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Cloud-Based Machine Learning Models for Real-Time Diagnosis and Predictive Healthcare Analytics

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Abstract: Over the past decade, machine learning has become a game-changing technology in healthcare. In detecting and predicting severity of COVID-19, they build machine learning models that use two datasets: the CT images for COVID-19 patients and those of normal patients and are found to obtain an accuracy of 99.1 percent. Here, researchers propose a cloud approach using two machine learning models that are trained and tested on COVID-19 and non-COVID-19 (normal) patients by using only data of normal CT chest images. Each of their models predicts COVID-19 patients and severity levels. Major findings would help primary healthcare centers, general medical practitioners, and healthcare workers located far away from hospitals or web-based healthcare systems to care for patients at risk of COVID-19. The rapid increase in health-related data opens a new dimension for information and knowledge discovery in the health domain. Machine learning (ML)/deep learning (DL) technology has attracted a lot of attention in healthcare data analytics among researchers from both academia and industry. ML/DL models are being developed to provide early expertise and intelligent decision support for healthcare systems. Traditional ML approaches rely heavily on a great deal of high-quality labeled data. However, circa 80% of healthcare data is typically stored in unstructured forms such as short messages, free-text records, or images. Such a high percentage of free-text data presents both an opportunity and a challenge for data mining in the healthcare domain. Free-text data offers a fantastic chance for healthcare analytics. However, the information contained in these unstructured data is often not utilized for reasons such as data sparsity, lack of clean patterns, or increased noise. Most regions of the world have stepped into the twenty-first century with a legacy health infrastructure largely based on conventional thinking. Health systems in many developing countries, especially, are still struggling to meet the basic needs of their populations. Many MICs face a tsunami of change, driven by urbanization, demographic transition to aging, and cancer and productivity loss due to COVID-19.
Accurate assessment of the health burden from these demographics for timely predictions of societal long-term impact is a major challenge. Despite facing many challenges, some LMICs have made rapid strides in improving the quality and efficiency of their health systems through leapfrogging. Earth observation offers an amazing potential to provide scalable information highly relevant to health inequalities. The integration of inferring and predicting health burden from earth observation and environmental and climate data with insights from artificial intelligence holds great potential in a further leap forward for the understanding of health inequalities and improvement of the equity of health decisions in sustainable urbanization and development. Cloud computing provides the construction of intelligent and scalable multimedia healthcare systems. However, the latest ML/DL approaches still lack reliable and practical public platforms.

Keywords: Cloud Computing,Machine Learning (ML),Real-Time Diagnosis,Predictive Analytics,Healthcare Analytics,Artificial Intelligence (AI),Health Data Streaming,Telemedicine,Medical Data Prediction,Cloud Infrastructure,Big Data in Healthcare,Data Security in Healthcare,Diagnostic Algorithms,Medical IoT (Internet of Things),Health Monitoring Systems

I. INTRODUCTION

The continuous growth of cloud-based digital communication, storage, and management has made the rapid growth of structured and unstructured data a reality. Given the complexities of living conditions and lifestyles, risk groups with high probability of illness are growing at a rate of 10-15% on a monthly basis. In the healthcare sector, catastrophic events can be largely avoided through effective predictions of impending design threats. Cloud computing and the Internet of Things (IoT) have changed the structure and characteristics of data. This has made new mechanisms for analytics mining, reporting, and communication easier to access than before. Intelligent diagnostic systems are critical in the war against catastrophic diseases such as HIV, TB, BP, obesity and cancer (breast, skin and so on). However, as diseases evolve, large data and platform independent models are required for mining and prediction. Traditionally, phylogenetic predictive models in healthcare have been site- and organization-specific and based on proprietary methods. These approaches need assessment and redevelopment with every addition of data or a new data generating source. The introduction of IoT has, however, presented a prospect for cloud-based analytics that utilize device independent models to cope with unforeseen test objects. The approach to data and computation management for a Wi-Fi and Internet based phygital healthy device chain created a formally defined question space open to models on both the cloud and local storage. The expected results enable the health monitoring, mining and optimal treatment of privacy sensitive measurements without complex pre-processing. As an end-to-end solution, the proposal consists of low-cost sensing, aggregating, wireless communication, data integrity checking, storage, machine learning, and a framework for data and computation deployment on the cloud. Safe on-device data assurance and anonymization are provided before the aggregation in case the data are required for further testing or comparison. Real time predictive analytics based on mined data streams are used to extract critical information regarding disease discovery, progression and chances of occurrence. Sophisticated features based on correlation analysis are used to construct a set of representative vectors of data, which are designated for continuously enhanced testing with usage. Efficient analytical models are created based on data imbalance and pre-processing techniques and hybrid cloud segmentation. These nonlinear methods generate results suitable for a multi-sample wide range of measurements as they need only processed state vectors and can take advantage of high performance computing on cloud so as not to overload the local device.

I.Background And Significance

Novel and affordable cloud computing technologies allow users to efficiently outsource, store, and manage their Personal Health Records (PHRs) over the cloud, and conveniently share with their caregivers or physicians. In addition, with the exponential growth of the stored large scale clinical data and the growing need for personalized care and treatment, researchers, practitioners, and companies are keen on developing novel data mining methodologies to learn efficient hidden patterns in such data. The storage of the data has become less costly and more powerful but at the same time much more complex. As this cleansing or filtering step is so difficult and requires intensive human efforts, the data mining process often has to deal with very noisy/ambiguous event sequences. Research studies have shown that to understand the content of the heterogeneous case, the collected dataset alone is not sufficient and the employed data mining approaches should be explicitly aware of the previous knowledge. Personalized patient care and treatment have received great attention in recent years with recent remarkable progress made in doctor-patient interaction modeling and patient behavior understanding. Cloud computing technologies offer a scalable and economic architecture for cloud-centric healthcare applications, which bring significant healthcare application development and deployment advantages.

The cloud adoption cycle in the healthcare industry has really been an encouraging success story. The cloud-based healthcare landscape is also very competitive with numerous public and private health clouds. Major institutions and organizations from both the healthcare industry and IT providers have already formed partnerships to offer secure cloud-based services. Many institutions and organizations have implemented cloud-based health record systems. Such cloud-based health record services allow users to efficiently share their health records with their trusted healthcare providers. However, the collected medical dataset is highly ambiguous and noisy. Therefore, developing effective, scalable, and accurate machine learning techniques for health-related knowledge discovery is crucial for real-time diagnostic clinical decision support systems and predictive healthcare analytics.

rediction:

$$\hat{y} = \sigma(W \cdot X + b)$$

Where:

- $\hat{y}$ is the predicted diagnosis (e.g., probability of disease presence).
- W is the weight matrix of the model.
- X is the input feature vector (patient data such as symptoms, test results).
- b is the bias term.
- σ is the activation function (e.g., sigmoid for binary classification).

Equ : 1 Real-Time Diagnosis P

II. OVERVIEW OF CLOUD COMPUTING IN HEALTHCARE

Cloud-based technologies offer new prospects for the development and widespread adoption of digital health solutions. However, concerns over privacy, security, compliance with regulations, system interoperability, clinical evaluation, and trust pose challenges that need to be overcome for the mass adoption of cloud-based digital health solutions. The growing adoption of electronic health records (EHRs) technologies worldwide has resulted in an abundance of health-related data, and the emergence of machine learning (ML) techniques in recent years has opened new opportunities for their analysis.

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Cloud computing provides on-demand computational resources and services that are flexible and scalable, and democratize the access to large-scale infrastructure and algorithms, producing a boom in the research and implementation of cloud-based digital health solutions. However, health-related data is generally highly privacy sensitive, requiring strict governance regarding their storage, access, and sharing. On that account, many countries have developed regulations over EHRs systems, the compliance of which with legislative requirements and data protection principles is generally evaluated by health authorities before their deployment. Nevertheless, most cloud-based digital health solutions deployed to date do not comply with such principles, limiting their acceptance and dissemination. These concerns have spurred a growing interest in the design and implementation of e-health architectures that comply with data protection legislative requirements which focus on the storage, sharing, and processing of health-related data - overall, e-health data governance. What has yet been addressed is the governance of analytic models applied to health-related data. Models are at the core component of analytic applications, and their governance is a pre-requisite for the deployment of federated cloud-based analytic solutions. Current model governance architectures apply to cloud-based federated bank architecture, but they do not account for FHIR-based health data. The proposed architecture and its implementation comply with the data protection principles provided by the European data protection regulation. This is the first model governance solution conceived to handle FHIR-based health data and that includes the provision of information on the access and processing of health data under the right to access and the right to procedural safeguards granted by the GDPR, respectively. The proposed architecture and its implementation have the potential to mitigate privacy and security concerns over the deployment of federated cloud-based analytic solutions in the area of digital health.

Equ : 2 Predictive Healthcare Analytics:

$$y(t) = \theta_0 + \sum_{i=1}^{n} \theta_i \cdot X_i(t) + \epsilon$$

Where:

- $y(t)$ is the predicted future health outcome (e.g., blood pressure, glucose level) at time t.
- $X_i(t)$ represents the feature set (e.g., age, lifestyle data, current health metrics) at time t.
- θ_i are the model coefficients.
- ϵ is the error term (residuals).

III. MACHINE LEARNING FUNDAMENTALS

Machine learning (ML) has been one of the most popular and powerful computing techniques for the past two decades. A computer program is said to learn from experience (data) E with respect to some task T and performance measure P, if its performance on T (and P) improves with experience. Simply speaking, ML is a collection of computer algorithms in order to discover knowledge (patterns) from data. Several common ML techniques will be introduced in this paper, including unsupervised learning, supervised learning, reinforcement learning, and semi-supervised learning.
The goal of supervised learning is to learn a function or a model (classifier/estimator) from labeled training examples, such that the predictions on unseen or new data can be made. The performance of the learned model can be evaluated with the classification accuracy (CA), average precision (AP), the area under the receiver operating characteristic curve (AUC), F-measure, root mean squared error (RMSE), R-squared (R2), etc. Unsupervised learning finds hidden patterns or structures in input data that has no previously assigned labels or classes. Clustering, dimensionality reduction, topic modeling, etc. are common types of unsupervised learning tasks. The performance of unsupervised learning is more difficult to evaluate since no class labels are available.
Basically, reinforcement learning (RL) consists of an agent, an environment, a set of actions, a reward function, and an experience replay buffer. The agent interacts with the environment and takes some actions. The action will hit the environment and the state may change. Feedback from the environment will be sent to the agent, including the next state and a reward for the action taken (that is, how good/bad the action is). This setting is modeled as a Markov decision process (MDP). The agent will learn to take actions that maximize rewards. The learned policy can be deterministic or stochastic.

Equ : 3 Cloud Data Integration and Model Aggregation (Federated Learning):

$$\theta_{global} = \sum_{k=1}^{K} \frac{n_k}{N} \cdot \theta_k$$

Where:

- θ_{global} is the aggregated model's parameters.
- θ_k is the model's parameters from the k-th client.
- n_k is the number of data samples on the k-th client.
- N is the total number of data samples across all clients.
- K is the number of clients.

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IV. REAL-TIME DIAGNOSIS: IMPORTANCE AND CHALLENGES

Real-time detection of diseases from collected vital signs is essential for healthcare practitioners and clinical organizations. The fast monitoring of patients' vital signs is important in emergency cases, such as ambulance monitoring and ICU patient monitoring. Timely detection systems can assist healthcare personnel in understanding the severity of patients' health and determining appropriate treatment methods. Sudden high blood pressures in critical cases may cause a stroke, necessitating cloud-based detection. Wrong diagnosis, especially in early scheduling diseases such as Emphysema and Colon cancer, is essential. Hence, preventive measures are critical and must be taken, and cloud-based early detection systems are proposed as a solution. Such systems can assist in predicting the likelihood of patients being affected by a disease and help schedule patients efficiently.

Another challenge is feature extraction, as manually selecting characteristics from a variable sample is difficult. Neural networks can automatically extract high-level features, and moving-feature filters can be implemented over the data streams to ensure the desired features are generated. But another challenge may be introduced by the high cost of different neural networks' training requirements to tackle. Health status changes are gradual. However, many machine learning models only detect abrupt changes to patient observation behaviors. This can miss subtle trends, resulting in misdiagnoses and nasty consequences. A distribution model is fitted to the observation variables, and its marginal maps are provided with explicit temporal information. At the same time, the Kullback-Leibler divergence is used to denote the difference between prior observations (known state) and new observations (unknown state).

Fig: 1 The Diagnostic Process Improving Diagnosis in Health Care

V. PREDICTIVE ANALYTICS IN HEALTHCARE

Healthcare predictive analytics is a technique that uses vast amounts of historical health data, patient records, and other variables to create algorithms that can forecast outcomes. By examining data patterns and relationships across diverse datasets over time, machine learning algorithms can establish statistical connections between input variables and targeted output variables, as well as find novel relationships between variables. Predictive models can be used by healthcare organizations to develop patient monitoring, clinical risk assessment, and outbreak prevention programs, as well as support chronic disease identification and hospital readmission risk prediction. Other potential applications for predictive analytics can include enhanced resource allocation, improved care planning, and serious complication prediction. Currently, many predictive healthcare analytics models are being developed using machine learning techniques.

Predictive analysis applies machine learning algorithms to predict target information based on predefined data. This paper presents a model that allows diagnostic healthcare data to be used in predictive analysis (at a patient level). Unlike existing predictive analytics algorithms that generate predictions using only historical data for a given analysis unit, this paper's diagnosis model generates predictions as functions of both historical and unseen data. As a result, the predicted diagnosis is similar to how the diagnosis is defined in the healthcare domain, incorporating both health records and biomedical events.

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Scalable, visual predictive analytics software for the critically ill is able to analyze large-scale observational data from the medical domain. A large variety of models can be generated through this software due to its wide coverage of various learning types and model techniques.

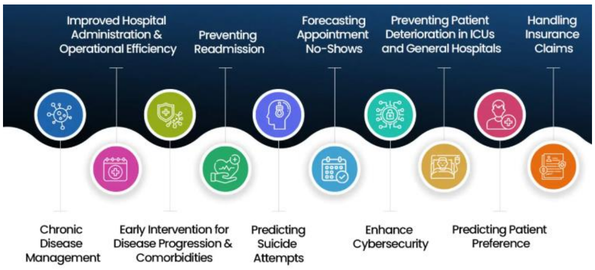

Fig: 2 Predictive Analytics in Healthcare

VI. TYPES OF MACHINE LEARNING MODELS

Machine Learning (ML): ML is a branch of artificial intelligence that designs algorithms that allow computers to learn from previous experiences or data so that they do not have to be explicitly programmed to perform a required task. ML learns the relationship between the input and target variables using mathematical, probabilistic, statistical, and computational techniques. It requires a dataset containing sufficient variables related to the task to be performed. During the learning phase, it builds a mathematical model of the task to be performed using machine learning algorithms. After the learning phase, the models are theoretically able to make predictions on unseen data. Generally, all the above-mentioned steps are performed on the hardware platform of the user either in application software or on cloud infrastructure. Most of the emphasis in prediction task research and publications has been placed on 'Cloud-based prediction' technique.

A model is any mathematical abstraction of a physical or engineered system. In healthcare, models can be varied based on the type of structured data available for modeling. Depending on the type of ML method used to create the model, ML models can be classified broadly as: 1. Supervised Models 2. Semi-supervised Models 3. Unsupervised Models 4. Reinforcement Models

Considering the clinical perspective of models, ML models in healthcare can be classified broadly into four types based on the domain in which they are used, viz. 1. Diagnostic Models 2. Prognostic Models 3. Therapeutic Models 4. Public Health Models

This classification helps Healthcare ML model builders to isolate the problem they want to solve and propose the most appropriate prediction task.

6.1. Supervised Learning

Any learning algorithm for pattern recognition is assumed to learn either a function or its parameters from a training set of examples. The training set C consists of an arbitrary distribution of pairs of input stimuli and corresponding desired output decisions. The aim is to generalize to a given test set (not seen during training) of arbitrary pattern input stimuli, providing a desirable output decision. Supervised learning specifies a learning algorithm, which given the training set, produces the hypothesis. The hypothesis is either a two-part ordered list of candidate hypotheses with ordered confidence criteria, or a single estimated distribution over output hypotheses. The MA runs the learning algorithm on the training set, producing the hypothesis, which is then queried on the test set, followed by quantifying accuracy.

The various technologies and devices developed in this approach are focused on either pattern recognition or cost-effective low-power computation. The single-device solutions break down for multi-modality systems, as the output decisions are only pseudo-decisions requiring large-bandwidth wireless communication for other devices to access the output content. This is a bottleneck, as the logarithmic reliance on the classifier's confidence requires the distribution to be sparse. The multi-device method gets around this by confining the queries to the decisions made within the local alarms, thus allowing for very low width coupling between devices.

Machine Learning (ML) is an application of Artificial Intelligence (AI) that enables a machine to learn without explicitly programming it. The process of ML requires an appropriate theoretical framework that allows computers to learn by themselves. Although different formulations of ML exist, the fundamental philosophy formulation is based on conscious observation and experience. The machines with ML capabilities use the past data on a given task to make predictions on future tasks of the same kind. Earlier signs based on rules much in contrast with present statistical based learning signifies a major leap in the learning arena with numerous applications.

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6.2. Unsupervised Learning

Unsupervised learning (UL) approaches aim to train a model without labeled data, often using hidden distributions/tasks of data. With the emergence of active learning, it is possible to induce some labels for data with high uncertainty estimated using the model. Unsupervised approaches are often preferred due to their potential wide applicability. UL approaches for chest pneumonia detection from X-ray images are visually surveyed. X-ray images are among the most widely used screening methods for detecting pneumonia. However, whereas X-ray imaging is inexpensive and widely available, pneumonia screening necessitates trained medical specialists to examine and evaluate the X-ray, resulting in a significant burden. Computer-aided detection (CAD) systems, leveraging machine learning (ML) and deep learning (DL), are currently employed to assist specialists by processing chest X-ray images to extract patterns invisible to the naked eye, leading to the productive detection of pneumonia. The deep CNN architecture of the β-VCAEs model captures hierarchically discriminative and high-level feature descriptors for images. The objective function of the model is optimized using rapid sub-optimal schemes. Given a chest X-ray, the traditional process for pneumonia diagnosis is to examine the X-ray and determine the presence of pneumonia, a procedure requiring a trained medical specialist. However, this can result in erroneous diagnosis due to fatigue and loss of attention. An alternative computer-aided diagnosis approach using AI can mitigate fatigue and attention loss issues. The aim is to develop a classification system for pneumonia diagnosis from chest X-rays. As medical data is often private, external datasets must replicate the task. DNN models must extract high-level features from images and deal with inter/intra-class data variations.

6.3. Reinforcement Learning

Reinforcement learning (RL) is a fundamental technique that enables sequential decision-making and has recently gained great attention in personalized medicine. As electronic health record (EHR) data provides opportunities to find effective treatment for chronic diseases, recent RL based work has drawn significant interest in order to assist health care providers to minimize health risks and address major disease-related activities in an efficient manner. These RL based paradigms strive to recommend optimal health interventions to patients based on their current health role states in order to obtain maximal cumulative health rewards. Comprehensive surveys of the recent development of RL in personalized medicine and its associated topics of counterfactual treatment effect estimation and individual treatment rules have been provided. Among many factors that may impede the practical deployment of the personalized treatment regimes derived from RL policies, late patient recruitment, limited follow-up observations, explorative treatment regimes, shielding high health risks, and others are notable hurdles. To address these challenges, offline RL pursues the goal of extracting the optimal treatment regime from an already collected dataset of patient health history records. The RL paradigm in the current stage assumes a finite time horizon and thus considers treatment recommendations only in short time intervals, which does not reflect the nature of most real applications of persistent chronic disease treatment. Some recent work developed personalized treatment regime learning paradigms in the infinite time horizon setting where unobserved data arising from recommendations beyond the time-horizon or cohort of patients who have never been treated pose challenges in learning.

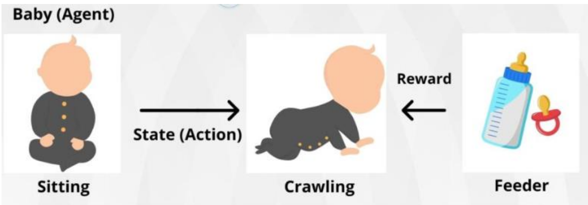

Fig: 3 Basics of Reinforcement Learning

VII. DATA SOURCES FOR HEALTHCARE ANALYTICS

Healthcare Data Analytics (HDA) is an emerging branch of analytics, a subset of Business Analytics which aims to analyze data and elicit actionable insights from it. Traditionally, the primary focus was on descriptive analytics, but this gradually transitioned into diagnostic analytics, with attempts to understand the underlying causative factors. A recent trend is toward predictive analytics, mostly based on Machine Learning and Data Mining techniques. Hence, this work emphasizes predictive models and analytics but includes processes aimed at developing actionable insights from healthcare data. It demonstrates a novel formulation of healthcare model creation while keeping analytics in the forefront. Hence, the title: Cloud-Based Machine Learning Models for Real-time Diagnosis and Predictive Healthcare Analytics.

For the purpose of developing machine learning models in real-time diagnosis, and predictive healthcare analytics, healthcare data sources are needed. Healthcare databases, in this context, include Electronic Health Records (EHRs), text-based documents in clinical narratives, and publicly available healthcare databases. Other data sources available to health data scientists include structured data from hand-held devices, Rapid Serial Visual Presentation (RSVP) data from

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the Eye-Tracking Unit of the Biomedical Engineering Research Center. Publicly available health data sources can be categorized as medical datasets from the UCI ML Repository and other data sources. Automatic health analytics and data processing create collaborative health records to exploit converged health data assets.

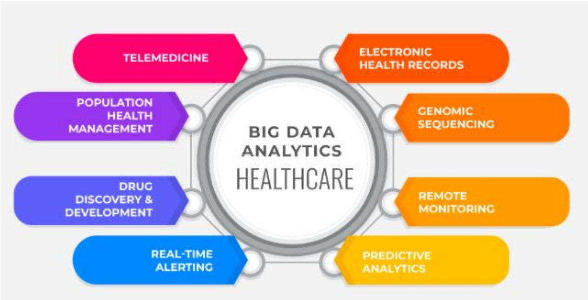

Fig: 4 Role of Big Data Analytics in Healthcare

7.1. Electronic Health Records

Most of the health data are collected daily during patient care using various systems. The operational management and organization of healthcare facilities regarding patient admission, transfer, medication administration or preoperative care, and general patient care (clinical disciplines) collect various data entries that need to be stored, retrieved, and analyzed for various statistical methods and decisions. In addition to operational data, the clinical disciplines collect data entries for further examining the patients providing the opportunity for new health analytics techniques and methods. Data entries originating from such daily collected data span multimodality data types such as free text clinical notes, structured numeric or categorical parameters, or images using various data-centric engineering methodologies such as processing, ingestion, integration, storage, and retrieval/analysis. Furthermore, the commonly used legacy Electronic Health Record systems in almost all hospitals do not support such data processing yet. To face those issues, a modularized, extensible, and open-source pipeline is developed to manage, store, and analyze heterogeneous patient data correlated with morbidity/mortality prediction. The pipeline is used successfully in a case study on a newly created cohort of patients, including all the most common diseases. The current knowledge of mortality prediction modeling is extended and validated, leading to one of the most accurate, open-source predictive models available that can instantly be integrated into any EHR system. Moreover, privacy and ethical concerns due to the sensitive nature of health data fueled the development of privacy-preserving health data processing and analysis techniques. Even though various applications cover part of the health data processing techniques, there is still a gap involving unsecured health data, especially from multi-cloud and edge analytics. Such health data privacy is crucial when performing any kind of analysis task on cloud/edge deployments. Without proper processing techniques on the cloud side, the private nature of the current data would be exposed to third parties during resting or analysis tasks. Preserving privacy standards is vital to avoid significant financial penalties, legal prosecution, and massive reputational damage. The necessity of designing and incorporating data anonymization techniques with the healthcare cloud/edge analysis of multi-modal and heterogeneous clinical data is outlined.

7.2. Wearable Devices

Wearable health monitoring devices may detect abnormal heart rates and usage trends and ultimately notify the user in real-time when abnormal events occur. The ongoing aging of society has increased the public health burden of chronic diseases. Chronic diseases such as heart disease and diabetes are common in the elderly and require long-term follow-up. In a healthcare system with limited medical resources, remote health management, which is different from traditional patient doctor models, is widely used in wearable sense medical devices, as opposed to personal health monitoring devices. Equipped with multiple sensors, wearable health sensing devices collect physiological characteristics and health status of subjects in real-time. With the rapid development of the Internet of Things (IoT), the recorded status can be analyzed in real-time to detect an abnormality. Compared to the laboratory Big Data Health Management, it is a common challenge for wearable analyzing devices to ensure that they have a compromised cost/accuracy balance.

Wearable ECG devices can meticulously monitor heart conditions. ECG monitoring devices record the health status of users in real-time. In routine health status monitoring, devices with too many features cause users to feel heavy and cumbersome. Develop low-power wearable ECG devices capable of reliably detecting and streaming the ECG signal. For users, the most urgent demand is usage security. If a health monitoring device does not securely access and transmit personal information, privacy may not be secured. Users are concerned that their health data may be hacked and used by criminals. Secure and private ECG devices with predefined passive roles have been designed, which ensure mutual authentication and derive a session key to keep future health data secure.

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7.3. Genomic Data

Most existing works on diagnosis prediction mainly focus on providing the deep neural model with a salient diagnosis prediction approach. While these efforts are promising, they still adopt an independent and static learning procedure that may be sub-optimal. Furthermore, mysterious pathological images or signals may lead to the wrong predictions of the current diagnosis models. Another research area, i.e., explanatory analysis, is used to understand black-box models with supporting evidence. The explanatory techniques can be seamlessly integrated into other comprehensive diagnosis models, which may effectively enhance model interpretability and robustness. It can also capture additional useful side information to update the temporal predictive models, which may improve prediction accuracy.

There are some open issues and potential directions. On one hand, the current research mainly focuses on developing deep learning techniques or generative adversarial models for diagnosis prediction on the physiological or genomic data. To comprehensively improve clinical decision-making and deliver timely healthcare decisions, it is crucial to develop robust models that can automatically analyze the noisy and corrupted clinical data. For example, robustness enhancement is still a great challenge for existing deep learning methods on raw physiological signals in real-world practice. On the other hand, how to conduct real-time and progressively-guided learning on cloud-based privacy-preserving data for service platforms is still a problem of great interest across many disciplines. Current efforts mainly utilize a strategy, i.e., implementing a service platform without considering the model selection or update issue. How to conduct robust progressive learning on the cloud with effective security protection is still an interesting and challenging research opportunity.

VIII. CLOUD INFRASTRUCTURE FOR MACHINE LEARNING

Cloud computing technology is rapidly emerging in every field of life such as education, bioinformatics, smart cities, and healthcare. In healthcare, keeping, storing, and analyzing patient data is a challenging task for healthcare organizations. Moreover, sharing the patient information with authorized users is also a sensitive task. The utilization of cloud computing facilities will help healthcare organizations to keep the patient data. However, cloud computing is a network of different resources to upload and download data on demand, and it will provide clients with information technology services (IaaS, SaaS, PaaS) and resources at lower costs. These services will address healthcare data management and analytics issues. However, the availability of patient data on the cloud will weaken control over sensitive data. Data security and privacy are the two primary hurdles in the path of cloud implementation in healthcare. Security and privacy of e-health will be a serious challenge for researchers to provide fast information sharing, lower cost, and bigger storage on the cloud. Using cloud computing in healthcare will help stakeholders, researchers, and patients to motivate the quality care services.

Cloud computing is also being viewed as a fantastic technology for establishing data-integrating infrastructure for diverse healthcare information systems to enhance information expansion and sharing. Spectacular growth in the number of data-generating healthcare devices enables the potential for advancing intelligent health monitoring and treatment methods. The impersonality, effectiveness, and multi-integration of cloud computing should motivate the adoption of cloud solutions in health. However, frequent diagnosis techniques such as a narrow bandwidth network and unavailability of a computerized translation system may restrict the wide spreading of intelligent diagnosis techniques. This paper presents a proper cloud healthcare architecture and its workflow, which provides the biomedical domain with a robust cloud-based platform for storing, transmitting, and analyzing data with a high volume of unstructured types. Furthermore, the primary healthcare companies need to implement security and privacy protections when establishing the necessary infrastructure among the contributors. Better picture recognition and the growth of smart smartphones may benefit the normalization of cloud-based biomedical data collection.

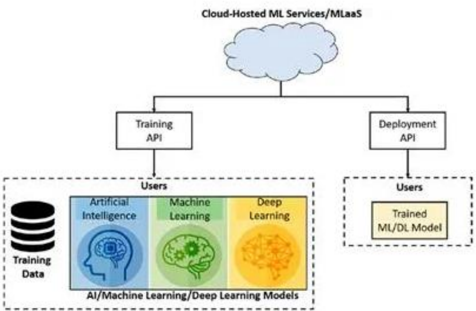

Fig: 5 The Role of AI and Machine Learning in Cloud Security

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8.1. Public Cloud Providers

Public cloud enables easy access to various software systems and libraries without enormous investments in expensive hardware and software solutions. Software as a Service (SaaS) simplifies integration and development of models and applications, accelerating the time to market. Most recent web technologies provide application support on various devices and platforms such as smartphones and tablets, further increasing their usability. This chapter focuses on several public cloud services and providers regarding Machine Learning and Predictive Analytics, including Microsoft Azure and AWS.

Machine Learning APIs Machine Learning APIs are easy to integrate services providing trained Machine Learning models in the form of a simple RESTful API. They handle all overhead issues such as security, scaling, and model training and adapting. All providers force users to register, but then provide a free usage quota, which is enough time to test the basic functionality of offered services. Free models have restrictions that are implemented as calls per minute, max call size, and daily max volume of requests. Consequently, they can be easily tested and analyzed for adoption for further usage.

Machine Learning Libraries Complete libraries as Cloud ML and Caffe provide all functionality for the implementation of Machine Learning models from scratch. They include code for data collection, cleaning, feature extraction, feature selection, training models with different algorithms, and their selection, static storage, and usage. PMML is a standard format defined by the Data Mining Group. Content of a PMML file and a simplified representation are depicted. It is easy to share knowledge between tools, but it avoids access and usage of critical algorithms and knowledge. Despite this drawback, PMML was selected as a transfer language for predictions. With the help of several libraries, it was possible to use equipment from AWS, Caffe, H2O, Weka, and Rapid-Miner on a variety of devices and software platforms.

8.2. Private Cloud Solutions

With the cost and flexibility advantages of public clouds, more and more healthcare services are migrating to a public cloud. However, storing electronic health records (EHRs) of patients on a public cloud is preventing healthcare institutions from switching to a cloud system to take advantage of the cloud service. A private cloud can be deployed in such cases. Private cloud solutions can be implemented on massive in-house storage infrastructures using open-source software. This eliminates the fear of violating HIPAA regulations. Since EHRs are stored inside the institution premises and not to a public cloud, the EHRs cannot be accessed by a third party and hence it is compliant with HIPAA. While the services are not directly released as SaaS systems, healthcare institutions can instead provide users a VPN access to the private cloud, where users can access the services without violating HIPAA and thus maintaining the privacy of records. In addition to offering a private cloud as a service, building the SaaS models directly on existing infrastructures allows more collaborative approaches for a large number of stakeholders beyond a single healthcare institution. Any detected anomaly can be shared with the other stakeholders on a big collaboration system, and with everyone collaborating, the detected anomalies can be much more accurate. With trusted parties over the collaborative system, such as a single server accepting raw data from institutions, cost-effective solutions can be developed to find patterns in data. This overcomes cost-heaviness and can involve institutions with less resources.

Even larger-to-the-scale collaborations can be built, where publicly accessible systems can ensure unfair practices among institutions and further assure collaborations. Since this involves heavy data communication and storage, in combination with limited input-output resources on smart health devices, value-added solutions need to be built to store either the health data or rights on the public systems and protect data privacy on the institution side. All these options for further deployments, from smaller scenarios of big collaboration systems with trusted parties to huge scenarios of blockchain-based systems, warrant for recent attention to be connected with construction of the main given learning models.

8.3. Hybrid Cloud Models

Cloud computing has proven a practical technology for communicating a large amount of data through the internet. The hybrids of public and private models of cloud computing are hybrid cloud models. In hybrid cloud computing, two or more IaaS infrastructures are interconnected by the LetsGCoN. To make more efficient hybrid cloud systems, a well-structured general architecture for various operational needs is introduced. The premise is that public and private clouds should keep their own data secure. The need for security and covering other operational requirements should be part of the solutions. Possible implementations of database models could be considered, as the infrastructure providers' services range from virtualized data space infrastructure and management systems to application services.

There exist various application areas in hybrid cloud computing systems, where users do not necessarily need to deal with those technical issues usually associated with monitoring and analyzing systems breach, but only utilize the storage and processing cloud capabilities. Those specific operational needs should be mapped to generic functions which well contribute to innovation and well investment in a detailed implementation of goals and architectural components. The distinction is made for the aims specifying breaches sequentially from one to the higher level four tiers for defining specific system characteristics and requirements.

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Generic functions should cover analysis, monitoring, data access, and accounting applications. Intended for usage outside organizations data or cloud layers, hybrid cloud systems should connect from direct data output to raw logs. Though a number of aggregated information should be provided in a format and knowledge-agnostic way, loosely-coupled data types to be utilized elsewhere in possible services. As well as covering all functional user needs, potential technology complications, security issues the architecture should be clear enough in preventing misunderstanding and concerns.

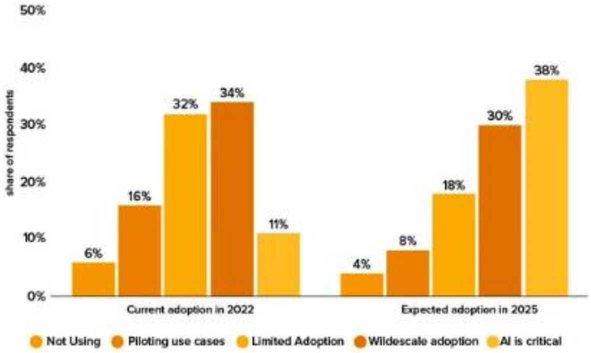

Fig: 6 Predictive Analytics and Machine Learning

IX.CONCLUSION

A wide range of real-time monitoring systems that utilize cloud-based machine learning models for diagnosis and predictive analysis in health-tech sectors, including pulse, ECG, finger oximeter, temperature, and blood pressure health detection systems, are presented in this article. Health monitoring-specific cloud-based server setup and Machine Learning model deployment methodologies are provided with illustrations. Different machine learning (ML) models were utilized along with time analysis for training on low-performance edge devices. The evaluation of accuracy and performance benchmarks for device processing are presented and discussed. The healthcare monitoring data or parameters collected by low-performance devices are processed/diagnosed through latency and light-weight ML models up to 91% accuracy and 31ms response delay, depending on use cases. The prospective work of the health monitoring cloud-based system would discuss security and confidentiality in connection to cloud-based data and platform management. These attachments may incorporate local encrypted information and ML model training along with a smart contract.

9.1. Future Trends

Recent advancements in rising technologies like AI have inspired enormous success and creativeness. The healthcare industry has taken this step to withstand digital transformation; it introduced IoT, AI, ML, and other new technologies in innovative ways. So, intelligent technologies are incorporated into numerous healthcare applications, such as personal healthcare assistants, smartphone applications for drug advice, and intelligent gadgets for diabetes detection. As a ground-breaking sector, healthcare provides significant opportunities for researchers to develop a better model for improving public health since it embraces massive volumes of data and a diversity of data streams. However, security and privacy risks present a serious challenge that monetary incentives have not yet addressed.

Healthcare data from the physiological or relative cardiovascular context can be of enormous use in determining general clinical and ill health. Researcher recommendation systems based on big data analytics may assist doctors, biomedical professionals, and healthcare providers in decision-making and timely medical evaluation. With the adoption of ML in healthcare analytics, the capability of the recommender system will evolve and grow. However, it is also hard to create, deploy, and manage ML models. Many machine learning models for predictive healthcare analytics have been deployed in production systems. As models and approaches advance, the need for extensive model training and feature engineering may create bottlenecks for continuous model deployment.

Early detection of heart disease is essential in increasing a patient's chance of survival because it allows for early treatment of the disease. Machine learning techniques are classified as supervised or unsupervised learning techniques. In supervised learning, training and target data is provided for better predictions. The internal structure of the unlabeled data is examined, allowing for clustering in unsupervised techniques. K-Nearest Neighbors, Decision Trees, and Random Forests come under supervised machine learning techniques used for classification. A-Algorithm and DBSCAN are two examples of clustering algorithms that realize unsupervised learning.

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