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Trends in using IoT with machine learning in smart health assessment

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***Abstract*---**The Internet of Things (IoT) provides a rich source of information that can be uncovered using machine learning (ML). The decision-making processes in several industries, such as education, security, business, and healthcare, have been aided by these hybrid technologies. For optimum prediction and recommendation systems, ML enhances the Internet of Things (IoT). Machines are already making medical records, diagnosing diseases, and monitoring patients using IoT and ML in the healthcare industry. Various datasets need different ML algorithms to perform well. It's possible that the total findings will be impacted if the predicted results are not consistent. In clinical decision-making, the variability of prediction outcomes is a major consideration. To effectively utilise IoT data in healthcare, it's critical to have a firm grasp of the various machine learning techniques in use. Algorithms for categorization and prediction that have been employed in the healthcare industry are highlighted in this article. As stated earlier, the purpose of this work is to provide readers with an in-depth look at current machine learning algorithms and how they apply to IoT medical data. We found that several ML prediction algorithms had various flaws after a comprehensive investigation. Predicting crucial healthcare data from IoT datasets necessitates selecting the best approach for the dataset in question. Some examples of IoT and machine learning are also included in the article.

***Keywords*---**IoT, ML, health prediction system, classification, prediction, supervised learning.

Introduction

By using health prediction algorithms, hospitals may quickly shift outpatients to treatment facilities that are less crowded. Increase the number of people who obtain medical care. They do this. Using a health prediction system, hospitals can handle the problem of unexpected shifts in patient flow. Emergency situations

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like ambulance arrivals during natural catastrophes and traffic accidents, as well as routine outpatient demand, boost the need for healthcare services in many hospitals [1]. Real-time data on patient flow is critical to ensuring that hospitals are able to keep up with demand, although neighbouring institutions may have a lower volume of patients. Internet of Things (IoT) connects virtual computers with real-world objects to enable communication between them. It makes use of cutting-edge microprocessor processors to collect data in real time. Health care is defined as the process of identifying and treating diseases in order to maintain and improve one's overall health. Ultrasound, magnetic resonance imaging (MRI), and computed tomography (CT) scans can detect abnormalities or ruptures beneath the skin's surface. Similarly, abnormal illnesses such as epilepsy and heart attack can be tracked [2]. Healthcare institutions are struggling to keep up with an expanding population and the irregular spread of chronic conditions. In general, there's a significant demand for medical resources including physicians, nurses, and hospital beds [3]. A reduction in the burden on healthcare systems while maintaining the quality and standards of health care facilities is necessary [4]. The Internet of Things (IoT) can help alleviate some of the load on healthcare services. Medical establishments, for example, employ RFID technologies to save costs and improve services. Moreover, doctors may readily monitor the heartbeats of patients using healthcare monitoring systems, which helps them make an accurate diagnosis [5]. Various wearable gadgets have been created to provide reliable wireless data transfer. Data security is a concern for both IT specialists and medical practitioners, notwithstanding the benefits of the IoT in healthcare [6]. Many research have examined the use of IoT and machine learning (ML) to monitor individuals with medical conditions as a way to ensure the integrity and confidentiality of their medical records.

IoT and machine learning applications in healthcare systems to predict future trends

With the Internet of Things and artificial intelligence (AI), people may wear gadgets like smart bands and smart jackets that monitor their health and transmit frequent information about their state to a database that can be accessed by physicians and medical practitioners. In addition to keeping track of a patient's vital signs and organ function, these devices can also send a progress report to a designated database for review. In addition, the system gathers and reports on the presence and symptoms of pathogens. This is a significant development that will aid the healthcare system in providing top-notch treatment. Wearable monitoring and smart medicines in healthcare are a boon to patients and providers alike. Using these tools, you can keep an eye out for warning symptoms of sickness and forecast how it will progress in the future. Automatic patient and illness monitoring saves time and can step in when all doctors are elsewhere busy, as is the case in an emergency [66]. For pandemics like COVID-19, the adoption of cutting-edge technologies is essential. In order for a doctor to diagnose a patient or deliver a prescription, the wearable monitoring devices collect and transmit data. Smart pills and smart bands (IoT) can be used to monitor and gather particular data from patients during pandemics, which can then be sent into a database. These gadgets assist doctors and other machines (machine learning) learn illness patterns and symptoms, allowing clinicians to interpret symptoms and analyse symptoms to generate rapid and safe diagnosis.

During periods of quarantine, machine learning technology eliminates physical contact with patients afflicted with fatal airborne viruses, enhancing the safety of both the patient and health practitioners.

An important aspect of the Internet of Things (IoT) market is cloud computing. Connecting a broad range of machine learning AI devices, it helps to analyse and store data Additionally, cloud computing has the ability to store a large quantity of data, which is essential to sustaining the healthcare system. Cloud computing's data-sharing features make it possible for several devices to access the same information. Cloud computing, on the other hand, is now confronted with significant difficulties that must be resolved. In order to make ML and IoT more useful in the healthcare sector, researchers may be able to take advantage of these new obstacles. Keeping personal information safe and secure is one of these issues. In the healthcare business, sensitive medical records must be guarded properly since they include protected health information for individuals (PHI). Therefore, HIPAA (Health Insurance Portability and Accountability Act) [72] has been enacted to ensure that sensitive data may only be accessed and analysed under rigorous constraints. Data mining and machine learning techniques like deep learning, which normally require a vast quantity of training data, are put to the test. In order to improve patient care, it may be necessary to share sensitive information. Artificial Intelligence (AI) may be used to protect the privacy of patients. For example, there's the concept of "federated learning" (FL). This new ML paradigm makes advantage of deep learning to train and allow mobile devices and servers to develop a shared, resilient ML model without exchanging data [73]. FL also gives researchers the ability to solve crucial challenges such as data security, data access rights, and heterogeneous access to the data. One of the drawbacks of using the cloud to store data is that a single server may be compromised if several devices are feeding into it and the generic model is being used to gather data from multiple sources. Additionally, an incorrectly trained model might have a severe impact on the accuracy of its predictions. As a result, decentralised data storage is presently one of the best practises. In terms of decentralised data storage, one technology to consider is blockchain. A variety of gadgets are available that can monitor a person's temperature, blood pressure, and pulse. They may be used to gather and store information on patients, which can aid in the diagnosing process. There are several ways in which the Internet of Things (IoT) and machine learning may benefit healthcare providers. Researchers and medical practitioners need a way to cross-examine and analyse results in real time, which is only possible with the preservation of diagnostic data and COVID-19 symptoms in a central database.

ML algorithms and classification

Artificial Intelligence (AI) is closely linked to the phenomena of machine learning (ML). With ML, a system is given the capacity to analyse and comprehend a variety of inputs on its own, without the assistance of a human [22]. Training and testing are two of the most important parts of developing an effective machine learning model. Unlabeled inputs and labelled inputs are sent to the system during the training phase. These training inputs are subsequently stored in the feature space for future predictions. To conclude testing, the system is supplied an unlabeled input for which it must anticipate the proper outcome. In a nutshell, machine learning (ML) predicts the outcomes of unlabeled data based on known data in its feature space. Because of this, a good ML model may use its past and present data to predict future outcomes. An accurate model is dependent on the correctness of its output and on the training of its models. Recent years have seen a significant uptick in the use of machine learning systems in healthcare settings. Many clinical decision support systems use machine learning algorithms of this type to develop more advanced learning models that improve the quality of healthcare services. In healthcare service applications, support vector machines (SVMs) and artificial neural networks (ANNs) are examples of ML integration. Cancer classification programmes employ these models to accurately identify the kind of cancer. Sensor data and data from other sources are evaluated by these algorithms. Patients' behavioural patterns and medical problems can be analysed using these algorithms. Algorithms are able to recognise changes in a patient's behaviours, such as changes in their daily routine, as well as changes in the patient's eating, drinking, and digestive routines. Healthcare applications and clinical decision support systems can leverage the behavioural patterns discovered by these algorithms to provide recommendations on how patients can alter their daily habits and routines, and what kinds of treatments and care they should get. Using this information, doctors may devise a treatment plan to guarantee that their patients implement the lifestyle adjustments they've been advised to make. Models for supervised, semi-supervised, and unaided learning exist in ML technology. Figure 1 indicates that each ML type contains a number of similar algorithms. Prediction and classification using machine learning (ML) algorithms are discussed in this section. Naive Bayes (KNN), Decision Trees (DTT), Support Vector Machine (SVM), Neural networks (NN) and Gradient Boosted Regression Tree (GBR) are examples of supervised learning techniques. Section 3 will go through each of these approaches in detail. When it comes to machine learning, this paper will first present the concept of data points and labels. Data and datasets must be collected from several sources in order to build an analytic model utilising ML technology, as shown in Figure 2.

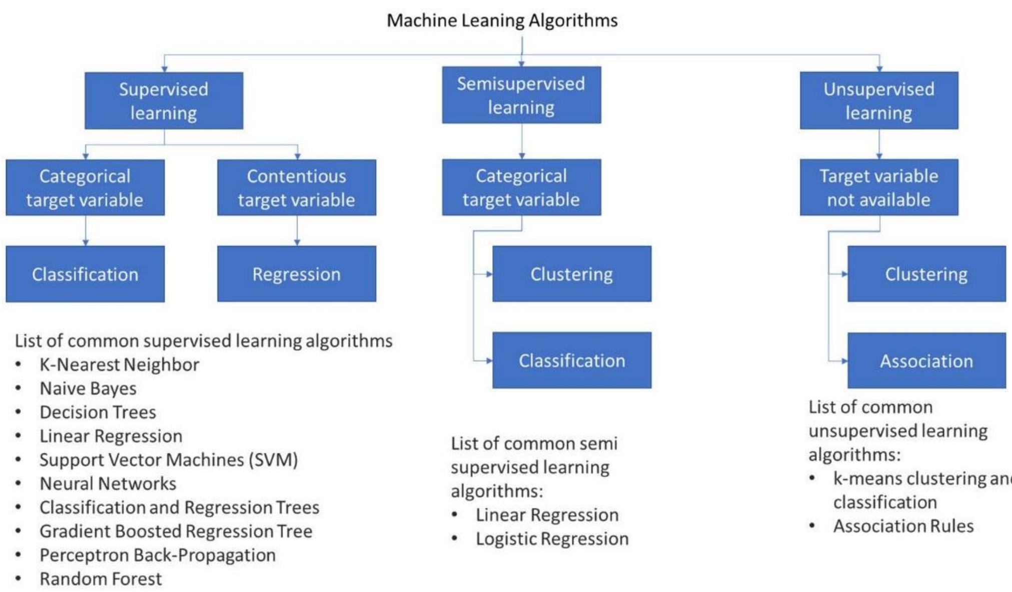

Figure 1. Machine learning algorithms' classification.

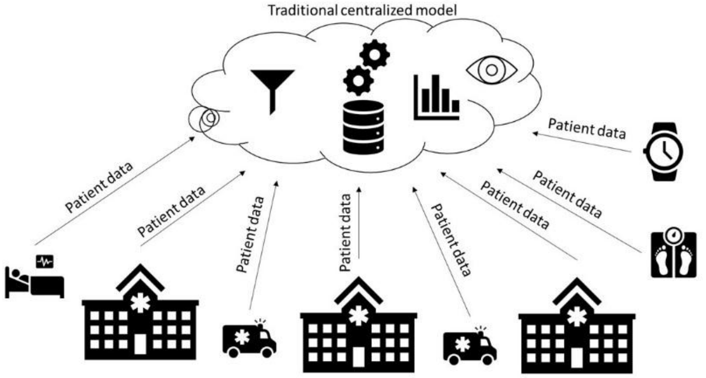

Figure 2. Traditional centralized learning: ML runs in the cloud, gathering data from different hospitals.

Commonly used machine learning methods

Researchers have created and accepted numerous well-known machine learning models for categorization and prediction. As an instance, consider the portions that follow.

- K-Nearest Neighbor (K-NN)
- Naïve Bayes Classification (NBC)
- Decision Tree (DT) Classification
- Random Forest
- Gradient-Boosted Decision Trees
- Neural Networks

Machine learning applications

Building a machine learning product begins with identifying an issue that can be solved using ML. It's no secret that the healthcare industry is rich with data. There must be an influence on patient treatment, even if a model is just for educational purposes. Table 1 provides an overview of some of the productive model-based applications that are discussed in the following paragraphs.

- Medical Imaging
- Diagnosis of Disease
- Behavioral Modification or Treatment
- Clinical Trial Research
- Records of Medical Care in the Digital Age
- Epidemic Outbreak Prediction
- Heart Disease Prediction
- Diagnostic and Prognostic Models for COVID-19
- Personalized Care

Table 1
Summary of the reviewed applications

Application Name	Brief Description	ML Algorithms
Medical imaging	The majority of today's medical imaging is still done manually, with a health care provider manually analysing pictures to look for anomalies. Automating and improving the imaging process may be achieved, however, through the use of machine learning techniques.	Convolutional neural networks (CNNs) and artificial neural networks (ANNs)
Diagnosis of diseases	Machine learning can help in clinical diagnosis by enhancing the quality and effectiveness of clinical judgements.	Image-based deep learning
Behaviour modification or treatment	The use of machine learning in behavioural change initiatives can aid in determining what works and what does not work.	Natural language processing (NLP) is only one of several machine learning and reasoning methods.
Clinical trial research	The development of machine learning algorithms capable of learning from clinical data on a continuous basis is required.	Deep learning techniques
Smart electronic health records	Using machine learning in electronic health records generates smart systems that can do disease diagnosis and progression prediction as well as assessing the risk of disease development.	Natural language processing and supervised machine learning are examples of deep learning
Epidemic outbreak prediction	Machine learning can help with disease monitoring by predicting epidemics and allowing for the installation of suitable precautions to prevent them.	The autoregressive integrated moving average (ARIMA), a deep neural network (DNN), and long short-term memory (LSTM) learning
Heart disease prediction	AI may be used to forecast cardiac disease, allowing individuals and medical professionals to create actions to reduce their risk.	Artificial neural networks and deep learning
Diagnostic and prognostic models for COVID-19	It was observed that the COVID-19 prediction models were inadequately built in this investigation.	Deep learning models
Personalized care	Person-centered care is now possible thanks to machine learning algorithms.	In-depth neural networks, deep

		learning, supervised learning, and unsupervised learning are a few examples.

Conclusion

The healthcare sector is one of the most complex in terms of the level of responsibility and strict regulations, which makes it an important and vital sector for innovations. The Internet of things (IoT) has opened up a world of possibilities in the healthcare sector and could be the solution to many problems. Applying the medical IoT will bring about great opportunities for telemedicine, remote monitoring of patients' condition, and much more. This could be possible with the help of ML models. In this article, we summarised the most powerful ML algorithms, listed some ML applications in the healthcare field, and analysed IoT and machine learning in the healthcare system to predict future trends.

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