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Amalgamation of Internet of Things and Machine Learning for Smart Healthcare Applications – A Review

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Abstract: The Internet of Things or IoT is altering human adaption of hi-tech gadgets in daily life. IoT applications are quite broad, ranging from vital applications such as smart cities and health-related sectors to industrial IoT. The IoT is critical to the fast automation of the healthcare industry. Collection and processing of data are key components of any IoT for healthcare applications. Machine learning (ML) techniques are being amalgamated with IoT (IoT-ML) to make the network more efficient and self-sufficient. The amalgamation of ML algorithms into IoT is critical because of the massive quantities of information involved in medical data management and the significant help that its precise forecasts offer to further improve the public healthcare sector. Considering the requirements of IoT and ML, their smooth amalgamation or integration necessitates a complete reworking of the communication stack (from starting physical layer to final application layer). As a result, the healthcare applications built on top of the upgraded stack will gain popularity greatly, and it will also be easier to extensively deploy the network. The present work reviews different state-of-the-art implementations of IoT that are being amalgamated with ML algorithms for healthcare applications. Several commonly utilized machine learning algorithms in healthcare were discussed briefly, and the amalgamation of IoT and ML for diverse healthcare needs was evaluated based on their benefits, capacity, and potential developments. The IoT-ML healthcare applications such as disease prognosis, diagnosis, infection-spread prediction and regulation, monitoring, assistive systems, and logistics control were highlighted. In healthcare, the actual usage of the IoT-ML model necessitates that it be very accurate and contains several safeguards against security breaches. Both advantages and disadvantages of IoT-ML techniques in healthcare were described. In addition, the future prospectives of IoT-ML for accurate predictions and effective practical applications in the public healthcare sector is addressed.

Keywords*— Internet of Things (IoT); Machine Learning (ML); Healthcare (HC); Disease Prognosis and Monitoring; Artificial Intelligence (AI).*

I. INTRODUCTION

Without a doubt, health is at the top of our priority list in the life. Humans have always struggled with diseases that bring demise; we constantly combat over several illnesses (such as COVID-19, HIV, Cancer, and so on) in the human lifetime, while simultaneously and drastically increasing life expectancy and health status. Medicine has historically been unable to heal a wider spectrum of diseases in desired time due to several issues such as malfunctioning of clinical equipment, sensors, and data analytical tools used to examine medical reports or healthcare data [1]. Traditional healthcare monitoring is inefficient, considering the effective usage of both resources and time. A skilled doctor must monitor the patient regularly and the analysis outcomes might take longer times for the reports preparation. Furthermore, after getting released from the health center, recovering patients might have to arrange additional sequel appointments for verifying that if their health is on the right track or not. Because everyone expects precision and accuracy in the healthcare industry, regardless of the cost, it is vital for individuals and businesses in this profession to provide the best services possible [2]. The need for enhanced medical insurance solutions in various health centers is spurred as a result of emergencies such as arrival of ambulances at the same time as frequent adversities and automobile crash incidents, as well as ordinary outpatient demand [3]. Hospitals that do not have live or up-to-date real-time tracking information about the patients admitted and/or discharged typically struggle in meeting the patients demands, whereas the close by institutions may not have many patients. To increase the quality of services (QoS), it is required to have a better awareness and proper understanding of new computational approaches to select the ideal methodology that meets the expectations of the medical professionals involved.

The IoT and ML have recently generated a new universal vision of information revolution to construct a robust worldwide framework via combining several physical and virtual 'things' with new extensibility and wireless communication sensors. The word ‘IoT’ was first destined to employ RFID (Radio-Frequency Identification) creative methods to include particularly recognizable things (goods) as well as corresponding electronic system devices/components within the frame of networks. Eventually, the catchy phrase "Internet of Things or IoT" came into existence for describing a diversity of sensors, including GPS applications, controllers, and telephones, to include all types of "things" [4]. The constant integration of all the sensors into an Internet-related platform and supporting equipment has produced a number of investigation difficulties, that includes engineering framework to knowledge-based data processing and task management and executions. Currently, IoT innovation has made rapid progress in wider systematic and automatic controls, notably in healthcare assistance [5]. Because of combining IoT and ML (IoT-ML) in healthcare today, the consequence is a move from medical center to residence with frequent clinical testing and supplementary health support, as well as making the use of medical equipment simpler to physicians, staff, and patients. IoT-ML techniques, mostly in times of emergency, might build healthcare more accessible to the people. Furthermore, hospitals might lessen the strain by moving practical services and fundamental activities to patent’s home surroundings using IoT-ML technology.

One main benefit is that the patients might stay away from hospital expenses every time they make appointments with the doctor. An additional obstacle is the existing inability of network structure to sustain real-time sensitive application tools that employ IoT; hence SDN (Software Defined Networking) is projected as suitable network structural design for these type of applications [6]. As a consequence, in the future, a smart technology in the healthcare business that needs to be developed to build advanced medical technology and make use of it to expediently track patients from different locations. Patients are monitored based on their physical conditions and descriptions of their medical requirements [7]. Upon introduction of IoT, there is tremendous increase in the number of embedded sensors, medical devices, implants, labels, etc in the healthcare sector. Transportable sensors can be utilized with IoT to gain clearer and accurate data. With the help of android software, a pharmaceutical record database of patients may be utilized to further enhance the medical device's applications. In this correct moment in time, the appropriate deployment of various smart modernizations like IoT can drastically transform any industry, particularly the medical profession [8]. The IoT would enhance people's living situations significantly. The employment of amalgamated systems would cause several advances in electronic data organization services, effective control of communications and improvement of processing systems [8, 9]. There are several wearable systems and applications that must be developed in various domains of healthcare [10]. This review will outline the vital elements of customized healthcare through the amalgamation of IoT and ML. Furthermore, this review discusses prior research studies on IoT and ML for individualized healthcare and highlights the relevant concerns and obstacles of the amalgamation of IoT and ML in the healthcare sector.

II. INTERNET OF THINGS AND HEALTHCARE

A. Internet of Things (IoT)

Due to recent improvements in semiconductors and allied technologies such as microelectromechanical sensors (MEMS) and other systems, the Internet of Things (IoT) has sparked considerable interest [11]. Throughout the years, WSNs (Wireless Sensor Networks) has expanded at an unparalleled rate in terms of scalability, interface, interoperability, data computation and applications [12]. These hi-tech progresses, together with other advances in wireless/cellular communication networks and RFID (Radio Frequency Identification), have established the necessary groundwork for the Internet of Things. In the context of supply chain management, the term "Internet of Things (IoT)” was coined by Kevin Ashton in the year 1999 [13]. The IoT is an intelligent network of interlinked things/devices (sensors, actuators, computers, and so on) interconnected via internet, every ‘thing’ with a distinctive tag and capable of constantly and consistently communicating with one another over the network in a common language and cooperatively making smart decisions by analyzing raw data [14]. As a result, IoT is concerned with a more elegant object world in which each gadget is linked to the internet [15]. Each of these elements, identified as ‘things’ in IoT, have unique electronic identifications and can therefore be remotely managed, controlled, and organized, expanding their scope beyond their physical bounds. As the production of smart things has expanded, IoT has enhanced nearly every aspect of our daily lives, and it continues to do so through a varied array of new, imaginative, and clever application tools [16]. As shown in Figure 1, some IoT applications comprise smart cities, smart healthcare, automobiles, smart agriculture, fleet trafficking, and wearables [12].

Fig. 1. Applications of Internet of Things (IoT)

B. *IoT in Healthcare*

Conventional healthcare monitoring is inefficient in terms of both resources and time. Physician normally checks patient and sometimes the diagnosis results might often take many days to get ready. In addition, after the patient gets discharged, improving patients might need to arrange some sequel visits to the hospital for verifying that their health is on the right track or not. Healthcare systems aid hospitals in reassigning out-side/waiting patients quickly to low crowded alternate patient-handling hospitals [17]. They improve the count of patients receiving sufficient medical treatment. A healthcare organization may resolve the frequent problem of unanticipated adjustments in hospital patient rushes. The need for better medical assistances at several hospitals is generated by crisis situations such as ambulance influx throughout natural calamities and automobile mishaps, as well as ordinary outpatient demands [3]. Hospitals that do not have concurrent records on patient inflow typically struggle to fulfill requisition, whereas close by clinics may contain fewer patients. With the rise of IoT, these challenges are being addressed methodically.

The IoT has spurred significant attention in the healthcare technology driven society in recent times. The healthcare area is extremely practical, and IoT brings up wider chances to further improve it. The IoT connects virtual computers and physical items to enable communications. It collects information in real-time by utilizing cutting-edge microprocessors. IoT uses wearable and implantable devices to continuously monitor patients' health, independent of time or place. Numerous modern medical gadgets and sensors may communicate via different networks, allowing an opportunity to obtain vital data regarding the health status of patients. This medical data may subsequently be utilized for different purposes, such as for remote patient monitoring, anticipating disease and recovery through enhanced symptom understanding, and overall enhancing of the diagnostic and treatment via increased automation and portability. As a result, in modern times, IoT has generated much excitement in the healthcare IoT field.

Among the most essential uses of IoT is the provision of universal and real-time healthcare services [18]. Medical systems must be linked to a WiFi (wireless communication) network to execute numerous important computer operations. Intelligent medical equipment can only be supported by IoT, which employs the recently released robust 5G wireless connection technology. Under the umbrella of IoT, wider components like people, machines, and objects, are connected to information space at anyplace in the world during all the times. The healthcare industry is incredibly practical, and IoT provide a plethora of possibilities to enhance it. The expansion and growth of IoT are vigorously revolutionizing the healthcare sector by launching smart healthcare systems (Figure 2), in which medical staff and equipment are linked via a global network that anyone, anywhere, and at any time can access [11]. Numerous contemporary clinical sensors and devices may hook up to diverse networks, enabling right of entry to vital patient status information. This input data may later be used for several applications, including distant monitoring of patients, illness and recovery prediction through improved symptom comprehension, and overall diagnostic and treatment process enhancement through greater automation and portability [19].

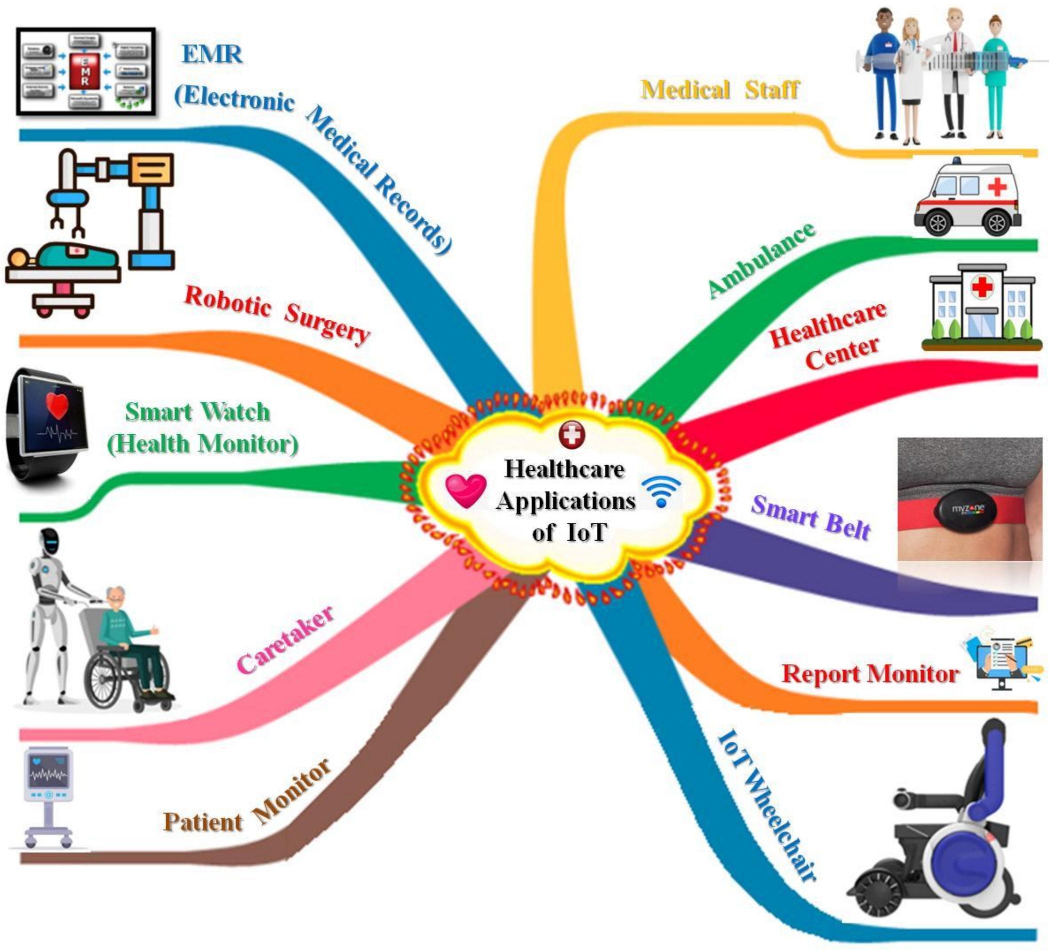

Fig. 2. Some important healthcare applications of IoT

C. Healthcare IoT Architecture

A healthcare IoT system is a complex network of all accessible health related data resources that are linked to one other for speedy data transport via the internet [20]. This implies that many medical resources, including hospitals, physicians, rehabilitation centers, and all healthcare sensors and devices, as well as patients, will be linked together for uninterrupted real-time information flow. The different sensors and actuators, in conjunction with the programs that infer their signals, can identify abnormalities and communicate patient information to hospitals/clinical practitioners for prognosis and examination, following which remedial operation may be recommended and implemented. As a result, IoT is a real system with relevant objects connected to network and allows remote items to be detected, analyzed, and managed. The healthcare applications of IoT began with attempts to establish connections with monitoring systems of isolated patients. Since then, investigation on different healthcare benefits of IoT has been steadily increasing, and current studies intend to incorporate IoT in numerous parts of healthcare, such as disease control, disease spread, efficient automated prognosis, and enhanced therapy.

Intelligent wellness, intelligent grid, and smart infrastructure (smart towns/cities, smart houses and hospitals, smart ambulance/transit, and so on) are all examples of IoT deployments. A computational framework has been designed to connect edge computers, allowing wearable sensors and intelligent gadgets to interact seamlessly. The layered architecture of IoT for healthcare applications is depicted in Figure 3a. In the five healthcare tiers with an back-to-back network, the core architecture of IoT generally includes (i) perception, (ii) network, (iii) support, (iv) application, and (v) business layers. The perception stage is in charge of collecting medical information from numerous sensors/devices appended to the test/patient subject that has to be supervised or inspected. The network layer is in charge of transmitting big data (BD) received from different sensors and relayed throughout the internet. The support layer uses computational techniques to examine information stored in websites/servers to create the appropriate response (decision-making). Smart devices rely heavily on computational methods (machine learning models) applied at this layer for the successful processing of healthcare information, as illustrated in Figure 3b [8]. The application stage is responsible for the compilation, visualization, and assessment of calculated results. The successfully proven models are systems handled in the business layer for commercial healthcare applications all around the world.

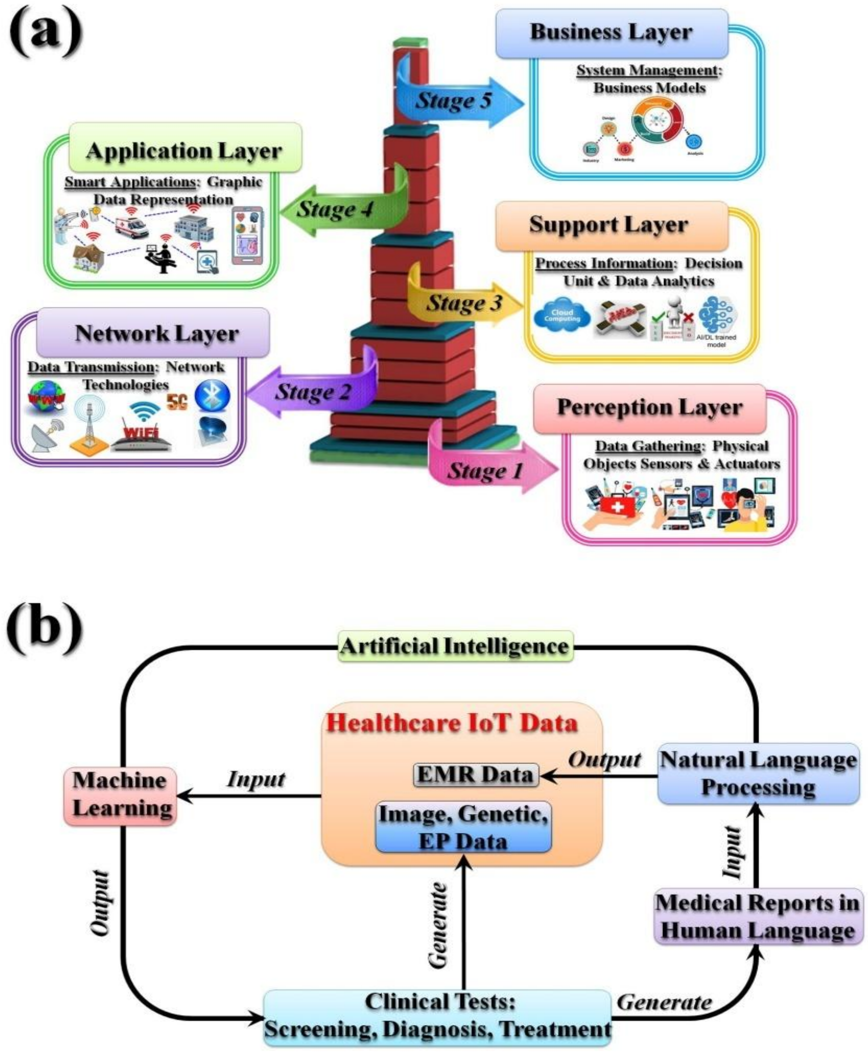

Fig. 3. A schematic of healthcare IoT's (a) architecture and (b) information processing

Despite the tremendous potential of IoT in healthcare sector, both IoT professionals and physicians are concerned about information security, massive data management, and data analytics [21]. Millions of sensors/devices are now attached to patients, constantly monitoring and gathering physical, environmental, behavioral, and physiological data. New developments also point to the appearance of medical super sensors with increased processing and memory power that may use the Improved Particle Swarm Optimization (IPSO) programming code to aid in precise delivery of drugs to various human body parts, identify if the drug has been delivered to the intended target-specific region of patient's body, and perform a variety of other tasks [22]. Obviously, these sensors/devices produce huge volumes of information every second. Big data (BD) deals with a vast quantity of heterogeneous data that is extremely redundant and linked [23]. In the simplistic scenario, all of this information must be dispatched to a unified web server for data mining and examination, introducing risks like network blocks for information transmission, inadequate computational resources, and power for real-time data examination. Numerous solutions were proposed to the aforementioned issues, including deletion of duplicate information and anomalies on the personal/local computer, accumulating the information prior to transferring it, performing an essential investigation via light mobile artificial intelligence (LMAI) models, and uploading data only if the findings indicate a trouble [24]. There have been more big data strategies employed for the examination of vast healthcare information from various sources in the smarter IoT-based healthcare sector. ML is a major strategy among these technologies for doing intricate studies, clever judgments, and ingenious problem-solving approach for working on handling large amounts of information. Many investigations have looked into the implementation of IoT in conjunction with ML to monitor patients with medical issues and IoT-ML ensures the data integrity.

III. Machine Learning and Healthcare

A. Machine Learning

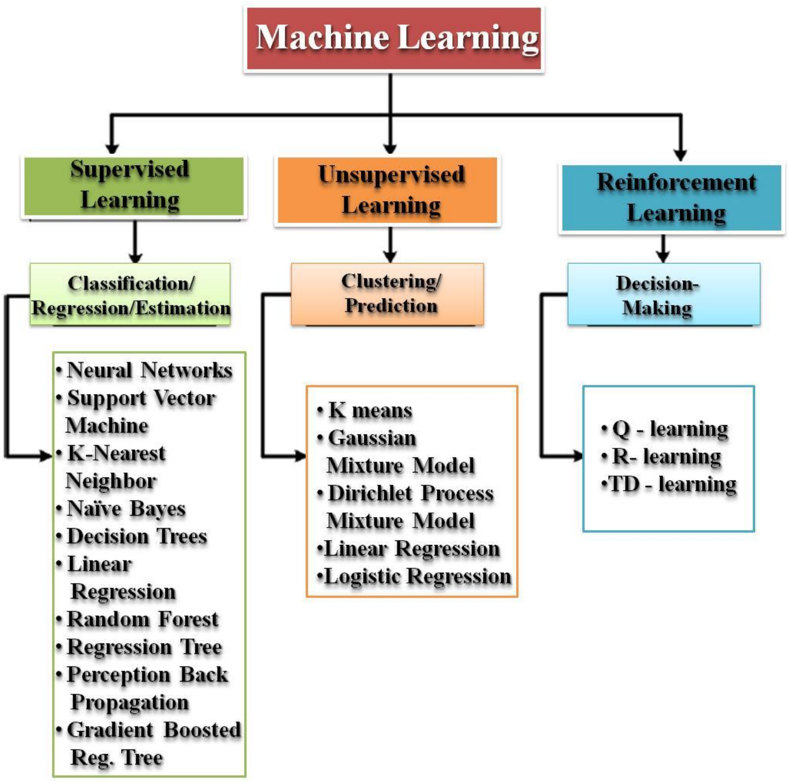

Fig. 4. A classification flowchart of machine learning techniques

Machine learning (ML) is a computer innovation inevitably related to artificial intelligence (AI) research. ML enables a computer system to grasp and examine the collection of inputs (raw data) on its own, without any involvement of human interaction [25]. Training and testing are critical phases in the development of a successful ML model. The training phase (which is highly research-intensive) involves giving the system marked or unlabeled inputs. These training inputs are then kept in the feature space to be used in potential predictions. Lastly, during the testing stage, the computer system is given an unlabeled input and is expected to predict the correct outcomes. Simply, machine learning predicts results for unlabeled input using known data from its feature space. As a consequence of its previous experiences and understandings, a competent ML model can anticipate outcomes. The precision of its output as well as model training determines the accuracy of such a model. ML is considered as revolutionary technology for healthcare transformation. Machine learning is the execution of algorithms that can learn from a given input or raw data. Big data and inexpensive computing resources drive machine learning development. Hence, machine learning is based on past observations made by machines and the relevant algorithms are created to incorporate them. In the most elementary sense, ML is derived from outcomes. Machine learning seeks to discover patterns in the healthcare data and it uses the learned patterns to make meaningful judgments [26]. Machine learning is a comprehensive multidisciplinary method that includes algebra, statistics, data collection, data examination, and so on. ML is a fundamental AI technology that draws knowledge via training of the input medical data.

B. Classification of ML Techniques

ML is divided into three types (i) supervised learning, (ii) reinforcement learning, and (iii) unsupervised learning, as shown in Figure 4 [27]. Every ML type includes numerous general algorithms [17]. This section describes extensively used ML algorithms for IoT healthcare prediction and categorization. Few examples of important machine learning methods comprises of Nave Bayes, K-Nearest Neighbor, Support Vector Machine (SVM), Gradient Boosted Regression Tree, Random Forest, Neural Networks, and Decision Trees,. All of these important ML strategies, in addition to others, will be explored and discussed in the following sections.

1) Supervised learning : The most significant ML design type is the supervised learning algorithm. This is mostly employed for assisting real-time applications of world [28]. Supervised learning model is utilized to anticipate results based on specific input sets and input/output instances. Each supervised training dataset has an input vector, a couple of input goals, and a supervisory signal, which is the expected output value. Following an examination of the training datasets, they are utilized for training ML model to get an inferred function (classifier). The purpose of supervised learning training algorithms is to assess the worth of one or more outputs based on a variety of input attributes. One distinguishing characteristics of the supervised learning model is the involvement of humans. The human role is vital to create a set of data that will ultimately work independently by learning and generalizing from the input cases. To generate a set of data, the ML model is given the first few pairs of inputs and intended outputs (training involves humans). This model then figures out how to generate outputs on its own. The primary challenge occurs if the model is asked to anticipate the consequence of a fresh input with no assistance of humans. As a result, assuring the accurateness of the anticipated model is crucial. Besides its clear success, supervised learning also has the disadvantage of necessitating a massive quantity of labeled information to produce a bulk-scale labeled set of data [29]. In classification and regression, supervised learning methods are commonly used. In contrast, this review will talk about the categorization using supervised learning process. Classification/prediction is the fundamental purpose of employing ML algorithms. To identify and forecast class labels, these algorithms use a specified set of instances. Classification samples are either completely categorized or do not fit into any classification. They are not categorized in any form. Missing values wreak havoc on the prediction and classification algorithms. The two methods of classification (supervised learning) are: (i) binary and (ii) multiclass. The binary classification is concerned with two classes. The input data is divided into these two classes. For instance, establishing YES/NO classification or prediction of e-mails into spam and non-spam types. The digits 0 and 1 represent these prediction classes. In contrast, multiclass classification concerns about three or more anticipatable classes. Determining the stage of tumour is another example. Classes are denoted by the numbers 0, 1, 2, and so on. Specific phases are often necessary for supervised learning, such as (i) data collection, (ii) data preparation, (iii) model selection, (iv) model training or validation, (v) model assessment, and (iv) prediction of outcomes [17].

2) Unsupervised learning : Unsupervised machine learning can identify hidden features within unlabeled data. This has been employed in many successful applications; nevertheless, evaluating these applications might be challenging at times. This is because of insufficient experience in unsupervised ML. As a result, there are no reward or errors indicators to assess potential solutions. The signal (reward) differs between supervised and unsupervised ML in this situation. Unsupervised learning is used in statistics to approximate density. ML models such as self-organizing maps (SOM), adaptive resonance theory (ART), and neural network (NN) involve unsupervised learning [17, 25]. Unsupervised learning entails manipulating and grouping datasets. Data in the dataset are modified during the transformation process to show them in a different, fresh form that people and machine algorithms can understand. Clustering models partition sets of data into meaningful catagories of correlated elements. K-means clustering is the most familiar and simpler unsupervised technique that discovers groups of linked data. The first stage in this strategy is to allocate every data point to the adjacent cluster center, and the second stage is to designate every cluster center as the mean of the data points selected near to it. The determination of successful outcomes in unsupervised learning is a fundamental challenge. Unsupervised learning success reveals whether or not the algorithm learned anything useful. Because unsupervised learning does not provide labels or outputs, the right output is uncertain. As a result, determining algorithm performance becomes very difficult. As a result, unsupervised learning is only utilized for exploratory objectives like enhancing data comprehension. Another essential aspect of unsupervised model is that it can be the preparation stage for supervised models. Identifying a novel model type for representation of data may enhance the performance of supervised models.

3) Reinforcement learning : Machine learning also includes reinforcement learning. This is in relation to taking proper behavior for maximizing the benefits in certain situation. Various apps and computers utilize it to evaluate the best probable action or course of action to take in a particular event. Reinforcement learning differs from supervised learning in that the training data contains the solution key, allowing the model to be trained with the correct answer; however, there is no answer in reinforcement learning, and the reinforcement agent selects what to do to fulfill the given task. In the lack of a training dataset, it is compelled to learn from its own experience. The initial stage from where the model will begin should be provided as input. The model will return an outcome depending on the input, and the user will select whether to reward or penalize the model based on its output. The model is always learning. There are several alternative outputs since there are numerous solutions to a certain problem. The optimal answer is determined by the highest possible payment. So, reinforcement learning is all about making successive judgments. In basic terms, the output is determined by the state of the current input, and the next input is determined by the output of the previous input. Because the decision is contingent on reinforcement learning, the user assigns tags to sequences of related decisions. Through interaction/labeling, RL may be employed in machine learning and huge data processing. It is made up of a collection of algorithms like Q Learning and Monte Carlo methods. Park et al. presented the automatic diagnosis of large numbers of patients utilizing IoT devices and Q-learning method [30]. Zhao et al. used reinforcement learning to provide directions for crowds in a smart city. Such a technology might be critical in lifting of lockdowns all through COVID-19 pandemic crisis, while adhering to social distance standards [31]. Dourado et al. employed a Deep RL-IoT model to identify strokes using topographic pictures of the skull [32]. Similar models were employed by Liu et al. to identify lung cancer [33].

C. ML Techniques for Healthcare

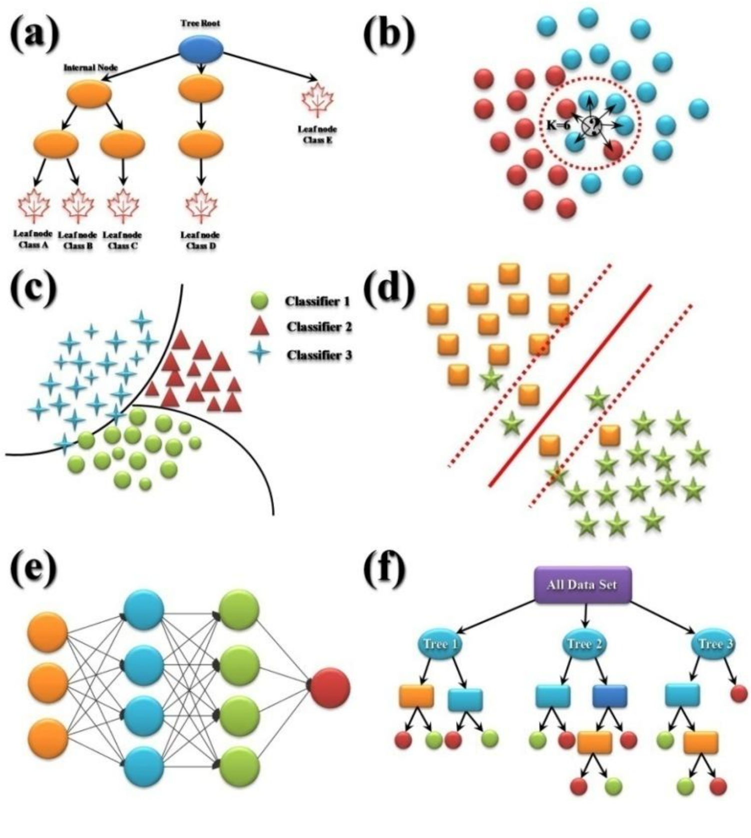

Fig. 5. A depiction of ML models: (a) DT, (b) KNN, (c) NB, (d) SVM, (e) NN, & (f) RF

Scientists have designed and utilized several popular ML models for prediction/classification processes. Some of them, as shown in Figure 5, are explained in subsequent sub-sections [17].

1) *Dimensionality reduction algorithms (DRA) :* DRA is a collection of algorithms that take huge amounts of data as input, detect patterns and correlations in them, and produce a considerably smaller set of data (in regards to the number of dimensions) without compromising any critical information originally provided. This removes redundant data, mistakes, and certain components of data that are highly connected. Substantial promises have been made for the identification of Parkinson's disease and breast cancer by combining IoT with DRA such as linear discriminant analysis (LDA) [34]. The need of combining IoT with DRA to improve diagnostic skills is greatly highlighted in the literature [35].

2) *Discriminant Analysis :* Discriminant analysis (DA) is a form of DRA that projects a set of data points into a space with lower dimensions in such a way that the classes are correctly segregated into non-overlay groupings. When just two groups are involved, this classification is comparable to multiple regression, but it becomes more sophisticated with the increase in number of groups. DA is used in healthcare to determine a patient's disease prognosis and severity. LDA finds combination (linear) of characteristics to classify, whereas a more generic MDA (multiple discriminant analysis) does the similar task in a non-linear space.

3) *Linear Regression :* It is a modeling procedure that finds a link connecting independent and dependent variables via a linear approach. It is preferred when there are just continuous independent variables. There are several strategies for creating a linear regression model, the most prevalent of which are conventional least squares and gradient descent. The former attempts to discover the coefficients by directly minimizing the total of squared errors, whereas the later utilizes a repetitive technique to minimize the total of squared residuals.

4) *Logistic Regression:* Logistic regression (LR) is a probability-related method whose sigmoidal function serves as the cost-function and has a value from zero to one. There are two kinds of logistic regression. When classifying observations into two groups, binary LR method is employed, but multinomial logistic regression is used when classifying more than two groups. When the dependent variable in the regression issue is dichotomous, logistic regression is extremely useful.

5) *Support Vector Machine (SVM) :* The notion of a classifying hyperplane is used in this technique. The aim is to discover a plane that divides the data into two parts/groups, while keeping the difference between the data points in the two groups as minimum as possible (Figure 5d). The maximum range is claimed for this hyperplane. Data on opposite regions of the hyperplanes are allocated to distinct groups. The size of the hyperplane is determined by the quantity of considered features. Here, the hyperplane is just a line for features with a number less than or equal to two. It converts to a two-dimensional plane for three features, but imagining it for larger than three features gets very hard. SVMs have the benefit of being particularly resistant to excess fitting concerns. SVMs can classify datasets using linear functions and it can also classify them via non-linear kernels. Ginantra et al. provided a SVM stereotype in which a classifier performed better than rest of classifiers in determining if a person has an influenza-type illness (ILI) i.e., acute respiratory infections [36]. SVM is the most precise method in position confirmation with no need for channelling of features data [37]. SVMs were also utilized to create approaches for tackling the challenge of classifying healthcare implant materials [38].

6) *K Nearest Neighbors (KNN) :* The notion of a classifying hyperplane is used in this technique. The goal is to find a plane that separates the set of data into the k-closest neighbors. The distance is obtained by considering the difference between the attributes of the neighbors and adding them together (Figure 5b). The vote is carried out to identify which group the bulk of the k-closest neighbors will be categorized into for the chosen data. The k-value is decided by the procedure of tuning of the parameters. It is normally selected to be close to the square root of the sum of items number. The k-value is usually an odd number to reduce numerous categories receiving equal votes. KNN is useful for categorization of data (labeled) even if the data from training set is tiny. This is extensively utilized in a variety of ML applications. To predict cardiac attacks, researchers used KNN model on the medical data received from devices employing IoT [39]. KNN was utilized to extract information obtained from 20 k-closest devices/sensors to determine the locations of various joints located within the body [40]. KNN classifiers were then employed with Minkowski and Euclidian distances for forecasting the present behavior of the users. Once categorization for a number of activities is created, this has a lot of promise for application in fitness measurement. Azimi et al. proposed estimating missing/lost points of data gathered to track pregnant women using repeated KNN imputations [41]. This program may be utilized with confidence as a healthcare B2C assistance or as a accessory for maternal health research. Hossain et al. demonstrated other activity measuring appliance that used LoRaWAN sensors and an accelerometer for recognition that employed KNN model with an accurateness of 80% [42].

7) *K-Means :* K-means identifies items based on whether they fall within the limits of a certain class. As a result, categorization is limited to "similar" and "dissimilar" types. Using Euclidean distances, the centroid of

the cluster for every category is identified, and a new item is simply classified according to the distance from each cluster. This method is employed by a number of web browsers and wireless sensor network (WSN) platforms. K-means categorization is also used in a number of other sectors, such as deploying wireless wearable networks to diagnose injuries within soldiers when they are away from their stations during a war and tracking ECGs of patients using data collected by wearable IoT nodes [43, 44]. Sood and Mahajan proposed employing fog computing and fuzzy k-means to track the likelihood of disease transmission and to give remote diagnostics for a chikungunya pandemic [45]. This is a tried-and-true system that might be expanded to include monitoring of COVID-19 patients data. Kim et al. also demonstrated the use of k-means clusters on MRI images for information extraction to speed up the detection of brain tumors [46].

8) Decision Tree (DT) : A decision tree (DT) consists of three parts: leaf nodes, core nodes, and branches that signify decision rules, outcomes, and attributes (Figure 5a). The entropy and Gini index are two tools often used for data classification. Cho utilized DTs to monitor people's locations during the pandemic [47]. Using pulse amplitudes and intervals as characteristics, Xie et al. created a system for classification of heartbeat that recognizes PVC (premature ventricular contraction) to identify arrhythmia [48].

9) Random Forest (RF) : DTs change depending on the used data to train them. When the training data for a decision tree is changed, the outcomes vary greatly. This algorithm has a high computational cost. Because turning back after splitting is impossible, local optima are usually determined. These constraints are addressed by the random forest (RF) approach (Figure 5f). Several decision trees are trained concurrently in this model to create a single result. This type of decision tree merging is known as 'bagging'. Al Hossain et al., for example, revealed how a RF model surpassed other models with accuracy of 95% in forecasting the total number of persons contaminated with influenza virus at community locations [49]. It has a high accuracy since it can collect the results of all DTs. Gupta et al. developed a RF classifier model that beat SVM, DT, and KNN in detecting aberrant crowd movements with 77.8% accuracy [50].

10) Naive Bayes (NB) : The Bayes theorem serves as the conceptual foundation for NB classification (Figure 5c). The term 'naive' relates to the assumption that every feature is independent of other. The information is separated into a response vector and feature matrix. The feature matrix rows reflect the entire collection of data as vectors, each one symbolizing a different kind of variable. Aternatively, every response vector row indicates a resultant group. Assery et al. and Sadhukhan et al. described cases in which NB surpassed all other classifiers in classifying tweets, which can aid in the management of social networking concerns during catastrophes or pandemic times [51, 52].

11) Gradient Boosting & Adaboost : For typical scenario of poor beginners, the precision of learning is roughly equal to that of a random result generator. As a result, combining these learners with more than one ML models to generate a powerful learner is an excellent method to use them. Ensemble learning is another term for utilizing several learners for training a model. Boosting is one example of an ensemble learning strategy in which decision boundaries are created for each weak learner and weights are assigned depending on how effectively the borders are categorized or assessed from the data. The procedure is continued till a good prototype is obtained. Adaboost assigns equal weight to each observation (for the first boundary) at the start, then increases the weights for poorly identified items and changes the borders correspondingly until all observations are correctly categorized. Many borders (learners) are continuously formed in gradient boosting, in such a way that every successive learner accounts for part of the faults of the prior one. With 92.1% accuracy, extreme gradient boosting may detect irregular cycles in cardiac patients [53]. Similarly, wearable gadgets speech signals may be employed to perceive early indicators of PD (Parkinson's disease), while prognostic analytics may be utilized to identify diabetes in customers [54, 55]. Constricted IoT healthcare systems may also be utilized to identify seizures efficiently [56].

12) Convolutional Neural Network (CNN) : CNN is a feed-forward network utilized for classification type problems [57]. It seggregates the input data into components and sends the components to a convolution layer (Figure 5e), which combines them in various ways till patterns appear (or convolution occur). The input images are then mapped against these patterns by a rectified linear unit (ReLU) layer, which finally proceeds them to a pooling layer. The pooling layer compresses the map to form a pooled feature map, which is flattened into a linear vector and supplied into a fully linked network to classify the input. CNNs are widely utilized in applications that demand visual understanding of images having a grid-like architecture. Alhussein et al. interpreted brain wave data obtained as a 2D time series to predict epileptic events and warn health officials immediately [58]. Ke et al. suggested using raw EEG (electroencephalogram) data to assess patients suffering from depression with Lightweight CNN [59]. Ciocca et al. employed images to identify food and calories of consumers, which have applications in fitness and nutrition [60]. Alhussein and Muhammad employed deep learning on pitch tones to diagnose vocal disorders utilizing mobile healthcare frameworks [61]. Using the

LUNA16 dataset, Bansal et al. suggested a RESNET-based framework for 3D segmentation of images and classification of lung cancer, attaining high accuracies for segmentation (92.7%) and lung cancer detection (88.3%) [62].

13) Artificial Neural Network (ANN) : An artificial neural network (ANN) is a ML model which mimics the process of learning of the human brain. It contains (i) an input layer that collects the information to be processed, (ii) numerous layers that analyze the data, and (iii) an output layer that gives the output. In ANNs, the hidden layers accept intermediate inputs, allocate a random weight and bias to each input, and compute different weighted sums, that are then transferred via other layers (with weights and sums) till they get to the final layer, which determines the output using an activation function. Whenever the outputs are incorrect, they are sent back to the earlier layers in compliance with a cost-function to adjust the weights before suitable responses are obtained. ANNs are extremely dynamic and also have implications in pattern classification. Kim et al. used an unobtrusive ANN strategy that employed IR sensors set all through the house to track sleep, bathroom time, excursions, and movement to detect symptoms of unhappiness in elderly people via evaluating information obtained through telecom information [63]. Back propagation ANN was proposed by Bhatia and Sood to forecast stochastic health condition risks during exercise [64]. Sood and Mahajan [65] and Humayun [66] employed a fog-layer architecture to recognize and regulate hypertension (BP) outbursts and to handle information relevant to heart symptoms in patients, respectively. Hassija et al. created a traffic estimate system using a neural network-based smart connection in combination with a blockchain network [67].

14) Natural Language Processing (NLP) : NLP is the use of machining learning techniques to teach computer systems to comprehend and understand normal human language, text, and speech. Its language mining qualities help handling and quantifying unstructured data quite straightforward. Some of the most popular NLP libraries available today include NLTK, Scikit-learn, TextBlob, and spaCY. NLP implementations go further than their reliance on text or image data to collect information and are thus used in a wide range of applications, including food consumption and nutrition tracking, along with assessing the patient's emotive response to medicine ingestion [68. 69]. Amin et al. advised using NLP to evaluate facial expressions, speech, movement, etc in actual live data via smart city networks to diagnose patients and provide them with essential crisis aid [70]. This method has also been used in a variety of psychological applications, where NLP was applied to information from both social networks and IoT applications [71].

15) Cognitive Automation (CA) : Cognitive automation (CA) is a subset of artificial intelligence. It employs modern automations such as emotion detection, data mining, cognitive reasoning, and NLP to mimic human intelligence. Cognitive automation uses technology to solve issues in an attempt to mimic human intellect. It serves as a driving force behind the efficient and enhanced responses provided via an AI tool. CA, by providing a better collaborative stratergy to healthcare IoT, aids in implications requiring the concurrent usage of biiological and emotional systems for coping with healthcare crises. Muhammad et al. created a 5G CA-based medical surveillance system which might revolutionize medical systems, particularly in smart cities, through concurrently operating database and resources cognitive system [72]. Alhussein et al. investigated CA-based IoT architectures designed for surveillance and recognition of epilepsy [58].

Table 1 covers all of the ML approaches discussed in the preceding sections [17]. ML techniques are utilized for analyzing, evaluating, and gathering information from collected data as well as enhancing decision-making processes because once taught, they do not require any further supervision and can execute their duties independently. Machine learning algorithms assist in distinguishing tough and wide trends of information and records them. This approach is ideal for medical applications, particularly for those dealing with highly developed genomics and proteomics. It can be utilized to diagnose and detect additional disorders. DL (deep learning) algorithms are employed in healthcare sector to advocate the adoption of advantageous healthcare plans to offer a preferred patient treatment service [27]. In many ways, ML can be used in healthcare, like (i) disease identification and diagnosis, (ii) personalized treatment/conduct change, (iii) pharmaceutical discovery and manufacturing, (iv) cliniical testing and illness evaluation, (v) radiology imaging (MRI, CT scans, etc) and nuclear medicine (radiation therapies), (vi) smart electronic medical reports (EMR), and (vii) pandemic outburst prediction [26]. By 2025, the economic outcomes of ML approaches in big data research, i.e., ML-dependent platforms and solutions, is predicted to be from $ 5.2 to $ 6.7 trillion per year [73]. This highlights the need for machine learning in huge data sets, particularly in IoT. ML enables IoT to understand concealed features in big data for successful forecasting and reinforcement systems. Recently, medical systems have incorporated ML-based methods to improve IoT applications, such as automated devices that assemble medical information, anticipate illness diagnoses, and conduct real-time patient monitoring. On various clinical datasets, different ML algorithms perform differently. Because projected results differ, overall outcomes may suffer. During the clinical decision-making process, the variability in prediction outcomes become more apparent. Despite extensive research in big data and ML, the IoT healthcare industry has made limited progress in ML-based solutions for large data examination. Understanding the ML methods used in medical systems to handle IoT medical data is therefore very crucial.

TABLE I. A LIST OF MACHINE LEARNING ALGORITHMS, USED METHODS, ADVANTAGES AND DISADVANTAGES.

ML Algorithm	Purpose Type	Used Method	Advantages	Disadvantages
KNN	Classification, Regression	Euclidean distance (using continuous variables) Hamming distance (using categorical variables)	Non-parametric method. Perceptive to recognize. Simple to execute. Do not need precise training. It is simple to adjust to changes by updating its set of labeled observations.	Calculating the similarity between datasets takes a lengthy time. Because of the skewed datasets, performance suffers. The performance is affected by the hyperparameter selection (K value). Because information may be lost, we must employ homogenous characteristics.
NB	Classification (Probability-based)	Maximum likelihood (using continuous variables)	Data searching *via* inspecting every feature independently. Acquiring easy per-class data from every characteristic aids in improving the correctness of the assumptions.	Small quantity of training input information is required. Variances of the elements for every class are determined.
DT	Prediction, Classification, Regression	Decrease in Variance (Continuous Target Variables) Gini Impurity (Categorical Target Variables) and involves strong prepruning	Simple to execute. DTs can work with both categorical and continuous characteristics. Little to no effort is required for preprocessing of data. Iteratively improves prediction performance.	The training dataset is sensitive to the unbalanced dataset and noise. Costly, and requires large memory. To avoid variance and bias, the depth of the node must be carefully chosen. It is necessary to fine-tune the parameters and may take some time to train. To avoid variance and bias, the depth of the node must be carefully chosen.
RF	Regression, Classification	Bagging	Lower correlations between decision trees. Increases the performance of decision trees.	Working with multi-dimensional, scanty information is difficult.
SVM	Nonlinear Classification, Classification (Binary)	Kernel trick, Soft margin, Decision boundary	More efficient in 3-D space. Employing the kernel gimmick is SVM's true strength.	Choosing the kernel gimmick and the optimum hyperplane is not simple.
NN	Prediction, Mapping	CNN, RNN (Recurrent Neural Networks), DL (Deep Learning), (MLP Multilayer perceptron)	Storing data throughout the whole network. Capability to operate with limited knowledge. Fault tolerance and distributed memory are added advantages. Ability to perform parallel processing.	It is dependent on the hardware utilized. The network's behavior is unexplained. Determining the best network structure is often difficult. Difficulty in communicating the problem to the network. The network's lifespan is unknown.

IV. AMALGAMATION OF IOT AND ML

As described in the preceding sections, both IoT and ML approaches have been used in a variety of smart systems made up of many smaller components, each delivering a unique function. A better healthcare service may be delivered to the public by amalgamating or merging IoT with ML (or IoT-ML). Computer vision, reinforcement learning, natural language processing, computer networks, and common logical methods are used in smart healthcare systems.

A. IoT-ML HC Applications

Several published papers detail the uses of IoT-ML in healthcare (HC) [74]. Figure 6a depicts the key components of IoT-ML for healthcare (HC) applications (fast diagnosis/prognosis of many kinds of diseases, real-time monitoring of patients health, and individual specific assistive care of patients). With the advancement of artificial intelligence software analytical tools, wireless internet technologies (like 5G), and robust medical data storage and handling systems, it is possible to effectively extend the IoT-ML to solve the crucial persistent and challenging healthcare problems and offer better services as needed. Figure 6b depicts many human body organs/parts where IoT-ML strategies are successfully used to identify HC solutions, such as illness detection, patient behavior analysis, and assistive care guidance. Disease diagnosis is often accomplished by determining the type of ailment that the patient is currently experiencing through the evaluation of symptoms detected by sensors. The sections that follow offer an overview of IoT-ML research conducted to improve HC systems.

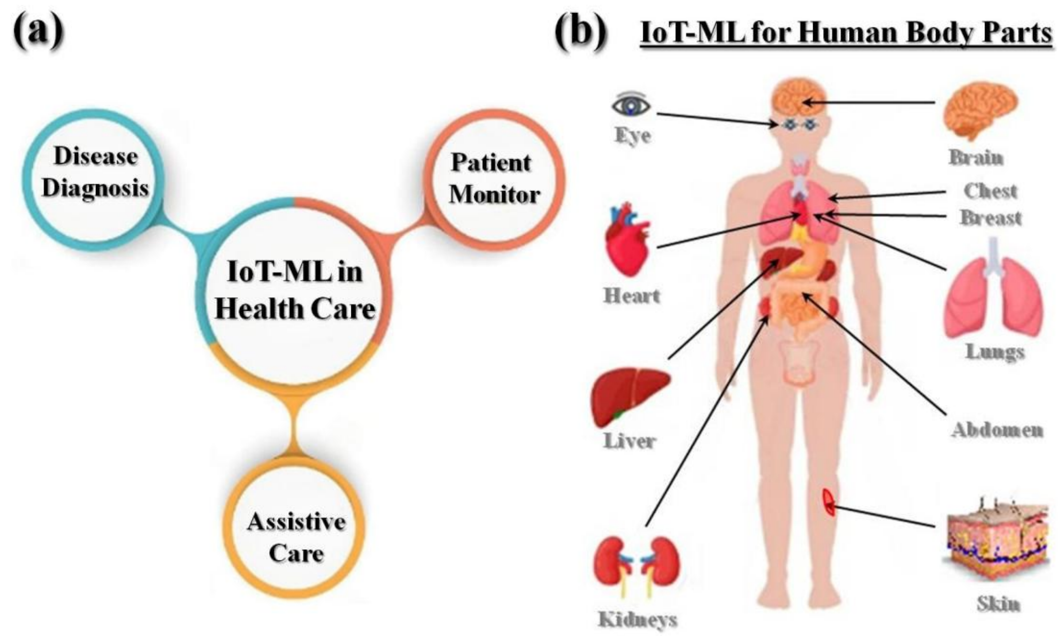

Fig. 6. A depiction of IoT-ML (a) components and (b) human organs for HC applications

1) Cardiovascular Disorders : Heart disease is one of the top causes of death throughout the world. Forecasting cardiac disease is a difficult endeavor. Nevertheless, the incorporation of IoT into medical systems has demonstrated as a great method of monitoring patients' health and detecting the irregularities. Body temperature, blood pressure, ECG, and heart pulse sensors data are the most regularly utilized ML input. The electrical activity of heart at rest is represented by ECG signals. It may be utilized to make assumptions about heart (cardiac beat rhythm and rate), and it may be utilized to diagnose heart enlargement caused by higher heart beat rate, high blood pressure, heart attacks or dysrhythmia. Gupta et al. [75] proposed employing wearable IoT technology to monitor numerous metrics in real-time to identify cardiac problems using an ML-based model. This case study's goal was to employ simultaneous temperature, ECG, and pulse supervision as data inputs to a trained forecasting ML model to predict whether or not the customer is at danger for any cardiac illness or arrhythmia. The pre-refined clinical data was divided into testing dataset and training datasets, with learning algorithm performed on the training data. The accuracy, hit rate, and other characteristics of various classifiers, including SVM, KNN, NB, RF, and DT, were assessed. Then, hardware prototypes for gathering of data, connectivity to cloud, and, most significantly, simultaneous forecasting were created. Khan [76] presented an IoT healthcare system that uses modified deep CNN to evaluate cardiac problems (MDCNN). A wristwatch and heart monitoring device was utilized to capture ECG and blood pressure data, which was then communicated to the webserver through LoRa. Depending on the submitted data, the MDCNN model evaluated the patient as having a healthy or an irregular cardiac situation and notified the clinician if an anomaly was detected. Using a bio-inspired optimization technique, the most significant characteristics for assessing cardiac disorders may be chosen (BIOA) [77]. The adaptive elephant herd optimization technique was utilized to optimize the weight values for the IoT-ML model. Finally, an AD8232 sensor was employed to collect ECG data. Interfacing was accomplished using a Raspberry Pi, which transmitted data to the cloud-based server through an SX1272 900MHz LoRa antenna. Azariadi et al. proposed employing ECG monitoring and categorization on an integrated IoT network to diagnose cardiac disease [78]. The created model might be employed with wearables (smart sensing devices) for ECG diagnosis, allowing for round-the-clock monitoring. For feature extraction, the discrete wavelet transform method was applied, while SVM was used for classification. After that, the technique was developed and deployed on Galileo (Intel's IoT Arduino board). The average accuracy of this approach for cardiac diagnosis was 97%.

2) Lung Cancer : Lung cancer is the high frequent tumor, accounting for ~1.8 million fatalities in 2018 [19]. Valluru and Jeya introduced a model depending on optimum SVM for categorizing CT (computed tomography) images of patient’s lung and for diagnosing lung cancer using optimized SVM parameters [79]. In this SVM model, features collection was accomplished by changing the GWO (grey wolf optimization) technique, which was associated with a genetic approach (GA). The entire lung cancer detection process is an easy linearly detachable problem with multi-dimensions, and the conversion is dependent on the SVM’s kernel function. The provided approach produces superior results on each test image, while many other factors are also considered. Above all, it obtains a mean classification accuracy value of ~94%, which is obviously greater than the comparison techniques, i.e., GA, BPSO, and BDE. Extensive analysis of test images shows that the suggested approach may be effectively utilized in simultaneous information processing in clinics and healthcare facilities. This suggested approach may be enhanced more by including DL models.

3) Neurological Disorders : EEG-based monitoring is very important way through which smart healthcare systems may help with patient monitoring for neural illnesses like Alzheimer's disease and epilepsy. It is a diagnostic technique that utilizes electrodes that are placed on the scalp to identify electrical impulses in the human brain. Magnetoencephalography (MEG) is another sort of cerebral signal imaging method, which has not been widely employed for diagnosis of neurological disorders in patients. MEG signals are not much dampened than the signals of EEG, making them a useful analytic tool. Amin et al. developed a cognitive IoT architecture for EEG-based disease identification [70]. In this architecture, multi-dimensional information from the electrodes of EEG were refined and delivered to a cloud-based intelligent cognition system, which assessed the neural condition of the patient and communicated this information to a DL program for illness identification. The DL program employed CNN model and transfered the classification findings to the intelligent cognition system, that eventually settled on the rescue operations and returned it to the healthcare specialists for additional study. Amin et al. suggested a model that employed two prominent CNN models, the AlexNet and the VGG-16 models, to run two sets of tests separately [70]. The VGG-16 model system attained ~86.6% accuracy, while the AlexNet system achieved ~87.3% accuracy, both of which are greater than the results produced by state-of-the-art models. In another work, Khalid et al., sought to develop a system for automated spike identification in MEG signal information [80]. The common spatial patterns approach is used to extract characteristics that distinguish between spike and non-spike data. These characteristics were discovered to have a normal distribution. As a result, LDA was selected as the classification approach. The average sensitivity and specificity were ~91.0% and ~94.2%, respectively. These findings suggested that detecting MEG spikes with LDA is a potential method for diagnosing epilepsy. The use of CNN models in EEG data resulted in the automatic identification of different epilepsy types. Acharya et al. used CNN to categorize EEG datasets without human intervention [81]. In addition, two types of activation functions were utilized in the model: (a) softmax and (b) rectified linear activation unit. The CNN-based model achieved 88.67% accuracy, 90% specificity, and 95% sensitivity. As a result, the application of CNN models for EEG-based categorization yields promising results in an illness diagnosis.

4) Diabetes and Pancreatic Cancer : Type 2 diabetes causes elevated sugar concentrations in blood and it is a common chronic diseases that can be deadly if not timely treated. Diabetes is becoming more common, with the majority of people falling as victims to Type 2 diabetes mellitus and it is misidentified in many cases. Effective diagnosis of unidentified diabetics will result in superior and more accurate disease handling and a lower overall death rate. Han et al. [82] used SVMs to develop a detection model for undiagnosed type 2 diabetic mellitus patients. Because SVMs are less understandable, instead of simply utilizing them in general form, a customized SVM program can be utilized for extracting the support vectors, which are then utilized to produce image-type information. Rules for diagnosing diabetes were eventually derived from this simulated data in a RF model. The mining ensemble strategy combines RF and SVM to enhance the accurateness of the initial SVM model. For automated segmentation of various abdominal organs, computed tomography images are used in CAD systems. The pancreas is particularly difficult to segment automatically due to its position in the body and substantial differences in its volume and form. Statistics based models for shape that are utilized for studying other type of organs does not produce appropriate outcomes when segmenting the pancreatic organ. A highly accurate approach for segmentation of pancreas can greatly enhance the analysis of CT images of patients suffering from diabetes and pancreatic tumor. Farag et al. used RF classification to categorize image patterns produced by excess segmentation [83]. CT scan images are split into meaningful patches termed superpixels, from which various patch-level image attributes are extracted for training RF classifier. Jaccard index, Dice similarity coefficient, volumetric recall, and volumetric accuracy were the assessment measures employed during the analysis. The response maps presented match the classification and dense labeling demonstrate success in pancreatic segmentation, with a Dice similarity coefficient value of ~71% and Jaccard index value of ~58%. The suggested method's main contribution is a shorter calculation duration of ~7 minutes per each case tested, in comparision to much larger (>10 hours) for previous techniques.

5) Chronic Kidney Disease : Chronic kidney disease (CKD) is a worldwide issue of public health, impacting roughly 9% of global population and causing ~1.2 million fatalities in 2017 and it was the world's 12th biggest reason for humans death [84]. Subasi et al. [85] conducted a comparison case study research on CKD diagnosis utilizing ML models like SVM, KNN, DT, RF, and ANN. RF obtained accuracy of 100%, whereas the DT reached accuracy of 99%. According to this paper, ML models can attain good levels of accuracy that is adequate for self-directed operation without any intervention of humans.

6) Medical Imaging : ML is utilized in discipline of medical imaging (MI) that deals with the techniques and technology used for creation of images of bodily components for therapy and diagnosis. Nowadays, two types of medical imaging modalities are widely employed: MRI (magnetic resonance imaging) and X-ray radiography. These photographs are now taken and carefully inspected by a health specialist to detect irregularities. This technique not only consumes time, but it is also vulnerable to many errors. As a result, the use of ML models enhances sickness prediction, detection, diagnostic accuracy, and timeliness [86]. Researchers demonstrated how artificial neural networks (ANN) and other ML approaches may be used in conjunction with MI to allow computer-assisted sickness detection, diagnosis, and prediction [86]. DL algorithms, namely CNNs, have been developed as strong video and image processing tools, that are critical in MI [87]. Medical imaging applications frequently employ images as input data, like CT scans and X-rays [86, 88]. CT scanners and X-ray machines are two examples of IoT devices that are commonly used in machine learning setups under healthcare settings [88]. For machine learning applications in medical imaging, supervised learning is commonly employed.

7) Behavioral Modification or Treatment : Behavioral modification (BM), as the name indicates, is the procedure of supporting a patient in modifying undesired behavior. BM is typical case for which common cure is given to patients with unhealthy habits that contributes to their poor health. The IoT permits the gathering of massive amounts of information about individuals, enable the use of ML for behavioral modification. As a consequence, ML models can be utilzed to assess individual behavior and recommend relevant alterations. Besides sending alarams and messages to urge modification, ML models may empower people with self-awareness with tools for BM. ML may also be used to assess behavioral modification programs to decide which model is best for a certain type of patients [89]. ML techniques utilized in BM to include network classifiers like NB, DT, and SVM [90]. These algorithms obtain input data using feature mining that generates information in table format [90]. As a result, IoT devices that mine data can be used to explain the behavior of humans, like images, recordings, and videos, are relevant.

8) Clinical Trials Research : Clinical trials are research studies that are carried out to establish the efficacy and security of behavioral, clinical, and pharmaceutical drugs. Because clinical trials include humans and they are typically the last phase in the clinical research protocols, which must be managed carefully to keep away from causing damage to the participators. ML may be utilzed to improve the clinical trial procedure by allowing the evaluation of freely accessible biological and clinical data, that is gathered from patient’s health records, and by realistic data facts procured from the sensing devices to be utilized to learn about the efficacy of therapies [91]. ML models permit clinical practitioners to evaluate enormous quantities of medical information to get intuition into the efficacy and security of a certain drug inside the patient’s body. For instance, machine learning can be utilized to develop drugs for treating diseases (like COVID-19) [92]. The initial step in using ML models for clinical trials is to mine features from the available datasets [92]. As a result, the images and tables linked to clinical trials are included in the input data. The IoT devices utilized must be capable of collecting data based on the clinical trial variables. Common sensor data includes blood glucose, weight, blood pressure, and heart rate.

9) Smart Electronic Records : Electronic medical records (EMR), that have substituted medical charts of patients, enable healthcare providers to provide better supervision by providing quick access to the patients information. Machine learning allows intelligence to be included in electronic health data. To put it another way, instead of merely storing patient information, EMR may be improved using ML to comprise smart applications. Smart EMRs, for example, might evaluate patient's information, suggest the best healing, and help in making appropriate clinical decisions. Indeed, merging ML with EMR information has been proven to enhance optometry/ophthalmology [93]. Furthermore, advanced computerized records can analyze big data to assess the condition and protection of supervision delivered at a healthcare facility and identifies the discrepancy spots for further development. ML models that may be implemented into EMR includes linear regression, LR, ANNs, and SVM [93]. As input EMR data, images, text, time series, and tables, can all be used. For instance, real-time data from medical record of a patient may be utilized for predicting postpartum depression [94]. Recurrent DL architectures are accurate for sickness prediction when embedded in electronic records [95]. IoT sensor data utilized in these ML models include temperature, blood glucose, weight, blood pressure, and heart rate. The authors reported that the sensor data revealed signs of the illness under investigation.

10) Epidemic Outbreak Prediction : Rapidly spreading diseases in a society may be overwhelming and hard to control. As a result, participants in the medical business are familiar with the necessity of developing gadgets and approaches for forecasting and preparing for epidemic outbreaks. Because large amounts of data are now available, administrators, regulators, and medical professionals may utilize ML models to forecast epidemics. DNN (deep neural network) and LSTM (long short-term memory) learning algorithms are two ML approaches utilized for sickness prediction [96]. Input data for ML models can include time series, text, category, and numerical information. For instance, simultaneous healthcare information might be utilized in a ML system to anticipate potential sickness developments. ML algorithms use data such as hotspots, population density, geo-mapping, vaccination levels, and clinical case classifications, to anticipate diseases [97]. Satellites and drones, for example, might be used to collect population densities and other geospatial information. Climate data and other kinds of environmental data that influence pandemic risk may also be gathered. Medical information of patient collected at the initial stage, like blood pressure, glucose levels, and temperature, is furthermore useful. In general, illness monitoring is crucial since it supports epidemic prevention and allows stakeholders to prepare for prospective outbreaks.

11) Personalized Care : Patient-centered care requires personalized services. Patients have the right to therapy that is personalized to their own needs, expectations, and beliefs. Personalized healthcare increases patient fulfillment and usage of prescribed medical services while enhancing clinical outcomes. Machine learning algorithms may assist healthcare professionals in reviewing every patient's data and developing tailored healthcare plans, thus allowing them to give customized therapy to the patient [98]. Machine learning algorithms amalgamate dissimilar information resources to uncover patient-centric symptoms of illness development using the capabilities of health records [99]. The knowledge gathered favors making of clinical decisions by permiting medical practitioners to offer tailored patient-specific therapy. Time series, tabular, and text data can be used as input data formats for ML personalized care. Using the right ML algorithms, tabular information from the medical records of patients may be utilized to decide the best route for treatment of the patients. Similarly, the ML algorithms may be fed with IoT input data, like weight, blood pressure, blood glucose, and heart rate.

12) Logistics and Security : This section covers a few ML applications that aim to enhance IoT-ML HC systems as a whole by enhancing logistics and security. These developments are especially vital because medical systems cannot be deployed unless safety issues are addressed, and as a result any improvements in logistics lead to enhanced performance of the medical systems, regardless of the intended IoT-ML HC applications [100, 101]. Overcrowding is a major issue in hospital emergency rooms. Patients must stay for longer durations for a medical bed to become ready, which harms their health and overall mortality rate, as well as hospital employee morale and efficiency. Such congestion may be prevented if the number of persons admitted to the hospital from the emergency department could be projected using hospital data, and the hospitals could further improve patient's healthcare. Furthermore, in crises requiring a tough emergency healthcare service, like COVID-19, it is vital to appreciate the requirement of logistics and security to prioritize patients according to their urgency, as well as in controlling of the time for medical staff's response, and making of the patient's treatment process more proficient. Because of insufficient resources, sensing network devices of body are usually exposed to safety laws in safeguarding susceptible patient health information. As a result, numerous techniques for providing security for wireless body area networks, or WBANs, have recently been developed

[102, 103]. With authentication assaults, attackers can participate in wireless communication networks among WBAN sensor nodes and disrupt the network functionality. Iris scanning, face recognition, ECG (electrocardiogram) patterns, PPG (photoplethysmogram) patterns and fingerprint scanning, are among the physiological, behavioral, and biometric attributes used in the cryptosystem approach.

Fig. 7. Images of some IoT-ML based healthcare systems

The number of IoT-ML-enabled healthcare system applications has continuously increased, and current research plans to include IoT in a variety of healthcare fields, such as efficient automated diagnosis, illness spread control, and offering a better therapy. The number of IoT-ML-enabled healthcare systems applications has constantly grown, and current research plans to include IoT-ML into a variety of fields of healthcare, including disease spread control, effective automated diagnosis, and improvised therapy. Figure 7 displays the numerous IoT-ML healthcare application systems (prognostic, diagnostic, spread control, monitoring, logistics, and assistive systems) [19]. Table 2 outlines the IoT-ML algorithms used in healthcare systems, as well as their advantages and disadvantages [17, 19].

TABLE II. SOME IOT-ML ALGORITHMS WITH HEALTHCARE APPLICATIONS BENEFITS AND LIMITATIONS.

Healthcare Application	IoT-ML Algorithm	Benefits	Limitations
Heart disease diagnosis	KNN	Wearable healthcare gadgets allow for real-time diagnostics.	More precision is necessary for actual applications.
Lung cancer diagnosis	Optimal SVM	Effective feature selection and parameter optimization result in an approach that is both accurate and practical.	The use of deep learning algorithms can result in even more multi-fold gains.
Pathology detection (using EEG)	CNN	Shows the potential for ML-based integrated smart frameworks to be used in smart health.	Requires advanced infrastructure, such as deep learning servers and a cloud-based cognitive engine.
Type-2 diabetes diagnosis	SVM + RF	The ensemble technique utilized improves dependability by making the model far more transparent than a basic black box model.	The resulting rule sets are quite tiny.
Chronic kidney disease diagnosis	SVM, DT, RF, ANN	Extremely high levels of accuracy show that the technology can be used without the requirement for human interaction.	It takes a very long time to become usable.

Early stage onset heart disease prediction	NB	Simple to utilize interface and fewer training needed.	Real- operation in world necessitates the incorporation of a number of minor parameters not covered in the NB model.
Influenza virus detection	NLP	Training time is reduced, and no preprocessing for missing values is required.	The information utilized is derived from restricted resources.
Epilepsy risk levels (classification)	KNN	Power spectral densities with reduced dimensions were employed to achieve higher output values.	There are a lot of false alarms.
Hemorrhagic shock recovery prediction	Logistic regression (LR)	In numerous testing methods, it outperforms the baseline classifier.	The test dataset is small.
COVID-19 disease identification	CNN	SARS-Cov-2 strains are easily recognized from other viruses.	A modest number of genome sequences were used to test the hypothesis.
Spread control of Ebola	DT	RFID and wearable sensors allow for simple large-scale application.	There is no model for estimating missing data.
Ocular data classification for navigation assistance applications.	SVM, ANN	Can help physically challenged persons and enhance their quality of life through improving communication.	There is a lot of noise in the utilized EEG signals that has to be reduced by preprocessing.
Robotic control with EEG impulses and typing systems	DL	The system is intended to be very adaptable to the user.	The ideal response cannot be guaranteed on the first attempt and takes numerous attempts to achieve the desired outcomes.
Identification of hand gestures for stroke rehabilitation	ML (dimensionality reduction)	Highly precise hand gesture recognition enables robot hands to replicate motions and aid in the rehabilitation of individuals who have suffered physical injuries.	Both training and verification data come from the same or a single source, and data from different patients is needed to make the model more user-independent.
Smartphone camera to measure blood pressure (BP) using cuff-less monitoring system.	LR	Blood pressure monitoring that is non-invasive and portable.	A large number of high-end smartphone cameras are required.
Continuous patient monitoring system to predict strokes.	RF, NB	Higher performance is achieved by combining various algorithms.	For autonomous data gathering, better ML-based medical sensor systems are necessary.
Using real-time monitoring data, predict future glucose levels.	ANN	The model can anticipate emergency diabetic cases.	For sudden data changes, it is inaccurate.
Fall alarm and fall forecast system	NB	The polynomial NB algorithm is utilized, and it surpasses all analogous ML methods.	The research is primarily aimed at hypertensive senior citizens.
Health monitoring system for Infants	Gradient boosting DT	Predicts whether or whether preterm newborns have bradycardia, allowing for early intervention.	A small number of bradycardia cases were studied.
System for patient prioritizing	K-means	Helps in the efficient deployment of resources and the priority of emergency cases.	Cloud-based, better range necessitates WiFi, which raises expenses.

Security system based on Gait detection.	ANN	Provides resistance to hacking methods such as medical dictionary attacks, and requires less computing than fingerprints.	The projected system is yet susceptible to brutal assaults; however the entire system is unlikely to be hacked.
Raw clinical data classification using ML	NLP	Structured data saved electronically may substantially increase the efficiency of the medical system.	It is untrustworthy with very complicated facts, such as lexical semantics.
Coexistence likelihood determination. using wireless technology	LR	Over-fitting has been reduced by employing least absolute shrinkage and feature selection in the selection operator.	Only a few protocols are applicable.
ML-based medical imaging	CNN, ANN	Improve the accuracy and patient-centeredness of the imaging process by automating this procedure and enhancing the quality of training datasets.	High reliance on quantity and quality of input (training datasets). Moral and lawful concerns around the usage of machine learning in medicine. It is sometimes hard to describe the logical outcomes of DL approaches.
Illness diagnosis	Image-based DL	Improving decision-making quality and efficiency by incorporating machine learning into electronic medical records to facilitate quick and accurate illness diagnosis.	The absence of clear rules and regulations governing the usage of ML in disease diagnosis. It is difficult to obtain well-annotated data for supervised learning.
Behaviour treatment or modification	NLP	ML incorporation into behavioural modification program scans, assist in decision making (of what is workable and what cannot be considered further).	The absence of a knowledge system for behavioural modification intervention that includes information science, protocol, and sources for interpretation of reports, an automatic annotator, ML and reasoning-based models, and a customer interface.
Research involving clinical trials	DL	Continuous learning from clinical data collected in real-time to increase the usability of deep learning in clinical research studies.	The issue in applying DL models to complicated healthcare data. The requirement for large quantities of properly-labelled input (training data). Machine learning raises moral concerns.
Smart EMR (electronic medical records)	DL, supervised ML	Intelligent medical systems capable of illness detection, progression prediction, and risk assessment for the proper management of various illnesses or ailments.	Preparing data before it is put into a machine learning system is still a difficult undertaking. Furthermore, including patient-specific features into machine learning models is tricky.
Prediction of epidemic outbreak	DNN	The application of predictive models to the surveillance and forecasting of a variety of infectious illnesses.	Predictive models' poor accuracy. The decision-making process. Parameters to be used with machine learning models.

Prediction of heart disease	DL, ANN	Clinical decision-making will incorporate patient-centred predictive analytics of cardiac illnesses, allowing for the deployment of preventative treatments.	The absence of ethical principles to govern the adoption of algorithms for prediction of heart disease. ML algorithms are incapable of solving very abstract reasoning issues.
COVID-19 diagnostic and prognostic models	DL models	Gather large-volume, high-feature data for training DL models of COVID-19 prediction.	Because of the insufficient training datasets employed, the created models are troublesome.
Personalized healthcare	DNN, DL, supervised ML, Unsupervised ML, and others	Developing systems that can be connected into EMR to encourage customized medicine, and for providing person-centered care.	Continuous collection of high-quality training datasets is required.

B. IoT-ML Healthcare Challenges

Table 2 demonstrates the intimate relationship between IoT-ML and healthcare systems [17, 19]. Many studies have been undertaken to illustrate the healthcare applications of IoT-ML medical systems [104]. Figure 7b shows images of certain medical systems that use IoT healthcare data to feed ML algorithms, as well as how the ML results offer solutions like patient behavior analysis, assistive care service, and sickness diagnosis. As a result of technological advancement, IoT-ML-based operative medical systems support will continue to have a substantial impact on human life. However, assistive healthcare will have to address problematic challenges like cost and usability [105]. Furthermore, privacy of internet users and verification flaws in IoT-ML sensing devices may draw the notice of hackers and pose difficulties since the vital medical records/data of the patients will be stolen/hacked if not adequately safeguarded [104, 105].

1) Resource Scarcity : Most IoT devices have limited energy and computational capabilities, like smartphones, sensors, RFIDs, actuators, gateways, and microcontrollers [106]. Moreover, the information given through these heavily dispersed limited-source sensing devices shows repeated and similar blueprints. Broadcasting this type of connected information over the internet requires a lot of energy, degrades QoS, and affects throughput [107]. To some extent, the issue of resource scarcity is addressed by combining IoT with the cloud-based computing archetypes. Nonetheless, it raises the expenses and difficulty to effectively handle the data. Because of the exclusive behaviour of IoT-based frameworks, numerous source organization issues like source modeling, provisioning, discovery, scheduling, monitoring, and estimating, are more important [108]. Moreover, in this context, optimization within resource allocation methodologies should be examined further. Because most present solutions are novel, lavish, lightweight, and energy-competent information aggregating methods that depend on IoT-ML are required. Furthermore, distinct systems that distribute workload across numerous IoT frameworks and fulfill the source limits of these IoT-ML networks, but deliver healthcare data with sufficient accuracy should be developed [109].

2) Data Security and Privacy : The IoT applications in healthcare is giving individualized services, i.e., rapid and customized accessibility to healthcare support, that was previously unachievable. For all of these IoT applications, healthcare, and technology equipment interact to deliver a variety of solutions. It is estimated that by 2025, health-related IoT-based ML technology would account for more than 40% of all IoT-related technology, thus accounting for a gigantic marketplace value share of USD >137 billion [12, 110]. Such improvements in this industry are groundbreaking; nonetheless, they must be handled with prudence due to the difficulties raised by healthcare-related data security, privacy, and sensitivity [111]. Contaminated data transmitted upstream not only destroys but also harms the underlying data aggregation process [112]. It exposes the underlying networks to various security risks, that include eavesdropping, DoS (denial of service), Sybil, sinkhole, and sleep deprivation assaults. Because of the field's rapid expansion and the increasing amount and complexity of possible software and hardware vulnerabilities, these risks remain a greater challenge. Furthermore, sensitive and secret healthcare data, like individual data, EMRs, family record, and genetic information, must be stored in private hard disks/devices. About 72% of malicious traffic is likely to target healthcare data [113]. As a result, it is vital to protect this kind of medical information from giving access to hackers via maintaining physical and online privacy and safety regulations [114]. Misconfigured, low security devices, and incorrect system settings are all issues. Additionally, information from these several kinds of sensing devices are mostly diverse in nature and are typically kept by third party, building data security, privacy, and governance a challenging problem [115]. Moreover, standard security solutions are not preferable choices owing to the source limits of IoT-ML healthcare devices. Proposal of energy-efficient and lightweight information collection systems which not only make safe, but also protect data privacy, confidentiality, and security is a fascinating topic that should be researched further.

3) *Interoperability :* We have recently witnessed the great progress in computer software and hardware technologies, but the fundamental issue is need for worldwide standards that can be acknowledged and approved upon by the total public across the world. As a result, interoperability difficulties with healthcare IoT-ML devices are substantial. To promote healthy lifestyles, designers must focus not only on creation but also on interoperability across all features of IoT-ML-based healthcare, like body area sensors, smart wearables, and enlarged omnipresent healthcare [116]. Interoperable technology provides improved internet speed, fewer accidental power outages, and cheaper upholding expenses. Clinical information rhetoric interoperability should be the focus of future research.

4) *Energy Management :* Energy management (EM) is other problematic portion of IoT-ML healthcare implications. Energy is often a constraint for wearables and sensors related to the human body. They only have a finite amount of energy [117]. The battery replacement in different electronic equipment and sensors is tedious, if not unfeasible in some situations. Additional healthcare staff are required to check these sensing devices and electronic gadgets regularly for replacement of batteries, when the energy surpass specified parameters and additional maintaining expenses. It can cause mismanagement and fatigue because of the active nature of the healthcare staff's job. Energy efficiency has become an important factor in determining the accomplishment of the essential implications [117]. To surmount these difficulties and boost the conservation of energy, less power consuming sensors which does not need regular battery replacements yet offer a continuous source of electricity are essential. Furthermore, power consumption minimization models with smart EM tactics have gotten less notice and, as a result, they demand immediate attention from IoT-ML healthcare professionals [118]. An additional research area is the optimization of direction-finding systems which employ correlation of data before reaching their final destination, sometimes known as 'data aggregation' techniques. These solutions eliminate duplication while cutting the communication costs, conserving the energy, and extending the network lifetime.

5) *Big Data Analytics :* One tough part of IoT-ML healthcare is big data analytics, which addresses massive volumes of unstructured information. Significant breakthroughs in computer software and hardware technologies, and incorporation of them in broader and unique IoT-ML healthcare applications have lately occurred. Furthermore, using a massive amount of networked information resources and global infrastructure platforms for communication and information, the IoT-ML's future development forecast is much overstated. Therefore, vast amounts of information are generated. This vast and generally redundant information is sent around the global network for decision-making and analysis. The transmission of this type of big data via the global network may harm the performance of network. This presents a plethora of demanding problems which must be addressed with considerable prudence [119]. It would be exciting to investigate how various ML- and DL-enabled methodologies may be utilized to get perception into such big data for efficient maneuver and improved decision-making in this IoT healthcare environment [120]. It is vital to develop new big data analytics software programs and methodologies that execute investigation and mine relevant data. Ground-breaking noise reduction strategies are necessary to improve the information signal, aggregated data value, and network total power consumption [121]. More crucially, most medical gadgets perform simultaneous monitoring and information analysis of the patients. It is of interest to observe new IoT-ML models that leverage simultaneous data analytics to monitor and react to current events in the future. To enhance security, QoS, and computing complexity, new data collection algorithms with anomaly minimization must be developed. Furthermore, data aggregation is more closely related to the network's fundamental structure. The underlying topologies have a big influence on how certain techniques function [122]. Clustering works better in stationary networks where the configuration of network stays stable throughout time. However, they must be analyzed in both dynamic and heterogeneous situations [123]. Finding the appropriate place for these IoT-ML healthcare devices must be investigated more in next-generation IoT-ML to serve diverse potential applications of healthcare in the years to come.

V. FUTURE PERSPECTIVES

The main benefit of IoT-ML automation in monitoring of diseases and patient-specific tasks is that it prevents wasting of time and intervenes while all healthcare professionals are engaged, such as during an emergency situation. This industry's AI technologies are important for rescuing lives all through pandemics (such as COVID-19). Wearables (monitoring devices) collect and transmit information to a cloud-server storing database, which a physician may later use to make a diagnosis of the patient and prescribe medication. During pandemics, victims may be given smart drugs and IoT-ML-based AI gadgets which supervise and gather patient-specific information for obtaining the medical database. These IoT healthcare devices let physicians and relevant ML running computer machines comprehend sickness blueprints and signs, thus permitting doctors to understand and evaluate disease indications to establish a quick and harmless disease analysis. Because IoT-ML strategy removes the direct touching of patients suffering from lethal aerial viruses during quarantine, such medical systems can increase safety of both patients and healthcare staff. In recent future, cloud-based computing can be a significant component of the 6G wireless network driven IoT-ML healthcare industry [124]. It is advantageous to link a variety of IoT-ML healthcare devices to comprehend information via examination and cloud-storage. Other critical aspect of cloud-based computing is its capacity for storing of big data, while meeting the requirements of the medical systems. Because of its data-transferring capabilities, cloud-based computing may let various IoT-ML healthcare devices to freely obtain the patients data. Cloud computing is presently confronted with several difficulties that must be resolved first. Such concerns may uncover novel research avenues for academicians and scientists looking for improvement in the usability of IoT-ML methods in the healthcare sector.

A couple of the IoT-ML issues are safety and confidentiality of patient-specific data. Because EMRs include individually identifiable health information about patients, they are highly sensitive in the healthcare industry and must be adequately maintained. As a result, severe legislation, like the HIPAA (Health Insurance Portability and Accountability Act), was created to oversee the operation of collecting and analyzing this patient-sensitive information. This is a major obstacle for current IoT-ML and data mining approaches like DL, that frequently requires big data (for training). Exchanging this patient-specific sensitive data through internet, for improvement of healthcare excellence, may risk patient's privacy. Several approaches for ensuring patient privacy through the use of machine learning technology have been presented. Federated learning (FL) is a unique ML model that utilizes sophisticated DL algorithms for training and allowing portable IoT devices and webservers to construct a single, strong IoT-ML model with no sharing of sensitive patient-specific information. FL assists scientists in addressing key problems like heterogeneous data access, data security, and data access rights. Another challenge for IoT-ML is storing data in a central cloud-based computing environment. This can cause an inaccurately trained model, lowering the accuracy of the predicted outcome. As a result, decentralized storage of data is now considered as best data management procedures. 'Blockchain' is an emerging technology which allows for decentralized storage of data. Some devices can monitor blood pressure, heart rate, and body temperature of a patient, all at the same time [125]. They are essential in collection and storing of patient's data that may aid in disease diagnosis and cure. The amalgamation of IoT and ML may aid healthcare practitioners to keep up with the new advances, which are essential for a healthy society. Because IoT-ML healthcare data may be preserved in a centralized data bank and made available only to the genuine doctors and scientists for real-time sharing of results, analysis, and cross-examination, storing of diagnostic information and disease-related symptoms data of patients is key for ensuring disease eradication or vaccine/drug discovery for future growth of healthcare sector.

VI. CONCLUSIONS

The healthcare business is very difficult considering accountability and tight regulations, making it a key and important area for innovation. The IoT has created a new universe of promises for healthcare business, through the capability of tackling wider array of challenging issues. Using medical IoT opens up new avenues for supervision of patient health condition remotely, telemedicine, etc. This is all made possible due to the advancements in IoT-ML models for solving healthcare issues. In this review, we summarized the dominant ML models, discussed numerous roles of ML in healthcare, and investigated amalgamation of IoT and ML in the healthcare systems to anticipate future developments. As mentioned earlier, IoT and ML have revolutionized the healthcare business by enabling individuals to wear equipment such as smart devices and premium gadgets, which supervise the patient's health status and transmit useful data to a database that physicians and other healthcare staff can readily access. The IoT-ML healthcare devices might examine a patient's important symptoms and body organs and later transmit this information to a selected healthcare database. Furthermore, the IoT-ML healthcare systems gather and report the disease existence and symptoms of the patients. This is a key innovation that will help the healthcare sector provide better treatment to the patients. The usage of wearable gadgets, sensors, monitoring devices, and smart drugs, appends significance to the healthcare business. The amalgamation of IoT and ML technologies may help further in the monitoring and prediction of disease symptoms and forecast the future trends associated with sickness patterns of the patients.

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