificial intelligence training, is what it is called [80].

3.2 Care for the Severely Ill

A growing amount of artificial intelligence is being used to treat individuals who are in an acute state of illness. Imaging methods, carcinomas, metastases, and proximity to areas that are suspected to be carcinogenic are some of the ways that practitioners in the field of oncology might more swiftly identify abnormalities. The underlying method makes use of technology that is based on deep learning, and the algorithm identifies places in the picture data that may be suspect. Since doctors no longer have to manually evaluate the imaging data, they enjoy significant time savings. The expressiveness of the images can also be improved with the help of AI. The tremendous potential offered by the implementation of artificial intelligence in cancer detection is seeing rapid expansion at the moment. The "AI in Pathology" effort will begin using AI to enhance colon cancer therapy and diagnostics in November of 2018 and will continue through October of 2020. A support system performs analysis on tissue samples that have been obtained during colonoscopies. It detects irregularities, assesses the likely progression of the condition, provides dietary supplements if they are required, and provides further digital analytical data [81]. In a research that was published in 2019, 157 dermatologists from twelve university clinics in Germany fought against a computer to determine who was better at detecting skin malignancies. 136 patients had their conditions properly identified by the system, as opposed to by human doctors [81].

3.3 Chronic Illness Therapy

Many persons who have a condition that is considered to be chronic are need to take medicine for the rest of their lives. Intelligent technology can help in the administration of medication and the determination of the proper dosage, therefore reducing stress and the likelihood of bad effects. If a person has diabetes, for instance, altering their diet, taking medication, or seeking medical treatment will all increase their need for insulin. Investigation into so-called closed-loop glucose systems is now under done with the goal of developing self-sufficient systems that can function in place of the pancreas. With such an intelligent system, an algorithm continually obtains data from a sugar-measuring device and runs an insulin pump based on this information to enable for continuous modifications to be made to blood sugar management [82,83].

Pure mental problems are usually persistent as well, and a physical illness that lasts for a long time frequently leads to a psychological illness, which adds to the stress that the patient and his family are already under. Artificial intelligence has the potential to assist in the identification and treatment of psychological issues at an earlier stage. It is possible for it to provide information that the patient, their loved ones, the nursing staff, or the doctor may use to treat them or, at the absolute least, to provide them with acts that are reassuring. Researchers at MIT have developed a model that is based on artificial neural networks and has the potential to identify depressive changes based on changes in speech patterns. The model was constructed with the use of data gathered from 142 clinical interviews. This would enable the development of at least one application for smart phones possible; the user's text and speech would be analyzed in search of strange patterns and any signals of aberrant behavior [84].

3.4 Respite Care

Several senior living institutions have transitioned to keeping records digitally, and outpatient care facilities are also increasingly using digital recordkeeping methods. At the same time, there is a growing trend among nurses towards an interest in contemporary technological developments. The costs of acquisition and maintenance are still considered to be of a pretty large amount. Caring for humans, on the other hand, is inherently a very complicated process that cannot be easily mechanized. This is due to the fact that human empathy and attachment will never be totally replicated by robots. In the care industry, which is even less digitized than other parts of the health industry, there are already potential uses for artificial intelligence. For example, it's feasible that care records may be supported by voice recognition software that's powered by artificial intelligence. This could make the difficult process a little easier to handle. The most recent discoveries of research in the field of robots supported by artificial intelligence that will be used to restore motor function following neurological disorders are also quite encouraging. The patient's specific information may be used in conjunction with learning processes to develop an optimal and adaptable training program for the patient [85-87].

“The Robotics Innovation Center at the German Research Center for Artificial Intelligence (DFKI) made a breakthrough in rehabilitation robotics with the RECUPERA project. The project participants created a mobile exoskeleton for upper body assistance with Rehaworks GmbH that is specifically made for stroke rehabilitation therapy” [88]. “Robots powered by artificial intelligence (AI) may one day assist in the rehabilitation of stroke victims by analyzing bio-signals (such as the activity of the brain and muscles or the direction of a view) in conjunction with environmental conditions. After a stroke, when motor skills are impaired, these systems detect movement intentions and redirect them. For instance, the patient might no longer be able to raise his right arm; the AI analyses brain activity and can utilize it to identify the issue and apply a robotics-based fix. Stroke victims will recover their motor abilities more quickly and rehabilitation will be successful. Such rehabilitation robots exhibit the great performance of learner systems because they need to process massive quantities of data quickly and effectively while consuming incredibly little energy so that they may be controlled via biosignals” [89].

3.5 Future Perspectives

AI may have a significant impact on future healthcare options. It is the most important capacity that underpins the development of precision medicine, which is unanimously regarded to be a vitally needed advance in the field of healthcare. Machine learning is one implementation of artificial intelligence. Despite the fact that early attempts to provide suggestions for diagnosis and therapy have proven challenging, it is anticipated that AI will eventually become proficient in that sector as well. With the fast developments being made in artificial intelligence for imaging analysis, it is possible that the majority of radiology and pathology pictures may soon be examined by a computer. Speech and text recognition may become more widely used in the future for a variety of applications, including patient communication and the transcription of clinical notes. The greatest challenge that artificial intelligence faces in a variety of areas of the healthcare industry is not deciding whether or not the technologies will be sophisticated enough to be useful; rather, it is ensuring that they will be accepted in ordinary clinical practice. It is necessary for AI systems to receive approval from regulatory bodies, to be incorporated with EHR systems, to be sufficiently standardized so that similar products function similarly, to be taught to clinicians, to be paid for by public or private payer organizations, and to be improved over time in the field. Only then will they see widespread adoption. These challenges will one day be overcome, but doing so will need a great deal more time and effort than it will require for technological progress to occur. As a result, it is projected that there will be some use of AI in clinical practice over the next five years, with this use becoming more common during the next ten years. In addition, it is becoming more and more evident that AI systems will not significantly replace human physicians in the field of patient care; rather, they will help human clinicians. In the long run, it's possible that human physicians would gravitate towards tasks and work arrangements that make use of uniquely human talents such as empathy, persuasion, and integration of the bigger picture. Individuals in the medical field who refuse to work in conjunction with artificial intelligence run the risk of being the sole ones to find they unemployed in the not too distant future.

4. CONCLUSIONS

ML has the potential to become an extremely useful tool in the hands of any medical professional, scientist, or researcher. It seems as though there is a new development in machine learning every single day. With each new development comes a novel application of machine learning (ML) that has the potential to solve a practical problem in the medical field. As machine learning technology continues to advance, this trend is being carefully monitored by the medical industry. Ideas from machine learning are being utilized by medical professionals to assist in the saving of lives, the early detection of illnesses and other health problems even before they manifest, improved patient management, more patient participation in the healing process, and a great deal more. Global enterprises are able to improve the delivery of healthcare by utilizing AI-driven solutions and machine learning models. Because of this technology, pharmaceutical firms and other enterprises are able to develop treatments for major ailments in a more rapid and effective manner. Businesses now have the ability to expedite their testing and observation processes by making use of techniques such as pattern recognition, sequencing, and virtual clinical trials. Health practices and socioeconomic factors such as income, social support networks, and level of education are also major determinants of overall health. In order to improve overall health, health organizations are aware that they need to focus on the "whole individual," which includes lifestyle choices and the surrounding environment. It is possible that ML models will act as the primary tools that will be used to identify individuals who have a higher risk of developing chronic diseases that may be treated, such as diabetes, heart disease, and others.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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DOI: 10.1145/3394486.3406461

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/98566