Artificial Intelligence/ Machine Learning In Health Sector: a review of the Current Status and Future Perspectives.

Abstract:

The developing fields of artificial intelligence (AI) and 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. All in all, AI/ML is a component of contemporary healthcare, and its further adoption is contingent on thoroughly addressing pertinent issues.

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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. By looking at a collection of images including various people, an ML system may be able to identify faces[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]. Modern technology has long been strongly backed by the healthcare sector. As they have in business and e-commerce, AI and ML have numerous uses in the healthcare sector[5, 6]. With this technology, the possibilities are almost endless. By using its cutting-edge applications, ML is helping to improve the healthcare sector. Due to mandated practices like electronic medical records, healthcare systems have already embraced big data tools for next-generation data analytics (EMR). ML tools are expected to enhance this process even further. In primary/tertiary patient care and public healthcare systems, these enhance the quality of automation and intelligent decision-making. As it can enhance the quality of life for billions of people worldwide, this may be the most significant effect of ML techniques[7-9].

There are several ways to employ ML technologies to enhance clinical trial research[10]. Medical personnel could assess a wider range of data by applying advanced predictive analytics to clinical trial applicants, cutting down on the cost and duration of necessary medical tests. Many ML applications can help determine the best sample sizes for clinical trials in order to maximize their effectiveness and minimize the likelihood of data errors by using electronic health records (EHRs)[11]. The scarcity of highly qualified radiologists across the globe is addressed by this strategy, which is a serious problem in the healthcare industry[12]. By merging personal health with predictive analytics, ML in the healthcare industry can provide individualized medicines that are more dynamic and effective. There are numerous possible uses for ML in research and clinical studies[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, it 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 of which contribute to the decrease in data-based errors[14]. Medical imaging data that has been electronically stored is widely available nowadays, and a number of 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 hemorrhage. 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 as well as or better than humans[16-18]. Today, algorithms already surpass radiologists in identifying cancerous tumors and advising researchers on how to create cohorts for expensive clinical trials. Nonetheless, we think it will 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?

Comment [DSARM4]: You mention the advantage of ML In Health, what about disadvantage

Healthcare services are getting better all the time, and we're getting better at treating complicated conditions. The dosage and duration of medicines depending on patient characteristics or for patient groups with scant clinical research, including children, remain major issues, though[20]. Hence, ML has been successfully included into pediatric care in recent years to foretell the finest and most individualized treatments for kids[21]. Since the COVID-19 pandemic's emergence, ML has come into the public eye. Organizations are using ML to boost 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]. One of the most intriguing areas of AI is machine learning, and many businesses are working to take advantage of it. ML is growing more and more well-liked. It uses algorithms to enable data-driven learning and is applicable in a variety of settings, including business and healthcare. Because new technologies and ideas are continuously being developed, healthcare is continually changing. In some of these novel situations, ML could help medical experts. With the help of modern technology, unstructured text that was once difficult to produce and use extensively can now yield valuable insights. Physicians and administrators may make timely, educated decisions about patient care and operational programmers that impact millions of lives with the help of this new richness of ML-derived intelligence[24-26].

Applications for machine learning (ML) can be found everywhere and are frequently used in practical settings. It is crucial in many fields, including healthcare and the safeguarding of patient data. To analyze medical records and forecast diseases, machine learning is used[27, 28].

2. Types of Machine Learning In Health Care sector:

Comment [DSARM5]: Style

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. An important component of artificial intelligence is machine learning. A significant amount of sample data is needed, and then, using sophisticated algorithms and pattern recognition, models are created. These models can then be improved and used in uncharted territory[29-31].

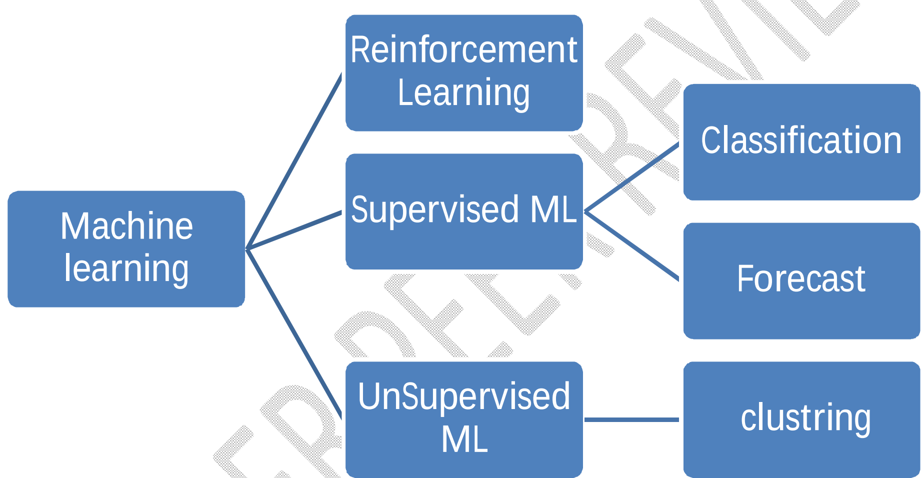

Figure 1 Machine learning

The learning styles of supervised, unsupervised, and reinforcement learning are fundamentally different from one another. For each of the three learning types, several techniques and strategies are employed. Deep learning has recently gained significance in this context due to its capacity to discern intricate big data patterns[32-34].

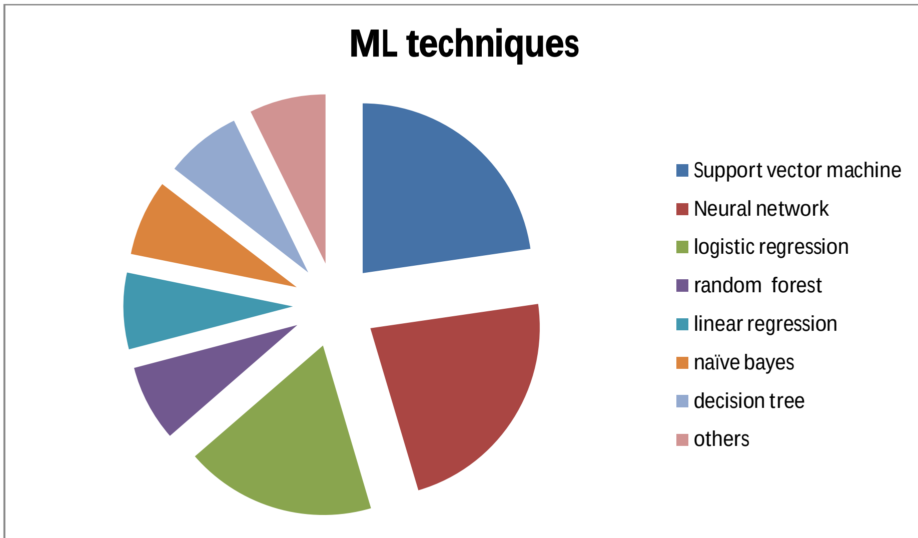

Figure 2 most common ML techniques in Health care sector

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 categories natural data using supervised learning (photos, handwriting, language, etc.). Moreover, one prominent area of application for supervised learning is so-called regression problems. Based on particular habits, the computers ought to be able to forecast things like consumer health [35-37].

Assume for the moment that someone wants to train algorithms to tell cancerous tumors from 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. It is crucial that the data collection displays the most variance possible. Simply said, the algorithm will assume that all tumors are malignant if your training set solely contains scans of benign tumors. Hence, the data set should attempt to map the real range of variations[38-40].

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 latter tasks of the algorithms strongly influence the training strategy to be used. In comparison to the other approaches, supervised learning is more effective for categorization and regression issues[43-45]. In general, monitored learning can be used to train algorithms so that they are completely ready for the application domain. The training materials are entirely under your control, so all you need to establish the algorithms right is enough input and time. The compilation must be done on a massive scale, with input clearly the focus. For developers and scientists, supervised learning requires a lot of work because each piece needs to have a name. Although there is a lot of work involved, it is quite simple to comprehend what is happening. While unsupervised learning leaves a lot of questions unanswered because the algorithms operate on their own without any real guidance, supervised learning clearly defines what the machine will accomplish. The trained algorithms then have to operate within the constraints that have been placed on them, which can be a drawback. You can't expect original answers[46].

2.2.Unsupervised ML:

Simply said, this learning technique employs an artificial neural network to examine a lot of data and identify contexts, patterns, and similarities across data. This technique is built on various steps. Group analysis or clustering is one of the methods utilized in this kind of learning. In this instance, the algorithms are in charge of creating groups on their own before finally assigning them to the data. For instance, the programme might categories all images of cancerous and non-cancerous tumors into one group during unsupervised analysis and all images of non-cancerous tumors into another. In contrast to supervised learning, this classification is not predetermined. Based on the similarities and differences between the photographs, algorithms independently make these decisions in unsupervised learning. The system mixes the data for sorting in this example according to the properties they share. Another way is mapping. Algorithms' task is to discover associations between items in this way, without requiring any similarity between them [47-51].

Machine learning is not only used to advance technology; it also makes many aspects of daily life easier while enhancing business, research, and daily living. Developers are not involved in the actual training process, in contrast to the other two learning approaches (monitored and reinforced), which could save time but also has another benefit that makes it easier to recognise patterns that were previously invisible. Algorithms can therefore generate original ideas based on unsupervised machine learning[52-54].

2.3.Reinforcement ML:

The prerequisite data is not necessary for reinforcement learning, in contrast to the other two techniques. Instead, during training, they are created and labeled in a simulation environment over the course of numerous runs. Reinforcement learning makes it possible for artificial intelligence to tackle complicated control issues without the need for prior human knowledge [55-57]. Such problems can be resolved several times faster, more effectively, and, in the ideal case, even optimally as compared to conventional engineering. RL is cited by top AI researchers as a strategy that holds promise for creating artificial intelligence. Learning through interactions with the environment is essentially what reinforced learning is all about. Finding the best guideline or value functions is the key to solving reinforcement problems. The problem that needs to be solved directly affects the representation of a policy and the reinforcement learning technique to be applied[58].

A software agent can independently learn a strategy through a variety of different techniques called reinforcement learning, as shown in Figure 3. Maximizing the benefits in a simulated environment is the aim of the learning process. Every time a time step is reached during training, the agent does activities within this environment and receives feedback. The optimum course of action in each circumstance is not revealed to the software agent beforehand. Instead, at specific periods, he is rewarded. The agent gains the ability to evaluate the effects of actions given circumstances in the simulated environment during training. He can create a long-term strategy to optimize the payoff based on this [59, 60].

3. Healthcare Applications Of AI And Machine Learning

Using wearable’s 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 tomographies, 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 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 of effectively 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].

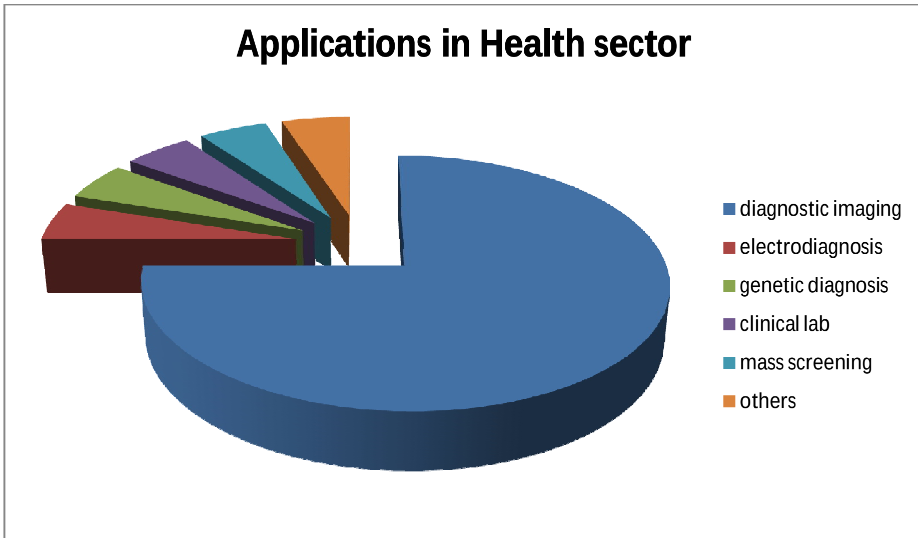

Figure 3 some applications of AL in health sector

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. Instead, 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].

Table 1ML teachnques and application in 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]

3.1.Health Monitoring and Prognosis

AI technologies are anticipated to be used more frequently in preventive medical exams to analyze health data and highlight potential hazards. This would enable quicker risk group identification for specific diseases as well as targeted testing and screening. Exams by the doctor might be the ideal solution in this case. In particular, AI can help in the early diagnosis of illnesses. In fact, it might be challenging to spot rare diseases early on from their mild symptoms[78].A smartphone app was recently created by researchers working on the EU project

I-PROGNOSIS with the goal of enabling 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. It can offer continuing risk assessments, assist in establishing objectives for a healthier way of life, and help develop training programmes. Global models could be trained using the local data gathered from end devices. Afterwards, you may produce recommendations 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:

Acutely unwell patients are being treated with an increasing amount of AI. In oncology, clinicians can more quickly spot anomalies by using imaging techniques, carcinomas, metastases, or nearby locations thought to be carcinogenic. The underlying process uses deep learning-based technology, and the system flags questionable spots in the image data. Physicians save important time by not having to manually assess the imaging data. AI can also aid in enhancing the photographs' expressiveness. The enormous potential of enabling artificial intelligence in cancer diagnosis is currently rising quickly. From November 2018 to October 2020, the "AI in Pathology" initiative will use AI to support colon cancer therapy and diagnosis. Tissue samples from colonoscopies are analysed by a support system. It finds anomalies, evaluates the potential disease course, supplements if necessary, and gives extra digital analysis data [81]. In a 2019 study that was released, 157 dermatologists from twelve German university clinics competed to identify skin cancers versus a computer. 136 cases were correctly diagnosed by the machine rather than by humans [81].

3.3.Chronic Illness Therapy

Many people who have a chronic illness must take medication for the remainder of their lives. Intelligent technologies can assist in medication administration and dosage determination, reducing stress and adverse effects. For instance, if you have diabetes, changing your diet, taking medicine, or getting medical attention will raise your demand for insulin. To create autonomous systems that can replace the pancreas, so-called closed-loop glucose systems are currently being explored. An algorithm in such an intelligent system continuously retrieves data from a sugar-measuring device and operates an insulin pump based on this information to allow for continuous blood sugar management adjustments[82, 83].

Pure mental disorders are also frequently persistent, and a chronic physical sickness frequently leads to a psychological one, increasing the strain on the patient or his family. AI has the ability to support treatment and early psychological problem diagnosis. It can give information that the patient, their loved ones, the nursing staff, or the doctor can use to treat them or at the very least take comforting actions. An artificial neural network-based model that may identify depressive changes based on speech patterns has been created by MIT researchers. 142 clinical interviews' worth of data were used to build the model. This would make one smartphone application conceivable; the user's text and speech are evaluated for unusual patterns and any indications of abnormal conduct[84].

Comment [DSARM6]: What is the mechanism of action

3.4.Respite care:

Digital records are now kept in many senior living facilities, and outpatient care facilities are also increasingly embracing this technology. Nurses are becoming more and more interested in the latest technology at the same time. Costs associated with acquisition and upkeep are still relatively significant. However, because human empathy and affection cannot be fully substituted by robots, caring for humans is fundamentally a very complex process that cannot be simply automated. There are already interesting applications for artificial intelligence in the care sector, which is even less digitalized than other health sector sectors. For instance, it's possible that speech recognition powered by AI might support the care records. This can make the laborious procedure even simpler. The most recent research findings in the area of robots backed by AI that will be utilised to restore motor function after neurological illnesses are also highly encouraging. Learning processes can design an ideal and flexible training programme for the patient based on personal data [85-87].

Comment [DSARM7]: How to protect this data and its cofedentiality

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].

Future Perspectives:

In our opinion, AI will have a significant impact on future healthcare options. It is the main capability underlying the development of precision medicine, which is universally acknowledged to be a critically needed improvement in healthcare. It takes the form of machine learning. Although early attempts at making recommendations for diagnosis and therapy have been difficult, we anticipate that AI will eventually become proficient in that field as well. It appears likely that the majority of radiology and pathology images will eventually be reviewed by a computer given the rapid advancements in AI for imaging analysis. It will become more common to use speech and text recognition for purposes like patient communication and clinical note transcription.Not determining whether the technologies will be capable enough to be beneficial, but rather guaranteeing their acceptance in routine clinical practise, is the biggest hurdle for AI in various healthcare sectors. In order for AI systems to be widely adopted, they need to be endorsed by regulatory bodies, integrated with EHR systems, sufficiently standardized so that similar products function similarly, taught to clinicians, paid for by public or private payer organizations, and improved over time in the field. These difficulties will eventually be resolved, but it will take considerably longer than it will for the technology to advance. We therefore anticipate modest AI usage in clinical practice by 5 years and more widespread use within 10 years.Furthermore, it is increasingly obvious that AI systems will not substantially replace human clinicians in patient care but rather support them. Human physicians may eventually gravitate towards duties and work arrangements that make use of particularly human abilities like empathy, persuasion, and big-picture integration. Those healthcare professionals who refuse to collaborate with artificial intelligence may end up being the only ones to lose their professions in the future.

Discussion

Comment [DSARM8]: Where is the discussion

Conclusions:

In the hands of any doctor, scientist, or researcher, ML has the potential to be a potent tool. There appears to be a breakthrough in machine learning every day. With every innovation, a fresh machine learning (ML) application appears that can address a real healthcare issue. The medical sector is closely monitoring this trend as ML technology continues to progress. Doctors and surgeons are using ML ideas to help save lives, identify diseases and other issues even before they manifest, better manage patients, involve patients more fully in the healing process, and do a lot more. Utilizing AI-driven solutions and machine learning models, global organizations enhance healthcare delivery. This technology helps businesses and pharmaceutical companies create therapies for serious illnesses more quickly and efficiently. By employing virtual clinical trials, sequencing, and pattern recognition, businesses may now quicken their testing and observation procedures. Other significant predictors of general health include health behaviors and socioeconomic elements including money, social support networks, and education. Health organizations understand that they must address the full individual, including lifestyle and environment, in order to enhance general health. ML models can identify people who are more likely to get chronic, treatable diseases like diabetes, heart disease, etc.

Recommendations

Comment [DSARM9]: Where is the recommendations, and if there is any limitation to applyML in health sector

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