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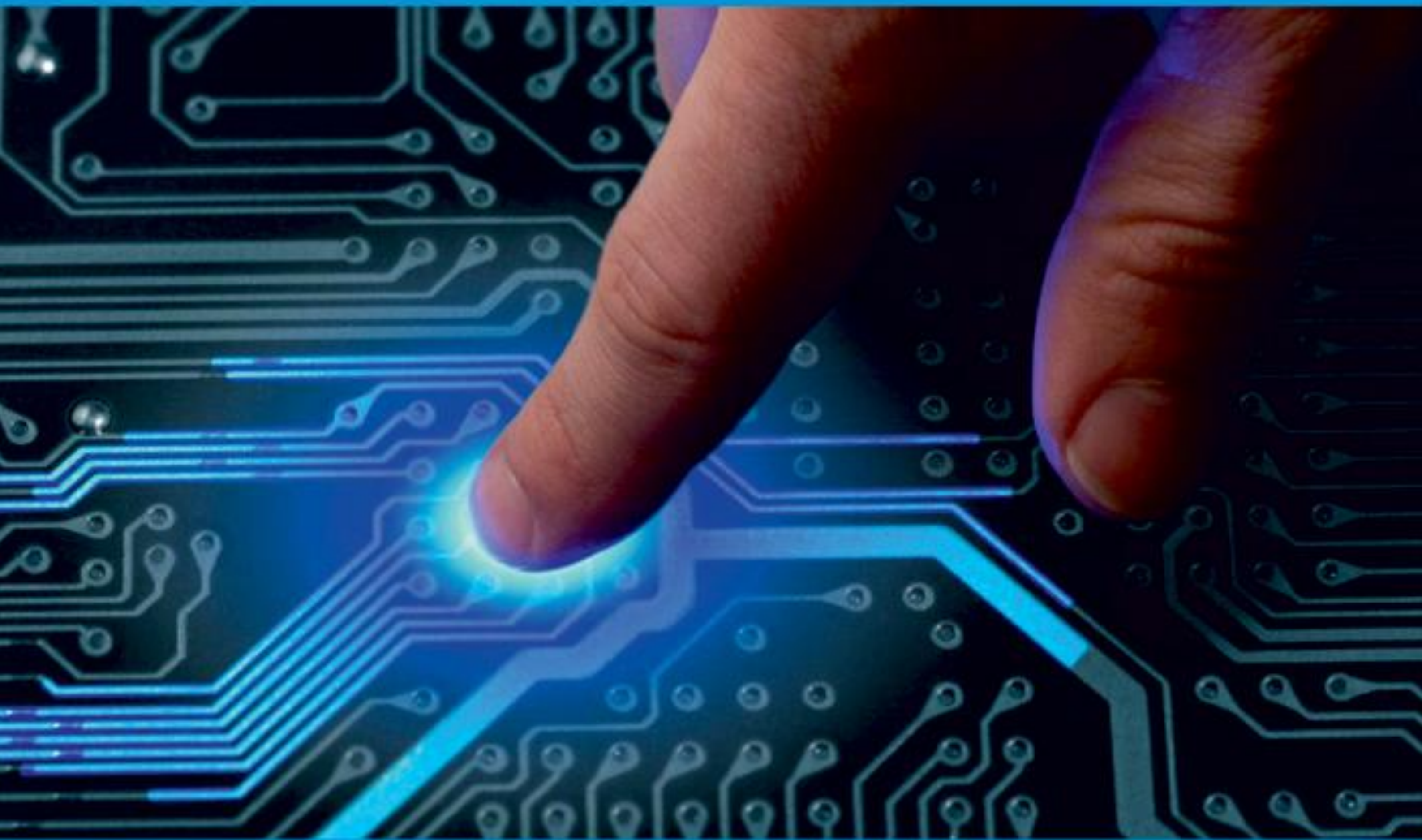

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The Review of How Machine Learning Revolutionize Healthcare Industry

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Abstract: Machine learning applications in health care are rapidly gaining traction, and they have the potential to make a big influence. The advantages of machine learning in healthcare are discussed in this research. How machine learning can be used to transform healthcare. Machine learning algorithms have made considerable advances in the realm of healthcare. This study looks at how machine learning may be used in health care. Machine learning will revolutionise health care in a few years.

I. INTRODUCTION

Machine learning has the potential to disrupt the medical industry by opening up new ways to handle healthcare data, transforming patient care, and streamlining administrative processes.[1] Machine learning has the potential to disrupt the medical industry by opening up new ways to handle healthcare data, transforming patient care, and streamlining administrative processes. [2]
There are several kindsof data in healthcare which is below:

1. First data in healthcare is an Omics data.
2. Second data in healthcare is a Clinical data.
3. Third data in healthcare is a Sensor data.

1. Omics data :
This is the first data in healthcare is the omics data. This data is a sort of high dimensional data. This data contains transcriptome , genome and proteome information.[3,4]

2. Clinical data:
This is the second data in healthcare is the Clinical data. This data contain electronic health records. This data is keep track of patient information gathered during therapy.[5]

3. Sensor data:
This is the third data in healthcare is the sensor data. This data is gathered through a variety of wearable and wireless devices.[6]
Manually handling this raw data is really challenging. Machine learning has developed as a crucial tool for data analysis. Machine learning employs a variety of statistical approaches and complex algorithms to more precisely anticipate the outcomes of healthcare data.[7] For analysis in machine learning, many types of algorithms such as supervised, unsupervised, and reinforcement are utilised. [8]

Health care is a broad phrase that refers to a system that entails the enhancement of medical services in order to meet people's medical needs. Patients, clinicians, suppliers, health corporations, and IT firms all work to save and restore health records in healthcare. [9] Over the last decade, Indian health care has been renowned as one of the world's fastest-growing industries. Machine learning is used in healthcare analysis to handle a variety of ailments such as cancer, diabetes, strokes, and so on. [10] One of the worst illnesses is cancer. Lung cancer, breast cancer, prostate cancer, stomach cancer, and other forms of cancer are all present in the human world.[11]
Public healthcare establishments do not trail far behind either. Last year, **an IDC study** among US, UK, and German hospitals showed that 50% of them already have an AI framework to support their organization. The remaining respondents planned to adopt AI/ML within the next two years. [12,13]
Using historical and real-time data, machine learning permits to create models that swiftly assess data and give outputs.[14]
Healthcare practitioners may use machine learning to create enhanced decisions about patient diagnoses and treatment alternatives, resulting in a complete enhancement in healthcare services.[15]

Because there were no technologies or tools accessible previously, it was difficult for healthcare practitioners to collect and evaluate large amounts of data for successful forecasts and treatments. It's a lot easier now with machine learning, because big data technologies like Hadoop are mature enough for widespread deployment.[16]

According to the Ventana Research Survey, 54 percent of firms are utilising or considering Hadoop as a big data processing platform to get vital insights into healthcare. Out of existing Hadoop users, 94 percent execute analyses on massive data, something they say was previously impossible.

Machine learning methods may also assist clinicians in obtaining crucial statistics, real-time data, and sophisticated analytics related to a patient's ailment, lab test outputs, family history, clinical trial data, blood pressure and so on. With these possibilities in mind, there are a number of field where machine learning may be used to alter the future of healthcare.[17]

Clinical decision support, for example, uses machine learning to assist physicians in activities that robots can accomplish better than humans. Machines outperform humans in terms of speed, boredom tolerance, endurance, and detection of events that aren't visible to the naked eye. Humans are stronger at inductive reasoning and automatically perceiving complicated patterns, such as recognising familiar faces, than other animals. We believe that we should continue to use well-designed machine learning algorithms for their intended purpose in order to fully achieve their potential. The key is for physicians to be involved in the creation of the ML systems they employ and to appreciate their limits. The doctor and the system should, in theory, perform better together than either could alone.[18]

One of ML's advantages is its capacity to "learn" how an individual's characteristics (risk variables), such as clinical and social data, may be translated into individualised risk forecasts (Alaa and van der Schaar 2018). While traditional epidemiological approaches, such as the Cox proportional hazards model, are unable to effectively combine data from a variety of sources and modalities (e.g. demographic, social, longitudinal, imaging, multi-omics), modern representation learning techniques based on neural networks can quickly and effectively learn from such diverse data to issue personalised risk predictions and update these predictions as features change over period. [19]For example, learning may be influenced by dynamic models of social interaction (Alaa et al. 2018; Xu et al. 2014), allowing researchers to anticipate whether or not a person has come into touch with a coronavirus carrier. This allows for improved distribution of testing kits, allowing those who are most likely to have been exposed to the virus to be identified and tested as soon as feasible. Disease prevention, monitoring, and detection can all benefit from such risk prediction techniques.[20]

1. **Types of healthcare dataa**

Clinical data, sensor data, Omics data, and other sorts of data are all being used in healthcare now days. This sort of data necessitates the use of various mining methods to extract the most significant elements, followed by the training of various methods for improved future prediction.[21]

1. Clinical data:

This is the first data in healthcare. Clinical data includes laboratory tests, radiological pictures, allergies, and other information obtained during a patient's continuous treatment, as well as data from the Electronic Health Record (EHR).

Clinical data is information obtained on a micro (patient care) to macro (clinical research) level for the goal of clinical research (broad applications within a health system). Clinical data can be gathered in a variety of methods, including:

- Electronic Health Records (EHRs) are essentially a patient's digital history and are often only available within a hospital system. They include everything from the patient's most recent diagnostics to any drugs they're currently taking, as well as everything in between.
- Patient/Disease Registries: These registries keep track of certain patient groups who have certain diseases or disorders. These groups' data is gathered in order to guide future research and, perhaps, improve patient outcomes. For example, the National Program of Cancer Registries collects data from local bodies to enable a better coordinated approach to cancer research.
- Data collected as part of a clinical trial, which is research into novel medication applications, treatment approaches, device testing, and other applications where data collection is required to evaluate patient results.[22]

2. **Sensor data:**

This is the second data in healthcare. Sensor data includes time series signals, which are an ordered succession of pairs produced by sensors. Computing equipment process these data pieces, which might be basic numerical or categorical values or more complicated data. The following writers are involved in sensor data research. Using data streams obtained from wearable sensors, Luca et al. [15] presented machine learning techniques to identify Parkinson's disease (PD).

Remote, patient-centered technology such as sensors and wearables have become critical components of clinical research, particularly in the age of Covid-19, when physical constraints on patients and clinical settings have hastened the development of virtual clinical trials. Beyond the pandemic, gathering high-fidelity sensor data is part of a growing trend in virtualizing clinical studies. In fact, by 2025, sensor use in clinical trials is expected to increase by 70%.

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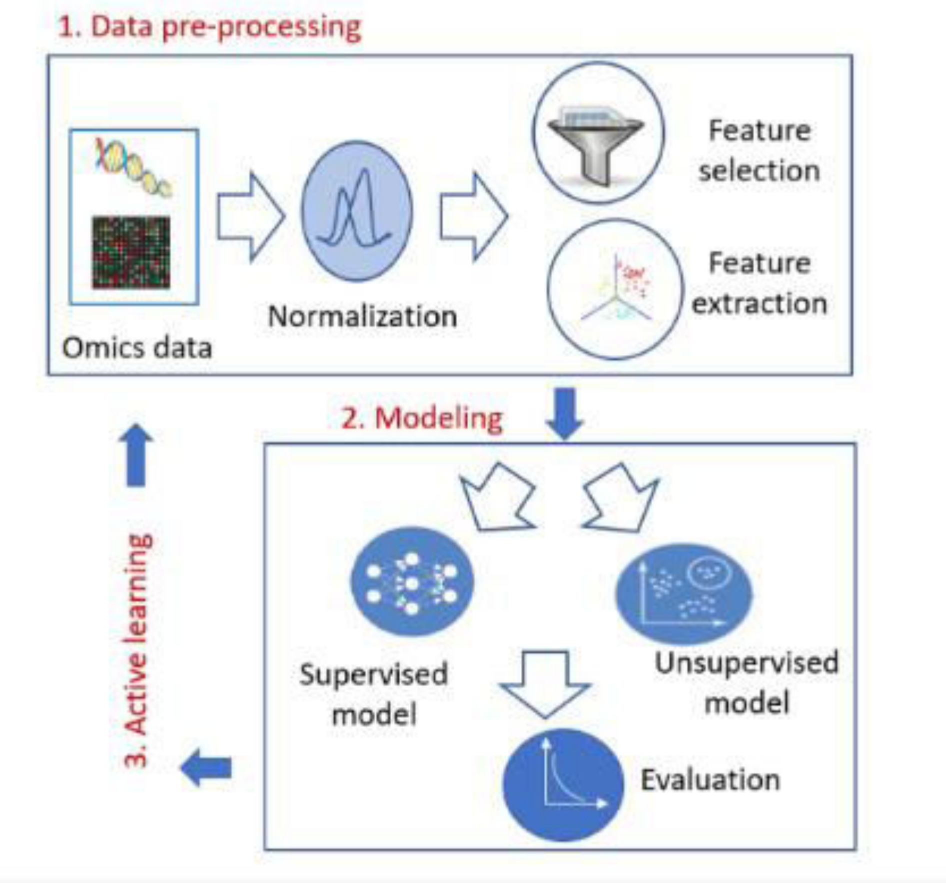
Sensors can assist measure a range of essential parameters such as respiration rate, sleeping habits, blood pressure, heart rate, and other critical health functions that were previously tracked during onsite visits and check-ins. [23]

3. **Omics data:**

This is the third data in healthcare. Omics data is a massive collection of complicated and high-dimensional data that includes genomic, transcriptomic, and proteomic information. Various strategies, including machine learning algorithms, were necessary to handle this sort of data.

In biology, machine learning analytics are employed to cope with complicated omics data and their integration. Figure depicts the machine learning analytics process for omics data. Data preparation, modelling, and active learning are all part of it.[24]



1. Data pre-processing:

First, normalisation of multiomics data is performed in order to handle data properly for analysis. Feature selection is used in the second stage to pick the subset of characteristics for modelling. The supervised techniques of Pearson correlation coefficient and mutual information are employed for feature selection, whereas the unsupervised approach of Principal Component Analysis (PCA) is applied.

2. Modeling:

A model is generated from training data using supervised or unsupervised learning, and then the model's performance is assessed using a variety of criteria. Supervised learning is a machine learning approach that infers a function from labelled data. Several machine learning algorithms are utilised to solve prediction challenges. The majority of the approaches are regression-based, such as KNN, Nave Bayes, and Neural network, SVM, and Ensemble method. The ensemble approach is the most widely utilised of all the methods. It happens when numerous models outperform a single model. Unsupervised learning is a type of machine learning in which inferences are formed from data without the use of class labels. In numerous identification challenges, clustering is the most often utilised unsupervised learning strategy. [25]

3. Active learning:

After the model has been built and evaluated, the model's uncertainty must be reduced. This is accomplished through the use of active learning, which directs the execution of subsequent experiments. Active learning was initially utilised

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in supervised situations, but it is now being used in unsupervised environments [7]. Active learning is mostly used to improve the accuracy of a machine learning system with a limited number of labelled training examples.[27]

4. **Genomic data:**

This is the fourth data in healthcare. In bioinformatics, genomic data is a collection of gene expression, copy number variation, sequence number, and DNA data.

5. **Transcriptomic data:**

This is the fifth data in healthcare. A collection of numerous mRNA transcripts data inside a biological sample is known as transcriptomic data. Different datasets are created by analysing and extracting these samples.[28]

6. **Proteomic data:**

This is the sixth data in healthcare.A collection of proteins expressed in the form of a cell, tissue, or organism is referred to as proteomic data. It is a depiction of the cell's real functioning molecules.

2. Machine learning applications in healthcare

ML has the power to make extraordinary improvements to the healthcare system thanks to reducing subjectivity and variability in clinical diagnosis. It has already shown promising results in helping clinicians diagnose cancer, tumors, rare diseases, and pathologies. ML-based systems can even outperform humans in certain tasks.

Diagnosis identification

As many as **a third of all healthcare AI SaaS companies** are focusing on diagnostics, partly or exclusively. With the ability to analyze data belonging to tens of thousands of past patients in seconds, machine learning can aid clinicians to correctly identify diseases and increase the quality of treatment. What's more, ML can also analyze additional data on a patient's condition, like their previous CT scans, tests, and screenings or their relative's chronic conditions to help doctors make a correct diagnosis and enable better care. [30]

Eko is a well-known example of machine learning applications in healthcare. It outperforms human physicians in detecting cardiac issues thanks to unique sensors and machine learning algorithms. Eko had a 99 percent success rate in identifying atrial fibrillation, compared to conventional practitioners' 70-80% accuracy rate. As a consequence, patients can obtain correct treatment more quickly, which can save their lives in some cases.[31]

Medical image analysis

Historically, radiologists devoted much time to painstakingly studying CT images to identify anomalies like cancer tumors or growing embolisms. But deep learning, which is a more advanced subset of ML, has the potential to change this. [32]

Deep learning in healthcare takes **medical image analysis** to the next level by enabling CT scans to be compared to hundreds of thousands of similar cases in the database and identify cells damaging the organism (like cancer cells) in a trice. It can then alert a doctor of anomalies found and even flag possible diagnoses, saving clinicians' time in the review process.[33]

For instance, **Arterys**, a cloud-based medical imaging platform, uses machine learning algorithms to create and compare pictures of blood flow. Thanks to this platform, cardiac analysis time can be cut from 40 to only six minutes.

Medical record management

Record keeping eats up a significant part of any physician's time. But using ML in healthcare can solve this issue. Along with natural language processing (NLP), which is another subset of AI, it can free physicians from many routine tasks. For instance, NLP algorithms can capture human dialogs during a patient's visit and transform them into text, so doctors no longer need to manually enter clinical notes.[34]

Besides, using NLP and optical character recognition (OCR) techniques can help unlock valuable unstructured data from EHR, allowing physicians to use this information for decision-making and analytics. What's more, these algorithms can also sort and bring clinical documentation into order while making it more suitable for machine learning purposes.

A great example is the Dutch startup **MedInReal** that provides an AI-based virtual care assistant for doctors. It helps them automate repetitive tasks and updates EHRs using NLP capabilities. Empowered by machine learning, it also identifies structured data elements, ensuring they match with medical terminology. Another example is **Google's Cloud Vision API**, which is already harnessing handwriting recognition technology to marshal information in electronic health records.[35]

Disease prediction

One of the most impressive examples of machine learning in healthcare is its usage in disease prediction. ML can help leverage patient's health information to find correlations between various patient's symptoms with an assumed

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disease. These correlations can help forecast possible health outcomes before any health conditions occur and give doctors an understanding of underlying patterns of disease.
Predicting diabetes, liver disease, and cancer at an early stage of development will probably mean that the greatest shift may be found in preventive medicine. A good example here is **IBM Watson Genomics** that associations cognitive computing with genome-based tumor sequencing to speed up the correct diagnoses of cancer.[36]

Mental health trends tracking
One of the machine learning use cases in healthcare is learning and predicting mental health issues globally or among specific demographic sectors. This analysis could help mental healthcare providers identify segments of the population most vulnerable to stressors like pandemics or natural disasters.
For instance, MIT and Harvard University researchers **used ML** to measure global pandemic mental health effects by analyzing the language people used to express their anxiety online. Their ML algorithm analyzed 800,000 online Reddit messages and found that topics of suicidality and loneliness had nearly doubled. The findings could help psychiatrists to better identify and help people whose mental health is suffering.[37]

Drug development and discovery
Deep learning in medicine can help facilitate the drug discovery process and generate new chemical structures. Together with other ML-based techniques, it has been used to assess biological activity, absorption, distribution, metabolism, and excretion (ADME) characteristics and select molecules with desirable biological activity and physicochemical properties.
A good example of this use case of ML in healthcare is the program **druGAN**. It is intended to generate new molecular fingerprints and drug designs incorporating necessary features based on predefined anticancer drug properties. It has already shown a tangible improvement in developing new drug designs with specific properties.

Clinical trials
Machine learning can improve and simplify not only a drug development process but also clinical trials. There are a lot of challenges pharmaceutical businesses face in this area. Organizing clinical trials has traditionally been a time-consuming and lengthy process with a lot of aspects to be considered.
For example.
To get reliable results, potential clinical trial candidates must be thoroughly selected based on a number of criteria (e.g., demographics, previous medical records, specific health conditions, etc.). Also, scientists must constantly monitor and analyze a huge amount of data during the trial to ensure that the drugs are safe and effective.
Applying machine learning can accelerate every stage of clinical trials and improve the accuracy of their results.
For example.
ML algorithms can help scientists choose perfect candidates for trials, analyze the information they provide during a trial in real-time, detect errors in data, and identify unexpected patterns. This can lead to enormous cost savings. But the biggest benefit is that the people who need the drugs that are being tested will be able to receive them faster.

Robotic surgery
It's currently too early to talk about surgeries solely performed by robots, but they can greatly assist doctors in manipulating surgical devices and performing certain tasks. Machine learning has been successfully used in areas like suturing automation, evaluating surgical skills, and improving robotic surgical materials and their workflow modeling.
For instance, Johns Hopkins University's smart tissue autonomous robot (STAR) has already shown that it can outperform human surgeons in some surgical operations like suturing and knot-tying.

Personalized treatment
Machine learning can help shift the focus in healthcare from a reactive to a preventive mode by providing personalized treatment plans. Being capable of identifying hidden patterns of data, ML algorithms can work around the clock and flag patients who may have health problems.
What's more,
Computer vision in healthcare applications can help doctors deliver highly personalized care based on individual patient characteristics and symptoms. This, in turn, will help lower the chances of patients suffering side effects from prescribed medicine.
For instance, **IBM Watson Oncology** already uses machine learning to analyze a patient's medical history and provide them with tailored treatment plans. This approach allows providers to improve the quality of personalized healthcare.

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First responder in epidemics

The use of machine learning algorithms in healthcare can help predict and track epidemic outbreaks. But that's not the only benefit. ML can also help decrease poor epidemic outcomes by playing the role of the first responder.

For example,

ML-based chatbots can help sort out the patients into risk groups based on the symptoms they indicate and even suggest diagnoses for the doctors to review and make decisions.

ML assistance can thus help healthcare professionals focus their time where it is most needed. Such a combination of human intelligence with the thoroughness of machine learning systems could be the best shot we have in case of future epidemics.

Patient engagement

Machine learning can improve the treatment process by increasing patient involvement and so bringing about better health outcomes. Combined with the Internet of Medical Things, ML can get more precise patient data and automate messaging alerts that trigger patient's actions at specific moments.

For instance, one successful use case is wearable non-invasive sensors that allow for continuous and convenient glucose monitoring for diabetes patients. Integration with ML can help notify patients when they need to take another insulin dose. In this way, ML can improve **patient engagement**, which naturally leads to the improvement of the overall treatment process.

These are only a few examples of harnessing the power of ML in the medical domain. Machine learning in the healthcare system has tremendous potential, yet certain challenges hinder its wide adoption. Let's take a closer look to learn more.[38]

III. LITERATURE SURVEY

Using Electronic Health Record (EHR) data, Zheng et al. [8] established a paradigm for identifying Type 2 Diabetes Mellitus (T2DM) patients. A total of 300 patient samples were collected, and 114 features were extracted, which were then subjected to several machine learning techniques such as k-Nearest Neighbor (kNN), Random Forest (RF), Decision Tree (DT), nave bayes, Support Vector Machine (SVM), and logistic regression. Based on the results, SVM delivers the best outcome, with a 96 percent accuracy.

Sumei et al. [9] created a computer assistance classification approach for diagnosing different types of brain tumours and grading gliomas by merging convolution MRI and profusion MRI data. Support vector machine recursive feature elimination (SVM-RFE), k-nearest neighbour, and linear discriminant analysis were used on samples from 102 brain tumour patients. The results revealed that SVM RFE had the best performance, with an accuracy of 85 percent for tumour classification and 88 percent for glioma grading.

For identifying high-risk surgical patients, Kristin et al. [10] established a number of machine learning techniques, including penalised logistic regression, random forest models, and extreme gradient boosted decision trees. The algorithms were trained using Pythia data, which included 194 clinical parameters such as patient demographics, smoking status, medicines, comorbidities, procedure information, and surgical patient proxies. The penalised logistic regression model, with an AUC of 0.924, generated the best results in the experiments.

Using EHR data, Maryam et al. [13] evaluated the Seattle heart failure model for the prediction of heart failure. To determine the survival score, 5044 patient samples were obtained and characteristics extracted. The authors used a Cox proportional regression model to calculate the survival score of heart patients who survived for one, two, or five years. Patients who died after five years were then excluded, and different machine learning models such as random forest, logistic regression, support vector regression, decision tree, and ada boost were used on the remaining patients. According to the findings of the trial, logistic regression performed the best, improving the AUV curve value by 11%.

On samples of 378,256 patients, Weng et al. [14] defined machine learning techniques such as random forest, logistic regression, gradient boosting machines, and neural networks for the prediction of cardiovascular risk. Following the preparation of data and the extraction of characteristics. The authors used a variety of machine learning methods and discovered that a neural network with an AUC of 0.72 mi performed the best.

3. The future of ML in healthcare

The healthcare industry welcomes the innovations brought by AI and machine learning. In 2020, AI in the global healthcare market has been valued at **$6.7 billion** and is forecast to grow among 2021 and 2028, the compound annual growth rate will be 41.8 percent.

Another important driver for massive ML adoption lies in the cost savings to the healthcare sector. According to **Accenture analysis**, by 2026, AI applications can potentially cut up to $150 billion of annual US healthcare costs.

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But there is also concern about using machine learning applications in medicine. Some market players believe that it may lead to medical staff cuts. Yet, the reality is the complete opposite. Active ML usage will help alleviate overwork among the shrinking healthcare workforce in North American countries by freeing medical staff from routine, mundane tasks.

IV. CONCLUSION

The direct influence of machine learning on health systems is the focus of this research; however, the indirect implications of machine learning in basic sciences, pharmaceutical development, and other supporting technologies on health systems have not been examined.

Prediction is integrallychallenging since technology varies its environment, resulting in new opportunities and limitations for technology. Because a type of general intelligence already exists in human brains, it will be reachable in the future. However, expanding current approaches to artificially re-create universal intelligence in the next 5-10 years seems unlikely.

The use of digital technology in healthcare, such as machine learning, is entering a new phase. Our understanding of both genetic and environmental aspects contributing to the genesis of complex disorders will rapidly accelerate when informatics, biology, engineering, chemistry, and computer science are combined. It's intriguing to think about how copy number differences may be used to predict cancer diagnosis. Machine learning might be used to produce an interpretable approach for detecting how the genomic landscape interacts with genes to determine hereditary cancer risk, which could lead to better patient treatment.

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