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A Survey of Voice Pathology Surveillance Systems Based on Internet of Things and Machine Learning Algorithms

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ABSTRACT The incorporation of the cloud technology with the Internet of Things (IoT) is significant in order to obtain better performance for a seamless, continuous, and ubiquitous framework. IoT has many applications in the healthcare sector, one of these applications is voice pathology monitoring. Unfortunately, voice pathology has not gained much attention, where there is an urgent need in this area due to the shortage of research and diagnosis of lethal diseases. Most of the researchers are focusing on the voice pathology and their finding is only to differentiating either the voice is normal (healthy) or pathological voice, where there is a lack of the current studies for detecting a certain disease such as laryngeal cancer. In this paper, we present an extensive review of the state-of-the-art techniques and studies of IoT frameworks and machine learning algorithms used in the healthcare in general and in the voice pathology surveillance systems in particular. Furthermore, this paper also presents applications, challenges and key issues of both IoT and machine learning algorithms in the healthcare. Finally, this paper highlights some open issues of IoT in healthcare that warrant further research and investigation in order to present an easy, comfortable and effective diagnosis and treatment of disease for both patients and doctors.

INDEX TERMS Internet of Things, machine learning algorithms, the healthcare sector, voice pathology surveillance systems.

I. INTRODUCTION

The healthcare sector is considered as one of the hottest applications areas in the IoT, where IoT has the possibility to enhance several of the medical applications such as elderly care, remote health monitoring, chronic diseases, and fitness programs. Therefore, many medical devices, diagnostic and imaging equipment and sensors can be seen as intelligent devices that are part of the essential elements in IoT [1]. Also, it is expected that the cost of the IoT-based healthcare services can be reduced and consequently the quality of life can be enhanced and enriches the experience of the users. From the viewpoint of the healthcare suppliers, the IoT has the possibility to minimize the downtime of the devices through the remote provision [2]. Moreover, the IoT presents the effective scheduling of limited resources by ensuring that their best service can be utilized by more patients. Fig. 1 illustrates the recent healthcare trends in IoT technologies. Ease of cost-efficient interactions during seamless connectivity across the patients, healthcare organizations and clinics are significant trends. The modern wireless technologies in the healthcare networks are expected to support early diagnosis, medical emergencies, chronic diseases and real-time monitoring [3], [4]. At this stage, a comprehensive understanding of present research in the IoT with respect to healthcare applications is expected to

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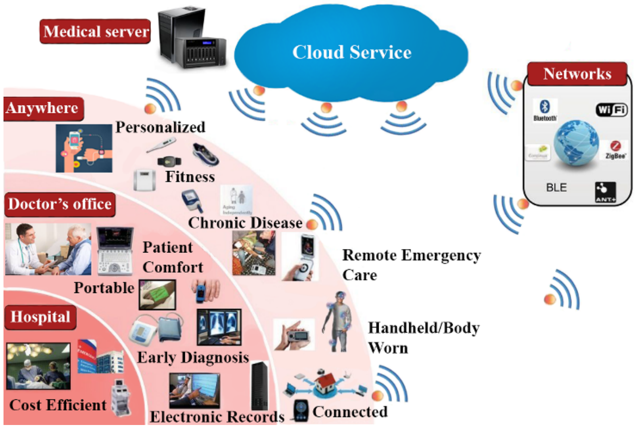

FIGURE 1. Healthcare trends in IoTs.

be beneficial for several stakeholders interested in further research.

Alongside the services of IoT in healthcare applications, machine learning offers tools, methods, and techniques that can assist in solving prognostic and diagnosis problems in different kinds of medical domains. Machine learning has been utilized in the analysis of clinical parameters and their combinations for prediction such as extraction of the knowledge of the medical for outcome research, the comprehensive management for the patient, treatment planning and support, and the prediction of illness progress [5], [6]. Integration of machine learning within the healthcare sector provides opportunities to ease and develop the medical expert's work and enhance the quality and efficiency of medical care [7].

The merging between the cloud and IoT can provide a broad application in social and daily life in general and in the healthcare domain in particular. This is due to the importance of this domain, where the healthcare applications can thrive through the adoption of the cloud and IoT model in the healthcare field which can lead to bringing various opportunities to medical IoT. For example, continuous monitoring applications where there are numerous cases of patients that require long-term monitoring such as a patient who has chronic disease [8], [9]. With regards to this, providing continuous monitoring is a vital issue. Moreover, the follow-up procedure is very important for a patient to optimize diagnosis and recovery time. For instance, to check the abnormal growth of the vocal folds and the quality of the voice.

In the healthcare sector, the diagnosis of some diseases is possible using certain features of speech signals [10]. Due to the nature of work and unhealthy social habits, certain people are prone to the risk of voice problem where the speech signal of pathological voice has become an important topic in this field [11]–[13].

Thus, in addition to IoT and machine learning, this paper also focuses on the implementation of these technologies in voice pathology field. Although voice pathology is a very important area, it has not gained much attention, and hence, there is an urgent need in this area due to the shortage of researches and diagnosis of the diseases by voice. One of these diseases is laryngeal cancer, where this cancer is one of the most common head and neck cancer worldwide [14]. This disease starts with the voice box problem or also known as larynx. Nowadays, laryngeal cancer is the most dangerous disease that affects the patient's voice and can lead to death [15]. Thus, a new and effective framework or technique to detect this cancer via patient's voice at an early stage is crucial, where there is a good chance of cure if this cancer is treated in the early stage. Regrettably, most of the researchers and developers are focusing on the voice pathology and their finding is only to differentiating either the voice is normal (healthy) or pathological voice such as in [16]–[19], where there is no sharp detection for diseases based on voice abnormality. Also, for machine learning algorithms, these technologies suffer from low prediction accuracy rate and time-consumption in the pathology monitoring approaches. Nevertheless, in this paper, we present an inclusive survey of recent studies and approaches for both IoT technologies and machine learning algorithms in the healthcare field in general, and in voice pathology area in particular. Also, this paper provides several major challenges which should be taken into account for future research.

The rest of the paper is organized as follows. Section II presents a brief concept of IoT. Section III presents the role of IoT in the healthcare area as well as IoT applications, IoT challenges and IoT voice pathology. Section IV discusses the state-of-the-art of IoT in the healthcare sector. Section V gives the concept of the machine learning. Section VI describes the key role of machine learning involved in the healthcare area, its applications, identifies many of the machine learning challenges and issues in healthcare and provides the implementation of machine learning in voice pathology area. Section VII discusses the recent studies and methods of machine learning algorithms used in the healthcare sector. Finally, Section VIII concludes the paper.

II. INTERNET OF THINGS (IoT)

The IoT is a term that was proposed by Kevin Ashton in 1999 [20]. IoT has gained more and more attention from academic researchers, government, and industry all over the world, wherein the IoT concept has become popular. IoT can be referred to all things (or objects) that are connected to the Internet via sensor devices. The Auto Identification Center (AIDC) is a center for technologies of radio frequency identification and wireless sensor network, where AIDC has played the main role to materialize the term of IoT [21]. There are several definitions of IoT that have reappeared, and the term is progressively evolving as technology advances and various ideas move forward [22]. The IoT expands into our daily lives over a wireless network of objects that can be uniquely identified [23]. One of the newest and important techniques in operating methods is Radio Frequency Determination (RFID). RFID is an innovative technology that once again utilizes the waves of radio to transmit data through an electronic tag, labelled, and linked to an object, via the reader for the objective of tracking and identifying the object.

RFID system consists of three parts: scanning antenna and transceiver (often combined into one as RFID reader) as well as central computer system [24], [25]. The RFID tag stores all information, and standard elements. Through the wireless network, the tags are conveyed to the central computer system. The object can be identified via the private flag. At the same time, these tags are able to be shared across the Internet in order to manage the object. Since the IoT has been invented in 1999 [22], it has been attributed to the variety of descriptions for such a network, where it has been described also as a paradigm network [26], [27], a concept [28], an Internet application [29] and a global network infrastructure [30]. Moreover, in the IoT phrase, the word 'Things' has been replaced with different alternative terms such as Internet of Everything (IoE) [31], Internet of Anything (IoA) [32], Internet of People (IoP) [33], [34], and the Internet of Signs (IoS) [35].

In overall, the Internet represents a common network, diffused across a broad geographical area. This network can be managed and shared through different protocols, known devices and connectors such as HTTP, HTTPS, modern computers, routers, switches, Bluetooth, Wi-Fi technology, fiber cables, Ethernet, and different personal computers, tablets, and smartphones [36].

III. IoT IN THE HEALTHCARE SECTOR

The healthcare sector is considered as one of the topmost challenges that are faced by every country nowadays. Although the healthcare industry invests heavily in information technology, organizations in healthcare nowadays still depend on the paper medical records and doctor's handwriting notes to relay information about the patients. This makes the sharing of patients' data between departments and clinicians are complex and limited, where doctors obtain information only by a physical assessment during their patient's visit to the hospital. On the other hand, using the IoT in healthcare can provide the doctor to be accessible to the patient's record easily, and at any time, besides being able to track the patient's condition in real-time. The cooperation between the IoT with the cloud in the healthcare field can lead to a better organization of the healthcare sector. In particular, the management of clinical services and patient's data will be more efficient. Moreover, public health surveillance, treatment and diagnostics can be done in a more convenient, trustable and efficient manner with less cost. IoT technology can also provide services such as online interaction with patients, tracking patients' condition and doctor's locations, and tracking medical reports for the patients [37].

IoT has the ability to connect different objects such as P2D (Patient-to-Doctor), S2M (Sensor-to-Mobile), D2M (Device-to-Machine), M2H (Mobile-to-Human), D2M (Doctor-to-Machine), O2O (Object-to-Object), T2R (Tag-to-Reader), and P2M (Patient-to-Machine). It connects smart devices, humans, dynamic systems and machines which provide and ensure an effective healthcare monitoring system. However, patients monitoring represents one of the biggest challenges in research directions using IoT in the healthcare field. The US Institute of Medicine revealed that medical errors remain despite advances in healthcare technology, where 3 persons die out of 400,000 people per year because of these errors. The main reason for these errors is due to failures in running proper tests or no follow up with doctors, delayed in the diagnosis, and disability to access patient's medical history [38]. IoT can support potentially life-saving applications within the healthcare industry by collecting data from the devices, showing the patient information, and diagnosing in real-time the entire system of patient care [39]. Fig. 2 shows some of IoT applications in the healthcare sector, where IoT devices can be used for different purposes such as medication reminder, heartbeat sensing and monitoring, and blood pressure measurement. Nowadays, there are many healthcare devices that operate in all over the world, and since these devices are related with people health, the diagnostic accuracy and data security should be highly effective, trusted and secured. Hence, diagnosis results can be dependable and proper treatment can be given to the patient. Using IoT technology, doctors or caregivers have the capability to efficiently manage and monitor patient health and can economize precious minutes each day. Using IoT, there is no need to physically visit the patients, where caregivers or doctors can provide a remote tracking and diagnosis for the patients. Using Wi-Fi and sensors in the hospital, the right department can be determined when retrieving the sensed information [40].

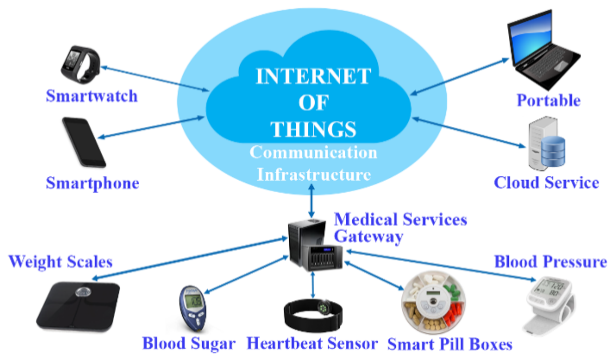

FIGURE 2. IoT devices in healthcare.

In terms of clinical care, any patients who require close attention or non-invasive monitoring due to their physiological status can be continuously monitored using the IoT-driven sensor. The sensor collects the physiological information from the patient to be analyzed and uses gateways to further transmit the information. The obtained information will be stored in the cloud. This information is then sent to the caregivers/doctors wirelessly for further analysis as shown in Fig. 3. Consequently, this improves the care quality and further decreases the cost of treatment for the patient.

Meanwhile, a remote health monitoring system that is based on IoT can track a patient's vital signals in real-time and responds if there is any problem in the patient's health. A sensor device can be attached to the patient as shown

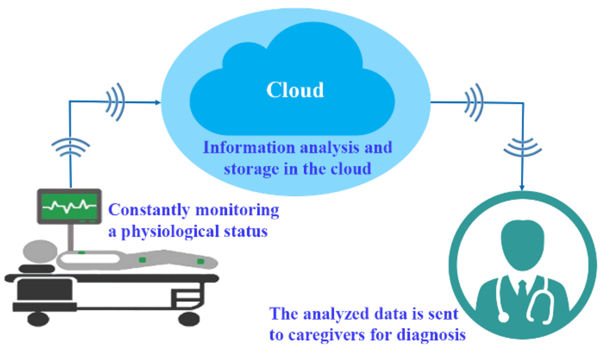

FIGURE 3. **Clinical care system for constantly monitoring the physiological status.**

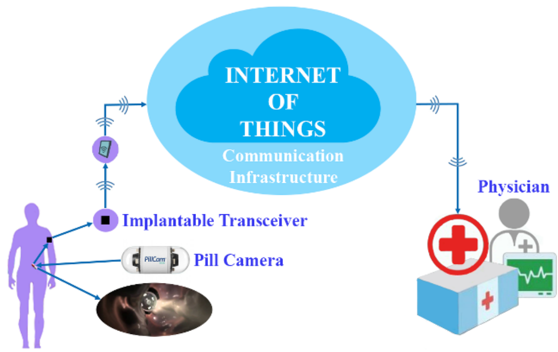

FIGURE 4. **The remote health monitoring system.**

in Fig. 4. It transmits data about the vital signs from the place where the patient is located. Through the telecom network, the transmitter is connected to the hospital [41]. The hospital system monitors and reads the patient's vital signs remotely. In the same way, when the sensor is implanted into the patient's body, the data can be electronically transmitted. The information which is transmitted will be securely sent to healthcare providers/caregivers.

A. IoT APPLICATIONS IN HEALTHCARE SECTOR

IoT technique plays a significant role in many applications and different aspects of the healthcare sector. IoT frameworks/techniques have been applied in several healthcare applications such as blood pressure monitoring to present an easy and comfortable way for patients [42], rehabilitation systems for patients after a certain disease [43], oxygen saturation monitoring to monitor the patient health condition [44], wheelchair management to interact with surroundings by the elderly and disabled people [45], and smartphones that have healthcare apps to present remote medical consulting and many services [46]. Moreover, IoT techniques present low-cost healthcare services for patients and high-quality drugs management and medication adherence. Thus, these IoT based applications can also reduce the error rate and improve the treatment outcomes of the patient. Brief explanations of specific healthcare applications based on IoT are given as follow:

1) BLOOD PRESSURE MONITORING

Blood pressure (BP) is one of the most important physiological parameters of the human body. Nowadays, the use of safe and simple blood pressure monitor at home has become common [42]. An electronic blood pressure monitor that is connected to the IoT sensor can collect real-time information of the patient's blood pressure level. This information can then be relayed to the doctors/caregivers via IoT system.

2) REHABILITATION SYSTEM

This system can improve and restore the functional capabilities and also enhance the quality of life for the people who are suffering from some disabilities in terms of mitigating problems which are related with ageing populations and when there is a lack of health experts [43]. An automated design method is proposed in [47] for IoT-based intelligent rehabilitation methods. This automated design has demonstrated that the IoT platform can connect effectively to all needed resources to present real-time information interactions. IoT technologies can form a valuable infrastructure in comprehensive rehabilitation to support remote consultation [48]. There are several rehabilitation methods which are based on IoT technologies. For instance, rehabilitation training method of hemiplegic patients [49], and medical rehabilitation method for a smart city [50].

3) OXYGEN SATURATION MONITORING

The pulse oximeter is a device which continuously monitors the blood oxygen saturation of the patient in a non-invasive way [44]. There are many advances in communication technology, for instance, wireless networks, and medical sensors which are booming at present days because of the low power consumption and low loss. The continuous monitoring using pulse oximeters are applied in many medical applications in order to know the oxygen levels in the blood and also the heart rate. The IoT sensor which is connected to the patient's body will monitor and sense the patient's heart rate and oxygen levels and hence can guide the patient to limit his/her physical activity [51].

4) WHEELCHAIR MANAGEMENT

Wheelchairs are normally used by the people who are suffering from physical illness or any other physical disabilities. Wheelchairs can be benefited from the IoT technology. Wireless Body Area Networks (WBANs) that can connect smart objects with the Internet can also be used as a people-centric sensing device for wheelchair users. For example, pressure cushion sensors (a type of resistive pressure sensor) that are attached to the wheelchair are able to detect movement such as when a person sitting on it falls down from the wheelchair. A smart wheelchair can also be equipped with another accelerator sensor which detects the falling of the wheelchair [45]. Consequently, the caregiver of a person using the wheelchair can continuously take care of his/her patient remotely without the need to be near the patient at all the time.

5) HEALTHCARE SOLUTIONS USING SMARTPHONES

Mobile devices and apps of healthcare offer numerous benefits for Health Care Professionals (HCPs). There are many medical healthcare applications which are now available in many ways and ready to be accessed such as health record, information and time, communication and consulting with doctors, patient continuous monitoring and proper clinical decision making [46]. With the use of smartphone apps and sensors, the point of care and the access to care have been increased and this supports the improvement of patient's outcomes.

B. CHALLENGES OF IoT IN HEALTHCARE SECTOR

Numerous researchers have worked on executing and designing different IoT-based healthcare services, and they intend to solve different architectural and technological problems related to these services. Nevertheless, there are many other open issues and challenges in IoT-based healthcare that require thorough investigation and discussion. These issues can be summarized as follows:

1) COST ANALYSIS

It has been acknowledged by researchers that IoT is a low-cost technology but unfortunately, there is no comparative study to present any evidence of this. Thus, cost analysis in particular in the healthcare field can be beneficial.

2) THE PROCESS OF APP DEVELOPMENT

When developing an app on the Android platform, there are four primary steps: the setup, development, debugging and testing, and publishing. Similar approaches are generally taken on other platforms. In the process of healthcare app development, the participation of an authorized body or association of medical experts is typically required to ensure an app of acceptable quality. In addition, regular updates on healthcare apps to keep abreast recent advances in medical science are vital.

3) TECHNOLOGY DEVELOPMENT

The organizations of the healthcare can improve their current devices and sensors across the healthcare field for smart resources by incorporating IoT approaches into the existing network configuration. Therefore, a seamless transition from the legacy system and setup to an IoT-based configuration is a major challenge. In other words, there is a need to ensure backward compatibility and flexibility in the integration of existing devices.

4) NETWORK TYPE

In the design approach, the network of the IoT healthcare can be one of three essentially different types: data-, service-, and patient-centric architectures. In the data-centric scheme, the healthcare structure can generally be separated into objects based on captured health data. In a service-centric scheme, the healthcare structure is allocated by the assembly of characteristics that they must provide. In the patient-centric scheme, healthcare systems are divided according to the involvement of patients and their family members they consider for treatment. In this regard, determining the appropriate network type for IoT based healthcare solutions becomes an open issue.

5) SCALABILITY

IoT healthcare services, networks, databases, and applications should be scalable because associated operations become more complicated with the addition of various applications as a result of the exponential growth of demands from both individuals and health organizations.

6) CONTINUOUS SURVEILLANCE

There are several cases that require long-term surveillance for the patients such as a patient with a chronic disease. Therefore, providing continuous monitoring for those patients with chronic diseases is very important to make them constantly connected and monitored with healthcare caregivers remotely. In other words, continuous network connectivity is crucial.

7) NEW ILLNESSES AND TURMOIL

The smartphones are being deemed as an interface for IoT healthcare device. Although there are many healthcare apps and new apps are being added to the list every day, the trend has been limited to a few categories of diseases. Research and development activities for new types of diseases and disorders are essential, and the discovery of methods that can make the early detection of rare diseases mobile has long been an important task.

8) IDENTIFICATION

The organizations of the healthcare deal with multi-patient environments generally, wherein many of caregivers perform their responsibilities. In this regard, the proper identification of the caregivers and the patients is needful.

9) DATA PROTECTION

The protection of the captured data from several devices and sensors in healthcare from unauthorized access is critical. Therefore, stringent policies and technical security measures should be introduced to share health data with authorized users, organizations, and applications. An optimal algorithm for collaboration between protection, detection, and reaction services to prevent various attacks, threats, and vulnerabilities is an open challenge.

10) PLATFORMS OF IoT-BASED HEALTHCARE

Hardware architecture of IoT healthcare is more advance than the usual IoT devices since it needs a real-time running system with more rigorous requirements. Therefore, customized computing platforms with run-time libraries are needed. Moreover, for a specific platform, libraries and proper frameworks should be designed so that the developers and designers of the healthcare software can make use of given classes, codes, documents, and other beneficial data more effectively. Hence, a special class of illness-oriented libraries can be helpful.

11) MOBILITY

IoT healthcare network should have the capability to support the movements of patients, where they can be connected anytime and anywhere. The current studies of IoT frameworks for monitoring a patient are still ignoring the movement area and comfort of the patient, where the patient's monitoring is being restricted in terms of place and time.

C. IoT VOICE PATHOLOGY

IoT has brought the sight of a more connected world into reality with a big amount of data and many services that are provided by the heterogeneous networks. On the other hand, cloud computing has protruded and it provides huge storage and gives opportunities for data sharing [52]. The merging of the cloud with the IoT can produce new and many opportunities for both technologies [53]. These technologies may unfold a new horizon of service sharing, the interconnection among the devices, ubiquitous sensing, and provides better cooperation and communication between the people and the things in a more dynamic and distributed performance [54]. Hence, the development of many applications is much needed in several fields of the healthcare sector.

Voice pathology is a quite significant area in the healthcare sector. There are many people who are suffering from voice pathologies due to various reasons such as extreme damage to certain organs, air pollution, smoking, and stress. In a recent study, it has been monitored that more than 7.5 percent of the entire population of the people in the USA suffer from voice pathology [55]. People in certain professions such as teachers and singers are suffering the most from voice turmoil because they utilize their voice exceedingly, where around 20 percent of American teachers have been infected with voice pathologies [55]. The detection or assessment of the voice pathology can be classified into two categories: objective and subjective. The objective assessment does not require specific equipment, where if the algorithm is proper, the outcomes are always unbiased. Meanwhile, the subjective assessment needs specific equipment and trained doctors and thus it incurs a high cost. In addition, the subjective assessment differs from doctor to doctor which relies on the doctor's expertise [56]. On the other hand, the objective assessment can be used only from initial screening, where the final decision must come from the medical doctors.

IV. RELATED WORKS OF IoT IN HEALTHCARE

Recent studies have witnessed a huge interest by researchers and developers in the field of voice pathologies that are based on IoT technology. Table 1 shows a brief summary of some related works for IoT techniques in the healthcare sector.

In [57] the authors have proposed a new framework of health surveillance by merging the IoT with the cloud. The paper presented a case study of a voice pathology surveillance in which the signals of the voice are captured through different IoTs and transmitted to a host device. To preserve the authenticity of the voice signals, the signals are watermarked by the patient's identification number. The proposed voice pathology monitoring achieves a very good accuracy with low computation time. The pathological monitoring framework can be enlarged to other kinds of health monitoring utilizing the IoTs and the cloud technologies.

The research paper in [58] presents a framework for smart healthcare surveillance that is connected to the smart city and smart devices for accessible and affordable healthcare. The authors have proposed a Voice Pathology Detection (VPD) approach that has two inputs, electroglottography (EGG) signal and the voice signal. The input devices are connected to the Internet and the obtained signals are sent to the cloud. These signals are then analyzed and classified as either pathological or normal. The results obtained from the signals are passed to the doctors for the ultimate decision to determine the next proper action. The Gaussian mixture model is used as a classification and Saarbruecken Voice Database (SVD) for the database. It has been shown in the paper that the precision of the proposed approach is more than 93 percent.

Meanwhile, the author in [59] has proposed a healthcare surveillance system in a smart home to achieve the needs of elderly people in order to have constant care. The patient's status in this proposed system is monitored via two inputs, speech and video. The microphones and the video cameras are installed in the smart homes; both of these sensors capture the patient's speech and video and send these data to the cloud. The data is processed in the cloud and the classification of the voice signals depend on the patient's case, whether the patient is tensed, normal, or in pain.

The authors in [60] have presented an energy-efficient architecture of the IoT in healthcare applications for scenarios such as home care and clinical. Since the movement of the patients in many statuses is restricted to a room or a building, the proposed architecture is based on the smartly wired gateways that utilize the power from Power over Ethernet (PoE) cables in order to achieve a low-cost and an energy-efficient system. Capabilities of PoE allow for powering sensors directly without the need for a different power grid or batteries. Moreover, these gateways connect the wired sensors and hospital devices to web services, which enables the hospital automation and collect the data and the vital signs in a suitable and cost-efficient. Medical sensors are used to measure the patient's status such as heart rate, ECG, temperature, glucose levels, pressure and etc.

The authors of this research paper [61] surveyed the methods and the approaches of the state-of-the-art in the design of efficient and secure healthcare surveillance. In addition, they have proposed an overall framework for the advanced system of healthcare surveillance by describing the complete surveillance life cycle. Also, they have highlighted the primary

TABLE 1. Summary of IoT techniques in the healthcare sector.

Years	Problems	Techniques	Contributions	Limitations	Ref.
2017	Audio pathology surveillance	IoT, Cloud, LBP, and ELM	Realize high efficiency of the detection, the data transmission is secured, and it is easy to use.	Lack of scalability when various inputs merge, such as smart devices and microphones. In addition, there is no framework for dealing with big data of normal and pathological audio in the cloud.	[57]
2017	Detection of the voice pathologies	Cloud, EGG signals, Local Features (LF) as a feature extraction and GMM.	The accuracy of the suggested approach has achieved 93 percent, where it outperformed some state-of-the-art.	In the proposed system, there is no disease diagnosis, where it focuses only on the issue whether the voice is normal or pathological.	[58]
2016	Surveillance of the elderly people and patients	Capturing the status of the elderly or patients in the smart home via video and speech.	The proposed system has achieved an accuracy of 94.68 percent, where it can be effectively utilized in the status surveillance of the patient in the smart home.	The measures of the safety and the security must be taken for ensuring the privacy of patients.	[59]
2015	Energy-consumption used in patient surveillance	IoT healthcare, wired gateways	Created wired gateways which have low-cost and can deploy them along the facilities of the hospital and thus an energy-efficient system in the healthcare.	The wired gateways have been utilized in a small building or room, where the movement was limited.	[60]
2015	Illegally access of patients in the healthcare surveillance system	IoT, WBANs	It presented an overall framework for advanced eHealth surveillance via describing the whole surveillance life cycle. The primary service components were also highlighted.	The authors have not applied solutions for eHealth monitoring in their paper.	[61]
2014	Remote patient surveillance	IoT healthcare, Cloud Computing and Electro Cardiogram (ECG) "Android App"	Building a new application for the Android platform in the healthcare field utilizing the cloud and IoT.	There are no processes in the cloud server in terms of features extraction and classify the signal, it only stores the data.	[62]

service components in the healthcare such as communication networks, servers of medical data processing, and clinic terminals. They have discussed the data collection of patients using WBANs and mobile crowd sensing. Furthermore, this paper has presented and discussed the challenges that need to be considered to develop a secure and efficient surveillance system for patients. Examples of these challenges are usability in terms of interactions between the patient and the system, efficient cost and the quality of the data collection, secure data processing and privacy-preserving.

The authors of this paper [62] presented their work which is an Android application platform in the healthcare field using IoT and cloud. The proposed application is named 'ECG Android App' which provides users with the visualization of their Electro Cardiogram (ECG) waves and also the functionality of data logging. The logged data is uploaded to the centralized cloud of the user's private or a particular medical cloud. The cloud saves all the monitored data and this can be accessed later for analysis by medical doctors.

In [63], the authors have addressed the usages of IoT in the healthcare sector. The chronic disorders prediction in the wearable healthcare devices has been discussed to bring smart healthcare solutions anywhere. In addition, they have discussed several IoT healthcare challenges such as processing enormous volumes of data at a high rapidity, limited network bandwidth, no uniform criteria for data created and hacking connected devices. Retention for a large amount of data could be a difficult task. However, clinically validated instructions and advice have not presented sufficiently.

In [43], an IoT-based smart rehabilitation system was presented. The rehabilitation system is established through Wi-Fi and other technologies such as RFID-based short-distance radio communication technique, Global Positioning System (GPS) technology, and Unique Identifier (UID). The architecture service-oriented is developed and used for designing, implementing, managing and other kinds of healthcare services. After designing and implementation of the IoT rehabilitation system, each and every patient will get good treatment and they are well diagnosed with two rehabilitation strategies, which are resources allocation plan and essential treatment activity information.

In [49], a wireless remote surveillance system for heart rate and oxygen saturation was proposed. In this research paper, the oxygen level in the blood and also the patient's heart rate is measured using the pulse oximeter. Then, this measured data is sent to the central surveillance station via WSN. The patient will be continuously monitored and the central monitoring station receives the information of the patient's oxygen saturation level and heart rate through WSN. If any problem occurs, an alarm will be activated automatically. A Graphical User Interface (GUI) is developed to display the results and measurements of the patients.

An IoT healthcare surveillance system is also introduced in [64]. A prototype (CC2451 sensor tag) is presented for the implementation of the proposed system to gather a patient's data such as humidity, temperature, accelerometer, and pressure. Moreover, they used a chest strap belt as a smart sensor to monitor the heart rate. It alerts about the patient's health condition in real-time, if any problem is experienced, or the patient needs any medical attention and hospitalization. The authors assumed that their work can decrease healthcare cost and increase the specialized care required. However, this work has not presented any development for decreasing the cost, where it is limited by using a present technology that is already available in most patients' homes such as chest strap belt.

Meanwhile, the authors of this paper [65] have worked on implementing fog computing in the healthcare IoT. They have highlighted on the benefit of fog computing, where they have presented a collection of services that make use of the healthcare IoT based on the implementation of an intelligent gateway for fog computing. These services are provided to address the main IoT challenges in the healthcare field such as usability, scalability, performance, and an enormous number of devices which are connected to the Internet that cause many available resources such as computing power and bandwidth.

The study in [66], suggested a system to improve healthcare performance which includes the rural regions by using IoT. The proposed system can monitor Ischemic Heart Disease (IHD) by using a mobile application to upload all patient measurements to the server between the patient and the clinic. These measurements are classified into three stages. Stage I has the patient information such as the sex, weight, height, waist measure, and body mass index. Stage II refers to cholesterol, diabetes, and thyroid. Stage III refers to personal habits, sleeping disturbance, genetic factors and family history. In this system, patients have to report those measurements once a week. Based on the doctors' experience, they will classify the risk of IHD as no danger, low, medium and high dangers. In the case of high danger, ambulance services and doctors have to support the patient rapidly. Patients with low and medium dangers will be informed to visit doctors and take medicines. However, patients' data are collected by patients themselves, where it is very possible for an error to occur when measuring that data and also not all patients have a medical measuring device for measuring cholesterol and diabetes.

V. MACHINE LEARNING

Machine learning was originally proposed as a unique method for Artificial Intelligence (AI) in the late 1950s. It has been gradually developed and has been applied in many applications such as bioinformatics, spam detection, speech recognition and data analysis [67]. Algorithms of machine learning are used as powerful predictors. Since the accuracy of these algorithms is known to improve especially with larger quantities of data to train on, the growing availability of such data in recent years has brought renewed interest to machine learning algorithms [68]. There are two major approaches to machine learning. The first is supervised learning. The supervised learning domain includes the training algorithms utilizing a set of examples. The machine obtains a number of inputs with a specific number of the correct outputs and the learning happens through contrasting empirical results with the correct outputs to recognize the errors [69]. This kind of learning is utilized when past history is used to predict events in the future [70]. The second approach is called unsupervised learning. In this approach, the machine needs to explore the data and try to develop some kind of structure or pattern. The models also should be developed from scratch. This method is often used to determine and differentiate the outliers [71].

VI. MACHINE LEARNING IN HEALTHCARE

Machine learning has a broad societal impact in the healthcare field. In the industry of smartwatches and smart devices that continually collect many health data, the benefit of machine learning in the data analysis is becoming increasingly significant [72]. It can be the resolution for decreasing the high cost of healthcare and also to help establish a better relationship between the patient and the doctor. Machine learning and big data can be applied in many applications of healthcare field; for examples assisting doctors to identify more personalized prescriptions and treatments for patients and also assisting when the patients should schedule appointments for follow up.

Currently, a huge amount of data is available in healthcare. This involves electronic medical records (EMRs) which contain either structured or unstructured data [73]. Structured data in healthcare refers to the information that is easy to classify in a database; they can include a set of categories and statistics such as patient temperatures, patient weights, and also general symptoms such a stomach pain, and headache [74]. However, most of the health data is unstructured data in the form of images, various notes, discharge summaries, reports, videos and audio recording. Data such as personal conversation can refer to numerous various directions [75]. For instance, two patients can have the same exact strain of a cold, but the conversation and data may vary according to the background of the doctor and the patient, and even differ based on various ways of the patient describing the illness symptoms. In general, unstructured data makes up 80 percent of present EMRs and 20 percent structured data.

Since the nature of medicine is related to a kind of narrative, the techniques of modern machine learning should be taken into account when establishing and organizing a relationship among huge amounts of unstructured raw data. The ability of understanding and using this kind of data on a wide scale will be very useful in applying the technologies of machine learning in the healthcare field [76]. For structured data, there are many artificial data technologies currently exist; however, only a few innovators and developers are focusing on the structured data, they only focus on the narratives in the healthcare field. Moreover, when machine learning is applied effectively, it can help doctors to make near-perfect diagnoses, determine the best medicines for patients, and improve the general health of the patients as well as reduce the cost [75].

As the cost of healthcare services stagnates at historically high prices, the used of machine learning in unstructured data can be the solution to this ever-growing issue. In the healthcare sector, 50 percent of the entire costs comes from 5 percent of entire patients; in addition, the number of chronic diseases that require continuous care has progressively increased in the world. Machine learning can recognize patients who may be more likely for frequent diseases. Moreover, close to 90 percent of visits to the emergency room are preventable, where machine learning can be employed to assist in diagnostic and to direct patients for appropriate treatment. Consequently, this reduces costs by keeping patients outside of costly emergency care rooms [75].

A. APPLICATIONS OF MACHINE LEARNING IN HEALTHCARE

The diagnostic reasoning in medical is a very significant area of intelligent systems. The expert systems in these frameworks [77]–[79] present mechanisms for the hypotheses generated from the patient data. For instance, extraction of the rules from the experts' knowledge to build the expert systems. Unfortunately, in numerous statuses, the experts may not be able to formulate which knowledge they should utilize to solve their problems.

Symbolic learning is a technique that can be categorized based on strategies of underlying learning such as learning from discovery, rote learning, learning from examples, and learning by analogy [80]. Techniques of symbolic learning are utilized to enhance learning, and capabilities of the knowledge management for the expert systems [81]. According to the set of clinical statuses, the learning in intelligent systems can be obtained by using the machine learning techniques which is able to produce a systematic explanation for those clinical features. As a result, the knowledge can be expressed in the shape of simple rules such as the KARDIO that has been developed to interpret ECGs.

The authors in [82] present an intelligent system which captures the patient data in real-time during surgery of the cardiac bypass and generates models for the abnormal and normal cardiac physiology to identify changes in patient's status. Moreover, these models can work as initial hypotheses for further experimentation. The learning from patient data faces many difficulties and challenges because of datasets incompleteness (losing of parameters), errors (random noise in the data), and inaccuracy (improper parameters choice for a particular task). Machine learning presents tools and mechanisms for dealing with these properties of medical datasets [83].

Another area of machine learning application in healthcare is the processing of biomedical signal [84]–[86]. Our knowledge of biological systems is incomplete since there are primary information and features hidden in the physiological signals which are not apparent. Furthermore, the effects among the various subsystems cannot be distinguished. Biological signals are distinguished by large variability because of the external stimuli or spontaneous internal mechanisms. Associations among various parameters may become so complicated to be solved with traditional techniques. Machine learning methods and techniques exploit these collections of data to make it simpler, and it can also assist to form relationships which exist among these data and extract features and parameters to improve healthcare. In general, the environment of healthcare depends heavily on computer technology. On the other hand, the application of machine learning methods and techniques can present beneficial aids to help doctors in several cases, tackles the issues related with human fatigue, and facilitates real-time diagnosis and presents fast identification of abnormalities.

B. CHALLENGES OF MACHINE LEARNING IN HEALTHCARE

Notwithstanding the promising results achieved utilizing the machine learning technologies, there are still various unsolved challenges in the clinical healthcare application using machine learning. We highlight the main issues and challenges as follows:

1) DATA SIZE

Machine learning indicates a collection of extremely intensive computational models such as neural networks which are completely connected multi-layer, where a lot of parameters in the network need to be estimated correctly. To obtain this objective, it should provide a huge amount of data. Moreover, understanding illnesses and their variability are more complex than other tasks. For instance, the recognition of the voice pathology type through the speech and or an image processing in the Magnetic Resonance Imaging (MRI) to predict Alzheimer illness. Therefore, from the perspective of the big data, it is crucial to have more amount of medical data to train a robust and effective model in machine learning.

2) THE QUALITY OF DATA

Data in healthcare are extremely heterogeneous, incomplete, and ambiguous. Training a good model in machine learning with such a collection of diversified and huge data is difficult and many issues need to be taken into account such as the sparsity of the data, losing values, and redundancy.

3) TEMPORALITY

The illnesses are constantly changing and progressing across time. However, several proposed models of machine learning in different healthcare fields, assume static inputs of vector-based. These static inputs could not deal with the time factor. A new machine learning method that can deal with temporal medical data is a significant aspect that will need to be developed. In other words, it is vital to design a new approach in machine learning that considers dynamic inputs.

4) FIELD COMPLEXITY

The problems in healthcare applications and biomedicine are becoming more and more complex. The illnesses are highly diverse and there is still no full knowledge of most of the illnesses, how they progress, and their causes. Furthermore, the number of patients in a practical clinical is usually limited, where we cannot ask for more patients as much as we want. Consequently, this leads to a lack of medical training data for an effective machine learning model.

C. MACHINE LEARNING VOICE PATHOLOGY

Machine learning techniques are useful for discriminatory classification processes. These techniques have been utilized in different applications of speech processing, where one of these applications is pathological voice analysis. The classification and the recognition of pathological voice methods are still one of the complicated fields in the research of speech processing. The pathological voice indicates problems in talking that are caused by injuring, mental disease, autism, speech organs abnormality, or other disabilities. The existence of pathologies in the vocal folds affects the natural vibration pattern of the glottis which can cause changes in voice quality. The traditional methods to detect voice pathology are inefficient. They essentially depend on the vocal fold's examination and the specialist study which may generate confused and various evaluations. Furthermore, these traditional methods are costly, consume more time, and need many kinds of equipment [87].

Recent years have witnessed a huge interest in the speech quality evaluation using machine learning techniques due to the importance of this area. The function of this evaluation is to recognize the disorder of the voice and to create a system that is capable of dealing with voice pathologies. The authors in [88] have presented an analysis method to differentiate between pathological and normal voices by applying Gaussian Mixture Model (GMM). GMM is a supervised classification method broadly applied for speaker detection. In addition, they have used Massachusetts Eye and Ear Infirmary (MEEI) database in their work and Mel Frequency Cepstral Coefficient (MFCC) as feature extraction. The authors in [89], also used GMM to distinguish between pathological and normal voices. In their study, normal samples are accurately classified up to 95 percent while 18.3 percent of pathological samples are improperly classified. GMM has been also used for the detection of pathological voices in this study [90], where this method presents a better performance than [89] with an error average reached 7 percent for normal samples 1.4 percent for pathological samples. However, the above-mentioned studies have used a limited database for both normal and pathological samples. In addition, there is no improvement in terms of the classification or the feature extraction processes and their studies were limited only in the differentiation of voices to either normal or pathological, where the diagnosis of disease was not included.

VII. RELATED WORKS OF MACHINE LEARNING IN HEALTHCARE

The state-of-the-art technology in healthcare systems has opened up many great opportunities in the implementation of smart environments and smart healthcare. Particularly in the health and medical field, several machine learning algorithms have been developed for different purposes such as to evaluate different types of vital signs speech recognition, voice pathology monitoring, analyses of the voice and diagnosing the disease and etc.

In [91], the authors have presented and developed an Arabic Voice Pathology Database (AVPD) by recording three vowels, isolated words and running speech. Moreover, the perceptual severity for each recorded sample has been provided to being a unique aspect of AVPD. Normal and disordered samples in AVPD were recorded by using the Computerized Speech Lab model 4500 with frequency 48 kHz. All samples were taken in distance of 15 cm between mouth and microphone. Around 51 percent of the total dataset are normal samples (82 female and 116 male) and the remaining are voice disorders samples. The AVPD has included five-voice disorders which are paralysis (14 percent), sulcus (11 percent), vocal fold cysts (7 percent), polyps (11 percent) and nodules (5 percent). In AVPD development, the authors have identified and avoided the shortcomings of various databases of voice disorder. They have used MFCC and Linear Prediction Coefficients (LPC) as speech features extraction and four various machine learning algorithms for the classification process which are GMM, Support Vector Machine (SVM), Vector Quantization (VQ) and Hidden Markov Model (HMM). The MFCC that is used in AVPD is shown in (1), where m refers to the corresponding frequency in Mel-scale and f refers to the frequency in Hz. In LPC features extraction, the analysis of Linear Prediction (LP) is applied to reverse filtering on speech signals in order to remove formants effects and thus estimate the source signal. The present sample of the source signal can be estimated through p previous samples as given in (2).

$$m = 2595\log_{10}\left(1 + \frac{f}{700}\right) \tag{1}$$

$$x'_r = \sum_{i=1}^{p} a_i x_{r-i}, \tag{2}$$

where, $x_1, x_2, \ldots, x_r$ are original speech signal samples and a_i's refers to the required LPC features. The accuracy of the classification process is calculated by the following equation:

$$Accuracy\,(\%) = \frac{Total\ Correctly\ Detected\ Samples}{Total\ Number\ of\ Samples} + 100 \tag{3}$$

The detection and classification processes results were compared with MEEI database. The highest acquired detection accuracy for AVPD is 81.6 percent and 92.9 percent for the classification, while the accuracy obtained in MEEI is 98.7 percent and 98.2 percent for the detection and classification respectively. Nevertheless, MEEI has overcome AVPD in terms of the classification and detection accuracies, where AVPD has failed in the comparison.

The paper [92] presents a new method named Incremental DBSCAN-SVM for noise detection as well as for voice classification and differentiation. This method utilizes a clustering algorithm called Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and incremental learning for noisy samples detection. DBSCAN is a clustering algorithm that has several advantages, where it can distinguish noises, it works efficiently even in large databases and it can detect clusters of arbitrary shape. Moreover, it used Mahalanobis distance to calculate the distance between the new object and the various means of clusters and also the points that are considered as noises by DBSCAN. The Mahalanobis distance can be calculated as shown in (4) and (5).

$$MD_i = ((x_i - t)^T C_n^{-1} (x_i - t))^{1/2} \tag{4}$$

where t refers to the multivariate location and C_n refers to the estimated covariance matrix:

$$C_n = \frac{1}{n-1} \sum\nolimits_{i=1}^{n} (x_i - \bar{X}_n)(x_i - \bar{X}_n)^T \tag{5}$$

The MFCC is used as feature extraction for each voice sample. Next, the output pattern is presented to the SVM classifier to distinguish among pathological and normal voices. This method has the capability of dealing with dynamic and incremental voices database that develops over time. This method has utilized the MEEI database for voice disorders detection, where it has tested 53 normal voices and 173 pathological voices (Adductor, Paralysis, Vocal Polyp and Keratosis). Results based on Incremental DBSCAN-SVM can reach up to 98 percent and outperformed traditional methods. However, the proposed system did not present a specific framework (i.e. IoT, smartphones, cloud) for collecting the voice from patients. Also, Incremental DBSCAN-SVM was evaluated in terms of the accuracy only, where there are other performance measurements that are significant such as G-mean, F-measure, precision, and recall.

The work in [93] proposed a new technique in the detection of voice pathological based on deep neural networks. The idea of this method is to use a recurrent Long Short-Term-Memory (LSTM) layers on a raw audio signal to skip the phase of building the feature vector. The authors obtained voice recordings of the continued vowel /a/ from the SVD database. They used 480 healthy samples and 480 pathological samples, where 70 percent is used for the training, 15 percent for validation and 15 percent for testing the system. Every recording is divided into 64 ms of Hamming windowed and 30 ms overlap. The experimental results have shown that the proposed model achieved 71.36 percent accuracy, 77.67 percent specificity, and 65.04 percent sensitivity based on 206 trained files. Meanwhile, based on 874 tested files, the accuracy of the proposed model is 68.08 percent, the specificity is 77.89 percent, and the sensitivity is 66.75 percent. However, this study needs an enormous amount of data to train the model as well as the accuracy has not achieved a high ratio in the classification process.

The authors in [94] have presented an intelligent solution to analyze voice pathologies by using co-occurrence matrices and GMM. Co-occurrence matrices have been essentially created to extract texture features from images, where these features have proved to be effective in the healthcare sector such as in [95]–[97]. The authors exploited the co-occurrence matrices advantage to design a system of voice pathology analysis. Two kinds of inputs were used: EGG signals and voice signals. The EGG electrodes were used to obtain EGG signals and smartphones were used as sensors to obtain voice signals. Both signals were sent to the cloud, which then were separately processed and combined after the individual classification phase. The experiments were evaluated based on the SVD database [98]. The authors analyzed around 400 samples that uttered vowel sound /a/. Pathological samples included in this method are vocal fold paralysis, sulcus, vocal fold cyst, vocal fold polyp and vocal fold nodules. The co-occurrence matrices are applied on the image in two distances ($d1$ and $d2$) and two directions($\emptyset = 0°, 90°$). The intention of $d1$ is to compare between two immediate neighbourhoods in terms of the energy levels, and $d2$ is to compare with the next nearest neighborhoods. The co-occurrence matrices are calculated based on 12 (frame) × 24 (filter) window which can be calculated as follows:

$$COOCCUR_{x,y} = \sum_{u=1}^{A} \sum_{\upsilon=1}^{B} \left(\mathrm{Im}_{u,\upsilon} = x\right) \bigwedge (\mathrm{Im}_{u',\upsilon'} = y) \tag{6}$$

where, Im refers to image size (A × B), x and y refer to filters energy levels, u' and υ' refer to distances ($d1$ and $d2$) and directions (0°, 90°). The accuracy of combined EGG and voice signals achieved 99.98 percent which is higher than the compared studies in [98]–[100]. However, there is no details explanation on the dataset used, where the number of normal samples and pathological samples used in the experiment is unknown. Moreover, the distance between the speaker and the EGG electrodes or smartphone is not mentioned.

The parameters of the MFCC (e.g. filter space, frame size, window length and filter bandwidths) are also considered in many other studies, such as in [101], [102]. In [101], the selected patients are suffering from spasmodic dysphonia. The authors have combined SVM and GMM classifiers and used RBF kernel (Radial Basis Function) to differentiate normal and pathological voices. Moreover, they have modified and used Bhattacharyya (Bh) and Kullback-Leibler (KL) distances for measuring the distance between GMMs in order to enhance the capacities of GMM discriminative. The obtained results have shown that the system has 2 percent and 4 percent of the sensitivity improvement when KL and Bh distances were utilized. However, the performance of SVM and GMM algorithms with MFCC as signal features is tested only on a limited dataset that is obtained from MEEI database. The work in [102] has presented a system to evaluate the voice signal in terms of voice pathology diagnosis. This system has three classes; the first one is for 36 samples of normal voices, and the second class for pathological voices, where it includes 19 samples of vocal fold nodules and 40 edemas samples. The third class is for the neuromuscular disorder that includes 59 vocal fold unilateral paralysis samples. It used two classes of voice pathology to verify which acoustic feature is more reliable and has more pathology information. The voices are obtained from MEEI database with the sustained vowel /a/ and it used GMM for the classification process. However, the obtained results have shown that the accuracy only reached 77.90 percent.

The SVM method is also applied in [103] to predict the existence of dysphonia and to study four kinds of pathology: spasmodic dysphonia, cysts, chronic laryngitis, and Reinke's edema. It has used MFCC as feature extraction and SVM as a classifier. The authors proposed a method that is based on Linear Discriminant Analysis (LDA) as a reduction method of MFCC dimensionality. The purpose of LDA is to estimate matrix parameters to determine features from h-dimensional to k-dimensional (k<h) and thus the matrix within the class will be minimized. This matrix is computed as below equation:

$$S_w = \frac{1}{N} \sum_{i=1}^{k} N_i \Sigma_i \tag{7}$$

where, N refers to the number of MFCC features. SVM method classified the pathological voice signal with an accuracy that is up to 86 percent. However, this method was only tested on a limited dataset. Indeed, only 40 healthy and 70 pathological voices were selected through SVD database.

The authors in [104] have proposed an analysis of the speech signal by applying the GMM classifier, MFCC extractor with various jitter and shimmer for the detection of the neurological disorder voice. Equations (8) and (9) are used to calculate Jitter and Shimmer in order to evaluate the percentage of the speech signal.

$$Jitter = \frac{\frac{1}{N-1}\sum_{\mathrm{k}=1}^{\mathrm{N}} |T_k - T_{k+1}|}{\frac{1}{N}\sum_{\mathrm{k}=1}^{\mathrm{N}} |T_k|} \tag{8}$$

$$Shimer = \frac{\frac{1}{N-1}\sum_{\mathrm{k}=1}^{\mathrm{N}} |A_k - A_{k+1}|}{\frac{1}{N}\sum_{\mathrm{k}=1}^{\mathrm{N}} |A_k|} \tag{9}$$

T_k refers to time, A_k indicates an amplitude, and N refers to number of cycles. For normal and pathological voices, authors used SVD dataset with vowel sounds /u/ and /a/, where they have chosen 52 normal samples and 29 pathological samples. However, this study was evaluated on a small set of SVD database involving only 52 healthy voices and 29 pathological voices.

Different classification models are explored and compared in [105] to obtain the capability of vocal parameters in distinguishing pathological voices from normal voices. The aim of this work is to distinguish pathological and normal voices of children by using various classification techniques such as SVM and Radial Basis Functional Neural Network (RBFNN). The dataset is created by recording voices from 20 children, in which 10 samples are pathological voices and 10 samples are normal voices). The total of samples is 8000 per second. These voices are used to train and test the classifiers. Next, the signal of the speech is analyzed to extract the vocal parameters such as frequencies, and signal energy. Results have shown that RBFNN has an accuracy that reached 91 percent, while the SVM achieved 83 percent accuracy. However, this study was performed on a limited dataset that involves children voices only, where the dataset should be varied and has different samples of the voice such as gender, age and different voice pathologies.

The research paper in [106] aims to extend the traditional Principal Component Analysis (PCA) by utilizing dynamic representation in the classification task. PCA is a method that is widely used as a feature extraction, where it can correctly select a relevant subset of original features. The method of dynamic features with PCA is proposed in order to reduce the feature space dimension which causes the complexity of the classifier and the computational cost. In this method, three classifiers have been used which are Bayes, SVM and GMM. These classifiers are applied in three scenarios to evaluate the performance of proposed dynamic features that used PCA method. In the first scenario, classifiers are applied without using any feature extraction. In the second scenario, the classifiers are applied by using feature extraction. Meanwhile, classifiers are used with the proposed dynamic feature extraction and PCA in the third scenario. This method is applied for pathology voice detection in the speech and it is evaluated based on two different databases of voice disorders, which are MEEI and Universidad Politécnica de Madrid (UPM). It used 53 of normal voices and 173 of the pathological voices. The dataset is divided into 70 percent for the training phase and 30 percent for testing. The recorded voices are framed with 40 ms and the dynamic feature consists of 32-time vectors which represent each whole voice sample. In the MEEI database, the accuracy rate can reach 95 percent and the space dimension decreased from 32 to 4 variables. On the other hand, in UPM database, the dimensionality decreased from 32 to 9 and achieved 80 percent of the accuracy rate. Furthermore, it is possible in the proposed system to identify the original dynamic features that are pertinent to the task of detecting pathological voice. However, the proposed method has failed in terms of sensitivity.

The SVM classifier is also used in [107] to differentiate between pathological voices and normal voices. The aim of this study is to reduce the recognition error rate by applying MFCC with Fast Fourier Transform (FFT). FFT-based MFCC parameters are obtained by calculating DCT (Discrete Cosine Transform) over the logarithm of the energy in different

TABLE 2. Summary of machine learning algorithms used in the pathological voices systems.

Years	Problems	Classifiers	Features Extractions	Databases	Pathological Samples	Normal Samples	Accuracy	Ref.
2020	Pathological voice detection	GEV, GMM and GNB	H-KLD, HASS-KLD and MFCC	MEEI	173	53	99.55%	[111]
2020	Voice pathologies detection and classification	SVM	HOS, EMD and DWT	SVD and Private-Tunis	SVD = 569 Private = 28	SVD = 561 Private = 30	SVD = 99.26% detection, 100% classification. Private = 94.82% detection, 94.44% classification	[112]
2020	Speech pathologies investigation	DPM	ZCR, SE and SH	SVD	126	687	95%	[113]
2020	Developmental dysphasia	SVM and FFNN	Glottal features, MFCC and openSMILE	SLI	54	44	SVM = 88% - 96%, and FFNN = 95% - 99%	[114]
2020	Parkinson disease detection	k-NN, MLP, SVM, and RF	Baseline features, MFCC, DWT and TQWT	Private-Turkey	564	193	94.7%	[115]
2019	Voice pathology surveillance	CNN	Parallel CNNs	SVD	1342	686	95.5%	[116]
2019	Dysphonia disease	CNN	STFT, FSST and FSST+DA	SVD	94	94	70%	[117]
2019	Voice pathology analysis	k-NN and SVM	DT-CWPT	MEEI and SVD	MEEI = 106 SVD = 244	MEEI = 201 SVD = 592	SVM (MEEI-SVD) = 94% - 97.69%. k-NN (MEEI-SVD) = 80% - 87%	[118]
2019	Voice disorders detection	SVM and k-NN	Glottal signal parameters	SVD and Private-ISR	71	34	SVM = 98.5% and k-NN = 88.2 %	[119]
2019	Voice pathology detection	SVM	CNN	TUH	998	1385	87.32%	[120]
2019	Detection of pathological voice	SVM	Glottal source features and MFCC	HUPA and SVD	HUPA = 200 SVD = 857	HUPA = 239 SVD = 661	HUPA = 78.37% and SVD = 74.32%	[121]
2018	Voice pathology detection	SVM	CNN	MEEI and SVD	MEEI = 95 SVD = 244	MEEI = 53 SVD = 262	MEEI = 73.3% SVD = 98.77%	[122]
2018	Voice pathology detection and classification	SVM	Frequency bands	MEEI, SVD and AVPD	MEEI = 101 SVD = 263 AVPD = 127	MEEI = 53 SVD = 266 AVPD = 169	MEEI = 99.54% SVD = 99.53% AVPD = 96%	[123]
2018	Voice disorder identification	SVM	HNR, Jitter, Shimmer and MFCC	SVD	685	685	85.77%	[124]
2018	Voice pathology detection	ANN and SVM	Glottal flow parameters	SVD and MEEI	SVD = 251 MEEI = 180	SVD = 260 MEEI = 53	SVD = 99.27% MEEI = 93.66%	[125]
2017	Arabic voice pathology surveillance system	SVM, VQ, GMM, and HMM	MFCC, LPC, LPCC, PLP, RASTAPLP, and MDVP	AVPD and MEEI	173	53	AVPD = 81.6% MEEI = 98.7%	[91]
2017	The distinguish	SVM.	MFCC	MEEI	173	53	98.63%	[92]

TABLE 2. ***(Continued.)*** **Summary of machine learning algorithms used in the pathological voices systems.**

	among pathological and healthy voices							
2017	The voice pathology detection	DNN	LSTM	SVD	1356	687	71.36%	[93]
2017	The differentiating pathological voices from normal voices	GMM	Co-occurrence matrices	SVD	1320	650	99.87%	[94]
2016	Pathological voices detection	SVM	Pitch and LPC	SVD	160	80	86%	[126]
2016	Voice pathology assessment for big data	SVM GMM and ELM	MPEG-7 and IDP features	SVD and MEEI	SVD = 1800 MEEI = 600	SVD = 1800 MEEI = 53	SVM = 73.2% GMM = 70.4% ELM = 80.4%	[127]
2016	Voice disorders identification	ANN	LDA and MFCC	SVD	70	50	87.82	[128]
2016	Detection of voice disorders	SVM and ANN	MMTLS	MEEI and Private	MEEI = 657 Private = 527	MEEI = 53 Private = 6	SVM = 94.51% ANN = 96.48 %	[129]
2016	Voice pathology detection	SVM and GMM	MFCC	SVD	40	60	96.5% - 95.5%	[101]
2015	The voice pathology identification system	GMM	MFCC	MEEI	118	36	77.90%	[102]
2015	The detection of pathological and normal samples of the voice	SVM	MFCC	SVD	70	50	86%	[103]
2014	The detection of the pathological voices in the spasmodic dysphonia	GMM	MFCC, jitter and shimmer	SVD	38	63	82.37%	[104]
2014	The distinguish among pathological and normal voices	SVM and RBFNN	Acoustic feature extraction	Private	10	10	83% for SVM and 91% for RBFNN	[105]
2009	The detection of the pathology existence in the speech	Bayes Classifier, SVM, and GMM	Dynamic feature extraction	MEEIVL and UPM	173	53	95% for MEEIVL and 80% for UPM	[106]
2005	The detection of the pathology existence from voice records	SVM	MFCC	MEEI	77	53	95%	[107]
2002	The automatic detection of normal and pathologies voices	HMM	MFCC	MEEI	662	53	99.44%	[108]

frequencies as shown in the following equation:

$$C_m = \sum_{k=1}^{M} \log(S_k) \cos\left[m(k-0.5)\frac{\pi}{M}\right] \tag{10}$$

where, $1 \leq m \leq L$ (L is the analysis order), S_k refers to several frequency bands and M is the band number in Mel scale. The features are calculated from short-time windows that are extracted from the utterances, where the window length is set to contain two consecutive pitch periods. In addition, feature extraction is applied using 40 ms and the rate of frames gained is 50 frames. Hamming windowing is selected with an overlap 50 percent among adjacent frames. The decision of the voice signal classification whether normal or pathological is based on the threshold over the number of frames. The threshold is based on 80 percent of the frame error, where if 80 percent frames are classified as normal voice, then the final decision is normal class, otherwise it will be classified as pathological class. Furthermore, the model has used MEEI database, where it has selected 53 normal samples and 77 pathological samples. In addition, 70 percent of the samples are used for training and 30 percent is for validation. The authors have concluded that FFT-based MFCC performed faster than Multilayer Perceptron (MLP). Moreover, SVM performance with FFT-based MFCC achieved 95 percent classification accuracy and 5 percent error rate.

With regards to the voice pathology recognition, HMM classifier is considered as a competitor to the other powerful classifiers. HMM is used to distinguish among pathological voices and normal voices in [108]. This study used 710 voice samples with 53 normal samples and 657 pathological samples. All samples are obtained from MEEI database. The authors focused on the sustained vowel /a/ in voice samples. Along with those samples, the dataset has also acoustic speech sample that is called "Rainbow passage" which has 662 pathological subjects that belong to the same patients who have provided the vowel /a/ samples. Also, for the normal class, there are 53 recordings with a length 12 sec of Rainbow passage. In addition, MFCC was modelled by GMM in HMM classifier. To compare and evaluate the proposed method results, there is an improvement factor that can be defined as follows:

$$improvement = \frac{Accuracy}{Base\_Accuracy} - 1 \tag{11}$$

where, *Base_Accuracy* refers to the rate of the correct classification of HMM classifier for the vowel /a/, and *Accuracy* refers to the rate of the correct classification for the data that has been processed. This study has outperformed other methods such as a Neural Network (NN) and Nearest Mean Classifier (NMC), where the classification accuracy rate for HMM is 99.40 percent and 98.59 percent for the Rainbow passage. However, the pathological voice samples are divided unequally, where there are many samples for a certain disease such as Hyper-function and also there are very few samples for another disease such as adductor spasmodic dysphonia. Consequently, this affects the classification accuracy rate.

From the recent studies in the above mentioned literature, many systems have been proposed for voice pathology detection [98]–[100], [109], [110]. However, these systems aimed to differentiate normal voices from pathological voices only, where there are research shortages in terms of voice disease diagnosis with respect to laryngeal cancer. In machine learning algorithms, there are cases where voice signals could not guarantee high accuracy and cause time-consumption in the pathology monitoring methods. Consequently, there is an urgent need for a study and highlights the most important issues and challenges facing voice pathology systems and the significance of the disease diagnosis in voice pathology. Furthermore, in terms of machine learning algorithms, we highly recommend choosing the best feature extraction method that can handle the audio pathology according to the dimensions of the feature extraction. Moreover, the machine learning classifier should be developed by either proposing a new activation function or tuning on a mathematical function of that classifier scheme. Thus, it can improve the performance of a system in terms of effectiveness and efficiency. Table 2 shows a brief summary of the related works for machine learning algorithms used in the pathological voices systems.

VIII. CONCLUSION

The technologies of IoT, cloud and machine learning algorithms are used in many aspects of the healthcare sector. These technologies will help to develop the healthcare applications in general and in the voice pathology surveillance methods in particular.

In this paper, we have provided an inclusive overview of the state of the art techniques which used IoT and machine learning methods in several healthcare fields, particularly in the voice pathology assessment systems. Moreover, we have highlighted and discussed the main related research results, issues, applications and recent studies which were implemented in the healthcare field and in particular in the voice pathology.

Based on this survey, we can summarize our review as follows:

- IoT is often not completely and correctly exploited in the healthcare area because of the excessively big interval between the data collection and the capability to process and analyze.
- The main problem that faces each patient, especially living in remote locations is the unavailability of doctors and treatment in critical cases. Thus, there is a need for providing a new framework by using IoT devices in those areas.
- There are many situations in which patients require long-term surveillance (e.g., a patient with a chronic disease). In this regard, the provision of constant monitoring is very important.
- Research and Development (R&D) activities for a new type of voice diseases and disorders are essential, and the

discovery of methods that can make the early detection of rare diseases mobile has long been an important task.

- The IoT healthcare network must have the ability to support the mobility of patients such that they can be connected anywhere. This would require a comprehensive IoT ecosystem which considers customization of connectivity, without compromising on the data security.
- Most of the researchers are focusing on the voice pathology and their finding is only limited to differentiating either the voice is normal (healthy) or pathological voice, where there is a need for a complete IoT framework for a specific disease detection such as laryngeal cancer. Since laryngeal cancer is life threatening illness, a new and effective framework/model for laryngeal cancer early detection is much needed.
- Some patients with sound disorder that could potentially be caused by laryngeal cancer, may not want to do further medical examination because they thought that the hoarseness in their voice is not important or dangerous in their life (caused by other diseases such as flu or inflammation of the larynx), or perhaps they do not have time to go there and undergo several processes. Therefore, this is a significant issue which requires a seamless framework that provides an effective and non-invasive method for the diagnosis of chronic diseases such as laryngeal cancer.
- Since machine learning algorithms are used in medical diagnosis, the accuracy of these algorithms must be high enough to avoid any errors in the classification process. Moreover, the developed algorithms must take into account data protection requirements, as well as ethical and regulatory issues in order to merit the trust of patients and healthcare providers and prevents unnecessary risks.
- The slow acceptance for applying the machine learning technology in the medical diagnosis, where this technology should obtain more support from organizations and integrated with the current instrumentation to present simple use for both doctors and patients.
- There are many features extractions and classifiers which are used in different domains such as image processing and text identification. In healthcare, the situation is so critical where one must choose the best feature extraction and classifier that are used accurately and effectively in the voice pathology detection.
- The lack of providing a specific dataset for a particular disease such as laryngeal cancer, where the existing dataset contains different voice diseases. In addition, the distribution of voice pathology samples is very unequal which makes the detection of voice pathology a difficult problem. The reason is due to a particular type of voice pathology which occurred only once in the whole dataset such as SVD. Thus, that type of voice pathology could not be trained well and resulting in low accuracy.

The above conclusions based on the conducted survey in this article must be carefully highlighted in future healthcare studies. Therefore, IoT frameworks and machine learning algorithms in such a field need to have high effectiveness and efficiency in order to present a simple process for patients to check up their health easily by IoT devices and also to obtain a high diagnostic accuracy of a particular disease by adopting machine learning classifiers.

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