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A review of enabling technologies for Internet of Medical Things (IoMT) Ecosystem

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ABSTRACT

The goal of Internet of Medical Things (IoMT) and digital healthcare systems is to provide people with the ease of receiving quality healthcare at the comfort of their homes. Hence, the aim of IoMT is the ubiquitous deployment of home-based healthcare systems. Making such systems intelligent and efficient for timely prediction of critical diseases can save millions of lives while simultaneously reducing the burden on the traditional healthcare systems e.g., hospitals. The advancement in IoT has enabled both patients and doctors to access real time data. This advancement has reduced the cost and energy consumption of digital healthcare systems by using efficient sensors and communication technologies. This paper provides a comprehensive review of various studies conducted for the development and improvement of IoMT. It analyses different sensors used for measurement of various parameters ranging from physiological to emotional signals. It also provides a detailed investigation of different communication technologies being used, their advantages, and limitations. Moreover, digital healthcare systems are now deploying machine learning technology for the prediction of health status of patients. These techniques and algorithms are also discussed. Data security and prediction accuracy are the main concerns in the development of this area. In conclusion, this paper reviews the various digital system designs in the context of healthcare, their methodology, limitations, and the present challenges faced by the e-health sector.

1. Introduction

Quality healthcare is a basic human right, but one which fails to be provided adequately worldwide. The economic, environmental, and social development of this world and subsequent lifestyle changes have led to a drastic increase in chronic diseases such as heart disease, cancer, and diabetes. These chronic illnesses symbolize the greatest threat to human health. Moreover, each time an infectious disease breaks out, the hospitals are flooded with people which takes a huge toll on healthcare services. For example, currently there is a continuous stress on the world′s healthcare resources with the rampant spread of COVID-19. This kind of situation leads to inefficiency in managing patients and their data.

Experts believe that digital healthcare systems in Internet of Things (IoT) environments seem to be a compelling solution to this major healthcare problem. The building blocks and general architecture of a system in the IoT environment is shown in Fig. 1. In the context of medical services, the traditionally proposed remote health monitoring system architectures are divided into three layers: the vitals′ data collection layer from sensors; the transmission layer; and the analysis layer. The collection layer consists of sensors in the body area network (BAN). BAN collects the sensor data and transmits it to a gateway node. The transmission layer stores that data and analyzes it using conventional threshold values to

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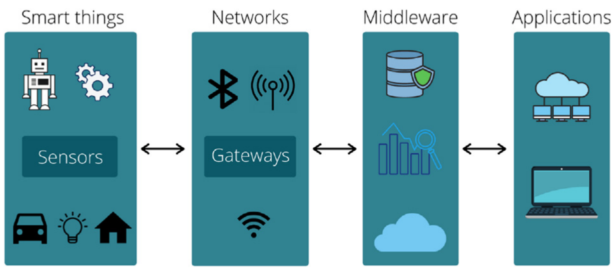

Fig. 1. The building blocks of a general IoT-based system.

report any abnormality. Additionally, the data may also be sent to the cloud for storage and heavy computations. In case of an intelligent system, machine learning and data mining algorithms are employed to detect any abnormality and make predictions about the patient′s health status. Finally, the analysis or the result of the data is sent to a cloud server. Using a web-based interface, medical professionals can login, check and verify the diagnostics and take corresponding measures.

It is observed in [1] that the above-mentioned system architecture is not very efficient in managing emergencies since there is a huge latency in results. BAN sensors send the health data to the cloud for the major processing. This increases the overall latency of the system, and a fast analysis cannot be provided to patients in emergency situations. The new paradigm of fog and edge computing aims to solve this latency problem. The concept of edge computing is to bring the computational services closer to the BAN layer i.e., on the edge. In [2], the authors have proposed a remote system which monitors the heart conditions of a patient with the help of an electrocardiogram (ECG) sensor and reports any abnormality. The gateways of this system are integrated into a fog layer which provides a number of advanced services in addition to solving the latency problem. Similarly, in [3], the authors propose a medical control system framework where various physiological parameters of a patient are measured. An emergency alert system is designed at the fog layer where the different measured parameters have specified threshold values. Whenever a sensor value crosses its nominal range, a notification is sent to the doctors via SMS or email.

[4] provides an overview of how environmental and physiological parameters can be used to monitor a person′s health. It is observed that measurement of environmental parameters only requires a stationary device but the measurement of physiological parameters require continuous monitoring of data. For this purpose, a light wearable system is designed by the authors that monitors a patient continuously and sends the data to a server. The paper also described the levels on which the data processing in divided into, namely data management level, data collection level, sensor node level, and data monitoring. The authors have proposed that their system can be applied in working environments, especially hazardous areas that might be dangerous to the workers.

In an IoT-based system, the energy consumption of the wireless sensor network (WSN) is of utmost importance. As most BAN sensors are wireless, it is important to consider their power consumption so as not to exhaust the limited power supply. For obvious reasons, sensors dying down while monitoring an at-risk patient is completely unacceptable. To counter this problem, [5] proposes an energy efficiency algorithm called Energy Efficient ON–OFF algorithm for transmission of medical data from sensors to the gateway nodes. In the paper, the authors perform an energy dissipation analysis of the sensors deploying the EEOOA algorithm which concludes that it works better than traditional techniques.

The digital healthcare solutions prevalent in the research community are not just focused on solving the problem of chronic illnesses in the world. A healthcare system in the IoT environment has many use cases including but not limited to, sleep monitoring, mental health monitoring, automatic insulin injection etc. Statistics discussing mental health reveal astounding results about the number of people who suffer from mental health problems. As awareness about the importance of mental health is at an all-time peak in the world, it is imperative to develop solutions for it. [6] discusses how signal processing and machine learning techniques can be used for continuous mental health monitoring. The paper also provides an overview of the standing challenges regarding such solutions. Although clinical help is available, but the limited number of professionals make it difficult to keep track of all patient activities. Signal processing can be used to model behavior on the instances that are most relevant for the required judgement.

Before embarking upon a research journey, it is important to study the various solutions that already exist. This paper aims at providing a one-stop review of various aspects of a healthcare system in the IoT environment. The remainder of the paper is structured as follows. Section II discusses monitors and sensors used to measure different body vitals and signals. Section III discusses the commonly employed wireless communication technologies in smart healthcare to send sensor data to a server. In section IV, the benefits and advantages of a cloud-based architecture are discussed. Section V analyses different machine learning techniques and algorithms deployed in various systems. Section VI deal with the available online techniques of data processing called edge computing. Section VII highlights different applications of IoT and ML in the medical sector. Lastly, Section VIII summarizes the paper by concluding the key findings along with emphasizing the areas where more research is required.

2. Sensors

The correct analysis of a person's health can be made by measuring different physiological parameters using sensors. Medical equipment is readily available, but it is costly and consumes a lot of power. Hence, to save power and implement low cost and economical solutions, sensors are used in IoT based medical systems. They measure different biological parameters and monitor real time patient data. The purpose of sensors is to enable IoT-based healthcare systems which help in reducing the number of patients who visit the hospital. With the use of these biomedical sensors, experts are now designing flexible systems relying on machine-to-machine interactions, saving time of both patients and medical personnel, and making treating patients at home congenial.

Table 1
Sensors Used in Healthcare Domain.

No.	Sensors	Parameters Measured
1	DHT11/22	Room Temperature, Humidity
2	LM-35	Body Temperature
3	TMP236	Body Temperature
4	AD8232	Heartbeat, ECG
5	IL300	Body Fat
6	SPO2	Blood Oxygen Saturation
7	KG011	Pulse Rate
8	DS18B20	Temperature (Room and Body)
9	ASDXAD015GAA5	Blood Pressure
10	ADXL335	Body Position
11	TCRT1000	Oxygen saturation in blood
12	Blood Pressure Monitor	Blood Pressure Measurement
13	MAX3010x	Blood Oxygen Saturation
14	BME280	Temperature, Humidity, Bar. pressure
15	LIS302DL	Body Position
16	Thermistor	Body Temperature
17	APDS9008	Pulse Rate

Table 1 displays some of the sensors used in different proposed designs. Sensors shown in this table are used to measure numerous physiological parameters. The three most important vitals required to determine a patient′s health status are temperature, ECG and pulse rate. Other parameters especially blood pressure can be measured using much simpler and smaller digital wrists. Blood pressure monitors are easily available and are almost present in every home. Accelerometers are used to determine body position and can come handy in time of stroke or if a patient faints. Live cameras are also being used to continuously monitor patient health while ensuring secure data transmission. In this section, the prevalent sensors used in healthcare systems are discussed.

2.1. Temperature Sensors

The most widely used temperature sensors are LM-35, TMP236, DS18B20 and MAX30205. TMP236 is an analogue and cost efficient sensor with high accuracy of ± 2 °C. The operating range is from $-10°$ to 125 °C. However, it is not used as much as it is an analogue temperature sensor and requires an external or internal ADC to obtain a digital output. On the other hand, DS18B20 is a digital sensor ranging from -55 °C to 125 °C with an accuracy of ± 2 °C. It is mostly used in buildings and machines for process monitoring. In [7], a wearable patient monitoring system is proposed which utilizes the DS18B20 to measure the patient′s body temperature.

The MAX30205 temperature sensor accurately measures temperature and provide an overtemperature alarm/interrupt/shutdown output. The MAX30205 offers High accuracy (0.1 °C) and low voltage operation (2.7–3.3 V), therefore it is ideal for wearable systems. Moreover, its digital functionality makes integration easier into any system. A pinout diagram of MAX30205 is shown in Fig. 2. LM-35 is most commonly used in wearable sensor networks due to its many applications in remote monitoring. It has greater range than DS18B20 i.e. from -55 °C to 150 °C with higher precision of 0.5 °C. A thermistor may also be used as a substitute for a temperature sensor as it is low cost, reliable and waterproof, measuring with an accuracy of up to 0.25 °C.

2.2. Pulse Rate Sensors

Pulse rate is monitored to see how well the heart is working. In case of an emergency, it can be used to instantly determine the cause. Different research papers use different techniques to determine heartbeat but the most widely employed pulse rate sensor is APDS-9008. It is an analogue output light sensor, which is being used in multiple mobile electronic devices by measurement of ambient light. To utilize it as a pulse rate sensor, a low intensity infrared green LED is used to detect the pulse by reflection of light with every heartbeat. This sensor works by responding to light intensity variation and the output is filtered of any high frequency noise by a low pass filter. The signal is then amplified by the Op-Amp MCP-6001 [8].

[9] has made a comparison between photoplethysmographic (PPG) sensors and radio frequency (RF) based architectures for measuring pulse rate. The paper concludes that PPG sensors are the most reasonable and effective choice for a healthcare application. In [10], the authors have developed an emergency monitoring system which measures heart rate, body temperature and ECG. The authors use a pulse sensor from which a PPG signal is obtained. The pulse rate of the patient is extracted from a part of this signal obtained over a time-period of 1826 ms.

2.3. Pulse Oximeters

Pulse oximeter is a non-invasive device that allows monitoring of a person′s blood oxygen saturation. This information can be used to monitor and identify any abnormality in a patients′ health. Health conditions identified by a blood oximeter can include asthma, pneumonia, anemia, lung related diseases etc. Although the reading of peripheral oxygen saturation (SpO_2) by a blood oximeter is not always similar to the arterial oxygen saturation (SpO_2), which is usually more preferable, it has been termed safe, convenient, noninvasive, and inexpensive. Pulse oximetry method has proved to be a valuable feature for measuring oxygen saturation in clinical use [11]. SpO_2 is usually measured using a sensor which is attached to the patient's finger. There are two techniques of SpO_2 measurement: transmissive and reflective. Out of these two, the transmissive method is commonly used. Such pulse oximeters work by transmitting a light through the blood in the finger, and then calculating the oxygen saturation in blood (known as SpO_2 level) by measuring the changes of light absorption in oxygenated or deoxygenated blood. The most widely used pulse oximeter sensor in smart healthcare is MAX30102, developed by Maxim Integrated [11]. The sensor operates on low power (1.8 V). It is small in size as seen in Fig. 3, and hence can be easily integrated into smart wearable devices or even smartphones. [12] employs a smart pulse oximeter sensor inside the passenger seat in an airplane. The purpose of installation of such a system in an airplane can be understood from the fact that during a flight, the cabin may suffer from low pressure, low oxygen levels and low humidity, all of which can endanger patients suffering from chronic obstructive pulmonary diseases. Therefore, it is vital to monitor their health and detect an abnormality timely so they can receive proper treatment.

2.4. ECG sensors

Electrocardiogram (ECG) data is required to monitor normal heartbeat and strength. It is important in the prediction and prevention of cardiovascular diseases. AD8232 is a widely used ECG

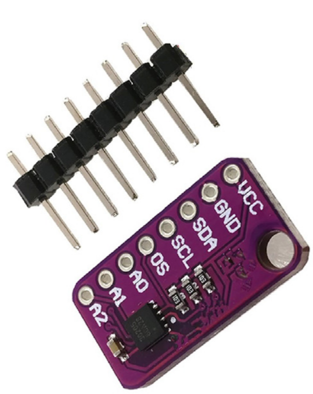

Fig. 2. MAX 30205 Human Body Temperature Sensor, Offers $\pm 0.1°$C (max) Accuracy for Thermometer Applications.

Fig. 3. MAX 30102, High-Sensitivity Pulse Oximeter and Heart-Rate Biosensor for Fitness & Healthcare.

measurement module, as shown in Fig. 4. It can be used as both a heartbeat sensor and an ECG graph sensor hence it has multiple functionalities. It can be used as a heartbeat sensor from the front end. It uses an amplifier, a buffer, and a filter to limit power consumption, amplify the ECG signal and reject half of cell capability of the electrode. The system has a fast circuit restore function that reduces the delay from low cutoff frequency of high pass filter.

[13] presents an ECG android app where patients can view their data for health monitoring purposes. In [14], the authors also present a remote monitoring system for the purpose of reducing visits to the hospital. In this system, an ECG sensor is used to measure the heart rate of the patient. In [15], the authors propose a monitoring system for ICU patients which incorporates multiple physiological and ambient sensors including an ECG sensor. Some threshold values are set for each of the sensed parameter and a push notification is sent to the doctors in case of any anomaly.

2.5. PPG sensors

Photoplethysmography (PPG) is an simple and inexpensive optical measurement method that is often used for monitoring heart rate. PPG has the advantage of being a non-invasive technology. The construction of a PPG sensor includes a light source and a photodetector at the surface of skin to measure the variations in blood circulation which can provide abundant information. Recently, numerous researchers have been keen on deriving further valuable information from the PPG signal such as blood pressure and respiration rate [16]. A PPG signal′s second derivative wave contains important health-related information. Thus, analysis of this waveform can help evaluate various cardiovascular diseases. The most common locations for placing the PPG sensor are the patient′s finger, earlobe or forehead. Researchers are considering other body locations as alternatives for easier measurement.

2.6. Respiration Rate Sensors

Monitoring respiration rate in healthcare applications is vital for diagnosis of a variety of diseases such as pneumonia, asthma etc. However, contemporary approaches are hardware extensive and inefficient. To solve this problem, non-invasive measurement methods have been developed which are now employed in smart healthcare applications. However, it is not feasible to constantly monitor a patient′s breathing rate because IoT systems need to be power efficient. The most used hardware module to measure breathing rate is a thermistor. Thermistor is less costly, runs on low power and its robust performance proves to be beneficial for healthcare applications. The proposed system in [17] uses this device along with a cloud enabled architecture to transmit patients′ data to a web application where authorized users can view the recorded data. In case an abnormality is detected in the breathing rate or the collected data, the medics as well as the patients are immediately notified. [18] discusses another non-invasive method for measuring respiratory health of a patient. The proposed system has embedded pressure sensor arrays in a mattress of the bed that the patient sleeps in. The system is as innovative as it is effective in monitoring the respiratory health of a person.

Respiratory monitoring has become a necessity in diagnosing various cardio-pulmonary diseases, and conventional instruments to measure the of respiration rate of any patient are usually inconvenient and difficult to wear. There has been significant published studies that have carried out respiration rate estimation using ECG signal [19]. Estimating respiration rate using the ECG signal results in less hardware equipment for monitoring purpose. It is known that an ECG wave has three main components:

- The P wave, which shows the depolarization of the atria
- QRS Complex, which represents depolarization of the ventricles
- T Wave, which constitutes of repolarization of the ventricles

For respiration rate extraction from ECG, heart rate variability and peak amplitude variation are utilized [20]. Another published study [21] has devised a MATLAB based algorithm to extract the exact amplitudes of the R-waves. This data is used to form pulsatile waves due to respiration, which is then used to estimate the respiration rate of the patient. Fig. 5 shows the result of a respiratory rate estimation algorithm using ECG and PPG signals. This mode of respiration rate monitoring is proving to be beneficial since it is non-invasive. Development of more specialized respiration rate monitors is also surfacing, like the Strados Labs invention [22] which uses a device to capture lung sounds and chest wall motions. It transmits that information wirelessly to a web application where the data is finally analyzed for estimating respiratory health.

2.7. Blood Pressure Sensors

There has been significant research regarding non-invasive blood pressure measurement including the contemporary approach (oscillometric method) which compresses blood vessels using an air-inflated cuff and measures systolic and diastolic pressure [24]. A typical example of such a contemporary monitor is shown in Fig. 6. In the other approach, a cuff-less blood pressure estimation technique is used which utilizes biomedical sensors like ECG and PPG sensors [25]. The conventional blood pressure mea-

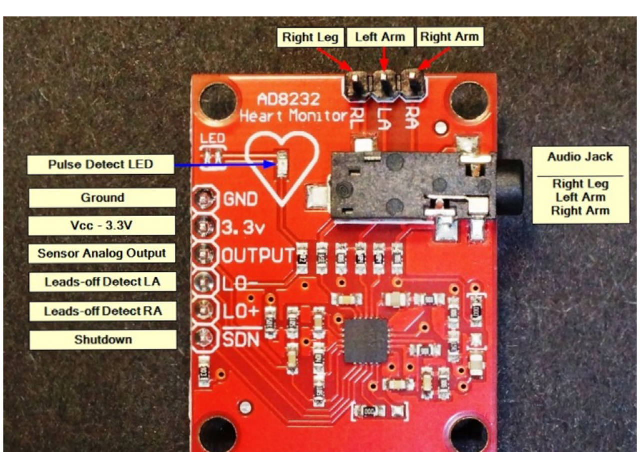

Fig. 4. AD8232, integrated signal conditioning block for ECG and other biopotential measurement applications.

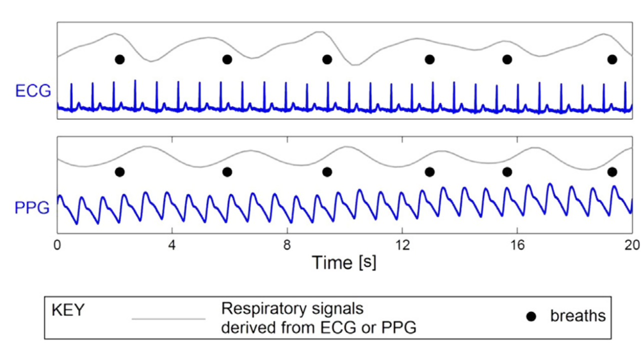

Fig. 5. Respiration Rate estimation using ECG & PPG [23].

Fig. 6. Typical cuff based Blood Pressure Monitor.

surement requires a lot of equipment, and therefore leads to a great hassle. Research advancements and studies in ECG and PPG signal processing have led to the development of a methodology which estimates and evaluates patients′ blood pressures. Such a method proves to be beneficial in the long run as it reduces the hardware costs of the system and it is more comfortable for the patient. [26,25] introduce the cuff less continuous blood pressure estimation from ECG and PPG signals using artificial neural networks (ANN). For each heartbeat wave shown by the ECG and PPG signal, 22 time domain features are extracted and analyzed for systolic pressure and diastolic pressure values. The features are fed into the ANN module that is trained on arterial blood pressure values taken from PhysioNet MIMIC II database along with PPG and ECG signals′ data. The measured performance for this system is based on calculating the difference between the actual ABP values of the data set and the values estimated by the ANN model. Results show that the ANN model has a high prediction accuracy. The authors have shown that this method of blood pressure measurement is highly efficient and non-invasive. In [27], blood pressure is estimated using only the ECG signal. The proposed system processes raw ECG data by filtering and segmenting it. Then a complexity analysis is carried out for feature extraction. A machine learning algorithm is also applied, which merges a stacking-based classification module and a regression module that predicts the following: systolic pressure, diastolic pressure, and mean arterial pressure. This method also allows for probability distribution based calibration. This means that the model is able to adapt to a particular user, and therefore proves to be vital in achieving high accuracy results.

2.8. Blood Glucose Monitors

Blood glucose monitors are essential for diabetic patients to keep their blood glucose levels in check. There are a wide variety of blood glucose monitors available. However, in an IoT environment, non-invasive and smart blood glucose monitors are desirable. [28] highlights the difficulties of invasive blood glucose monitors and their probable needle contamination which can lead to infections. Keeping this in mind, their proposed strategy consists of developing non-invasive blood glucose level monitors. These monitors incorporate infrared LED, photodiode, and AT-MEGA328 microcontroller in the sensor kit. Most of the published studies like this system detect blood glucose level using IR radiations. Moreover, certain systems also employ smart notification features that can alert the patient if an anomaly is detected. Such a system is discussed in [29], where the detected blood glucose level is wirelessly transferred to the patient′s smartphone and is used to control the insulin infusion pump. Another system named iGLU is proposed in [30]. In this system, an Intelligent Glucose Meter uses near infrared spectroscopy and machine learning models for processing and detecting any abnormality in the collected patient data. The data is forwarded to the cloud for the purpose of storage and analysis. These features allow for remote monitoring of the patient by their endocrinologists. A non-invasive blood glucose monitor is also developed in the industry by DIAMONTECH which is shown in Fig. 7.

2.9. EMG sensors

The Electromyography Sensor (EMG) is used for measuring the electrical activity of muscles. It is often used as a control signal for different prosthetic devices. This sensor enables doctors and medical professionals to monitor nerve and muscle disorders in a patient. Such sensors are also used in wearable devices to monitor behavior of the patient. EMG sensors prove to be vital in systems that employ emotion based intelligent information sensing. In [31] the proposed system uses EMG signal along with other body vital measuring biomedical sensors to determine variability in facial muscles and classify each change with its corresponding emotion. This system is able to determine the affected state of the patient′s health. In the industry, an Arduino powered EMG sensor is also developed by Advancer Technologies as shown in Fig. 8.

3. Wireless Communication Technologies

Many diverse communication technologies have been introduced in the recent era due to the inclination of researchers towards IoT technology. While some of these technologies were developed particularly for the IoT environment, the rest had other purposes, yet now they play an important role in IoT systems. Different communication platforms have distinct features which may help IoT based systems achieve optimum performance. However, there is no one-size-fits-all strategy. A particular communication technology for a system is chosen carefully with keen regard to the kind of application it will be used for. In this section, the most used protocols for wireless communication in IoT-based healthcare systems have been discussed and their tabular comparison is also provided in Table 2.

3.1. Cellular Networks

Mobile phone networks are based on cellular technology. This technology is based on the concept of employing multiple smaller transmitters instead of one big transmitter. It is most suitable for applications which require significantly high data rates. 3G, 4G, 5G and GSM are different kinds of network technologies based on cellular communication. These provide high data rates and direct connection to the internet, although at a cost of higher power consumption. In [32], the authors perform a comparison between 3G and Wi-Fi for a healthcare model comprising of two body sensors (temperature and ECG). Experimental comparisons between the two communication platforms yielded similar results, but the authors noticed that the system runs much more smoothly over Wi-Fi while it faces some problems with a 3G connection. A

Fig. 7. Non-Invasive Blood Glucose Monitor developed by DIAMONTECH.

Fig. 8. Arduino-powered, all-in-one electromyography (EMG) sensor from Advancer Technologies.

similar model is designed in [33] which measures multiple bio-signals from sensors connected to an Arduino. A GSM module is connected to the Arduino which is then used for sending sensor data to specialized health care providers.

3.2. Wi-Fi

Wi-Fi is the most prevalent wireless communication technology that allows a direct connection to the internet. It usually operates in the 2.4 GHz band. Wi-Fi is just a phrase that refers to the IEEE 802.11x family of standards. It has a nominal operating range of 20 to 100 m indoors. Wi-Fi provides a maximum data rate of 54 Mbps. It has a lot of benefits over other communication technologies. It is ubiquitous, easy to deploy, and has significantly high data rates and throughput. Wi-Fi is more suitable for applications like audio or video transmission due to the requirement of a higher bandwidth. A major disadvantage of using Wi-Fi in the IoT environment is that it is power hungry. Its excessive power consumption makes it unsuitable for battery operated IoT sensors. Moreover, it is highly prone to noise interference and channel obstruction. Wi-Fi is undoubtedly critical in providing high data rate connections. However, in the IoT paradigm, it has major limitations and setbacks that make it less popular. Even so, some researchers have used Wi-Fi in their proposed healthcare systems. [34] proposes a remote monitoring system that can help hospitals keep their patients' vitals in check. The system incorporates temperature and heart rate sensing with the help of an Arduino board which is equipped with a Wi-Fi module. The Arduino is used to send sensor data to a web server using a Wi-Fi connection, and the data is finally displayed on a web page. Such systems can help in the monitoring of at-risk patients, particularly operated ones. It also reduces the chance of human error and provides a recorded history of the patient. Similarly, in [35], the authors suggest integrating smart home testbeds with medical IoT systems to accommodate the residents with reliable health services. They propose a medical IoT framework that records multiple vital signs including ECG and gait. All the sensors are Wi-Fi enabled to simplify the integration with smart homes and buildings.

The authors of [36] have presented an alternative way of incorporating Wi-Fi in their system. They use Wi-Fi for passive sensing of different elderly care activities. In a novel approach, the authors use two Wi-Fi signals to achieve this. A signal is reflected from the patient's body and compared to a reference signal for estimating breathing rate, detecting falls, and classifying tremors. Experimental analysis by the authors reveals an accuracy of 87% in measuring breathing rate, 98% in detecting falls and 93% in distinguishing tremors.

3.3. Bluetooth Low Energy

Bluetooth Low Energy (BLE) is a wireless communication technology whose standard is maintained by the Bluetooth Special Interest Group (SIG). BLE also operates in the same 2.4 GHz band as classic Bluetooth, but it uses a different set of channels for its function. It has a nominal operating range of 10 to 30 m indoors. It was designed especially for low power applications, although there is a subsequent trade off of data rate. BLE features a bandwidth of 1 Mbps which is substantially less than its classic counterpart. BLE was designed to provide low power consumption in various applications, including mobile devices, while maintaining the same standard as classic Bluetooth. BLE has been regarded with special interest in the medical IoT sector because it is able to meet almost all requirements of any IoT based healthcare application. In [37], the authors have designed a sensor kit enabled by BLE for remote patient health monitoring. They have integrated a heart rate and temperature sensor in their system, which senses the vitals of the patient and transfers the data to an android device (which acts a gateway) using BLE. The system is also equipped with cloud connectivity and a web portal to display results. The authors have evaluated their device against traditional measurement techniques and the results seem promising. Similarly, in [38], the authors have designed an IoT enabled point-of-care system to counter chronic illnesses, specifically cardiovascular diseases. The proposed system comprises of monitoring kits that measure vital signs of the patients and transfers the sensor data to a gateway (smartphone or tablet) with wireless BLE connectivity, complete with the feature of alert system. The system equips doctors and caretakers with the ability to monitor their patients remotely and act quickly in case of an abnormality.

3.4. Zigbee

Zigbee is a standard of wireless communication technologies which is based on the IEEE 802.15.4 standard. The standard is maintained by the Zigbee Alliance. This technology was designed to be much simpler & less expensive than other communication technologies. Zigbee was intended for IoT applications like smart homes. Its low power consumption makes it an ideal choice for healthcare applications. Zigbee has a nominal range of 10 to 100 m indoors. It generally operates in the 2.4 GHz ISM band. Zigbee has a defined data rate of 250 kbps, which is highly suitable for simply transmitting sensor data. Many digital healthcare systems proposed by various researchers utilize the benefits of Zigbee in their applications. In [39], the authors have proposed a remote monitoring system which comprises of six different biomedical

Table 2
Wireless Communication Protocols Used in Healthcare Domain.

	Wi-Fi	Bluetooth Low Energy	Zigbee	6LowPAN
IEEE Standard	802.11	802.15.1	802.15.4	802.15.4
Frequency Band	2.4 GHz; 5 GHz	2.4 GHz	868/915 MHz; 2.4 GHz	2.4 GHz
Nominal Range	20–100 m	10–20 m	10–100 m	10–100 m
Max Data Rate	54 Mbps	1 Mbps	250 kbps	50 kbps
Power Consumption	High	Very Low	Low	Low
Topology	Star,Mesh	P2P,Star,Mesh	Star,Tree,Mesh	Star,Mesh

sensors. The sensors are all integrated with an Arduino microcontroller unit which is further attached to a Zigbee transmitter. The receiving antenna receives the data from the sensors and displays it on a monitor. Similarly, [40] reviews the Zigbee technology and integrates it within a remote monitoring system. Two basic human vitals, namely body temperature and pulse rate, are measured by Zigbee sensor nodes. The nodes use this technology to transmit data to a Zigbee base node. The Zigbee nodes are simply constructed by general sensors connected to a Zigbee communication module which enables them to transfer data using this protocol. In another approach, [41] proposes a general monitoring system which can be personalized for different use cases. The authors argue that battery life is of utmost importance in medical applications, thus instead of using GPS/GSM technologies, a Zigbee mesh network can be used for indoor positioning and sensor data transfer. They justify their use of Zigbee communication technologies by observing that it is much cheaper and simpler, features reduced software complexity and consumes way less power than its counterparts.

3.5. 6LoWPAN

6LoWPAN is a simpler way of saying IPv6 over Low-Power Wireless Personal Area Networks. It is inexpensive, consumes less power and is easily adaptable. These features make it suitable for IoT based applications. It is interoperable between the IPv6 and various IEEE 802.15.4 protocols. In [42], multiple physiological sensors are used to make a WSN whose data is then processed by a microcontroller unit (MCU). The MCU is equipped with the feature to convert data into 6LoWPAN packets which are then transmitted to a gateway device. Similarly, in [43], 6LoWPAN nodes are designed which incorporate multiple physiological sensors. Each node has a unique IP address, which is useful in providing real time feedback to a monitor. [44] highlights the fact that although traditional short range communication protocols like BLE are used in healthcare applications, interoperability of smart things in an IoT environment still remains a challenge. They propose an indoor monitoring system based on 6LoWPAN sensors which transmit their data to a gateway node utilizing this technology. They also introduce a gateway application which any PC can connect to, therefore providing ubiquitous services.

4. Cloud Computing

In [13] the authors highlight the problems faced by current healthcare systems where a large amount of data is unstructured, diverse, and growing at an exponential rate. Sensors are constantly streaming chunks of data while the medical personnel are failing to keep up with it. This huge volume of unstructured data produced is very complex to understand. Therefore, it becomes a necessity to utilize various data storage mechanisms for efficient allocation of memory and organization of the data. To address this problem, the advanced techniques and high capacities of cloud computing are utilized. By employing cloud technologies, processing of large amounts of data can be performed more efficiently to support Big Data analytics. In [13], the authors argue that if data is in one central location rather than being distributed, higher feasibility and data security can be achieved. Since it is imperative to maintain the security of critical medical data of patients, the encryption features of cloud platforms are in high demand. Moreover, a cloud architecture also decreases data redundancy and therefore would implement effective use of storage space within the cloud. This advancement implements one centralized database which paves way for AI to be implemented in healthcare systems. In such an AI enabled environment, the smart monitoring systems provide predictions and diagnosis to the patient based on the features extracted through the data collected from the sensors.

An IoT architecture without a cloud platform is like a car without any fuel. In fact, it is the data gathered by IoT devices and stored in the cloud that is useful in extracting meaningful information and performing trend analysis on the data. Data analytics is where cloud computing services shine. The cloud relieves the IoT subsystem of extensive computing by performing heavy functions that require storing, processing, and analyzing the collected patient health data from the system [51]. Hence, cloud platforms provide a computing infrastructure, database, storage, and applications needed for the processing and analysis of the data gathered by IoT devices. (See Table 3).

In layman׳s terms, a cloud is an interconnected network of powerful servers that performs any number of required services. The three main services provided are [52]:

1. Infrastructure as a Service (IaaS): Responsible for providing a physical infrastructure to the cloud such as storage, servers, etc.
2. Platform as a Service (PaaS): Equips the cloud-based infrastructure with certain tools and operations such as virtualization, networking, database management, etc.
3. Software as a Service (SaaS): Enables web-based applications for accessing the acquired data and performing various operations on them.

The above-mentioned services are common to the cloud architecture in healthcare systems. For an IoT based patient monitoring system, it is important to allow authorized users to work and manipulate the health data generated by several sensors. This is where SaaS shines by providing web-based applications to access and manipulate that data. Similarly, to manage these huge chunks of data, PaaS is utilized since it has the necessary tools such as database management and virtualization to accomplish this task. The significance of IaaS could be inferred from the above-mentioned use that it is the basic building block of any cloud based system since it provides a physical infrastructure such as servers and storage for the data. These different services can be utilized to accomplish various tasks in an IoT environment. However, the two key uses of these services in health management applications is Big Data management and data processing [52].

4.1. Big Data Management

The most important concern in Big Data management is that application development may suffer due to improper management of data. Therefore, it is imperative to design a system that can easily manage and handle features of a specific data set. With respect to the healthcare sector, there is a collection of huge chunks of data recorded at regular intervals with a wide variety of features such as patients׳ gender, name, age, vitals etc. There is a need for this data to be stored for system application. This is where Big Data management proves to be most useful since it will not only ensure accessibility, but also guarantee reliability & timeliness of the data. Several published studies indicate that performing diagnostics and providing treatment programs using machine learning algorithms have been extremely fruitful in improving quality of service in these healthcare systems. A cloud storage framework is vital for such e-healthcare systems. As the entirety of the characteristics of Big Data are imperative to medical services applications, ongoing explorations in this domain have focused on categorizing a wide assortment of data, produced by voluminous IoT frameworks, in a sorted way that might be valuable for data analysis later. The cloud infrastructure not only allows virtually unlimited storage space, but also with the establishing software platforms, it enables authorized medical health providers to access

Table 3
A tabular overview of the surveyed research work.

Citation	Year	Features	Limitations	Results
Patient health monitoring [45]	2019	Remote monitoring, emergency alert system, KNN classifier	Expensive computation for large data sets	98.02% accuracy on test set
IoT based Patient Monitoring [46]	2017	Model for monitoring of stroke effected elderly people, ensemble classifiers	Only vitals' monitoring limits stroke prediction accuracy	Random Forest ensemble classifier achieved 93% accuracy
Wearable IoT Enabled Monitoring [47]	2018	Remote monitoring model without a gateway	Sensors' limited computation, lack of quantitative results	An RFID reader and portable LCD can be used as a gateway substitute
Medical IoT-based Framework [5]	2018	Novel energy efficiency algorithm called EEOOA	No prototype or smart decision making module	Experimentally concluded that EEOOA works better than traditional algorithms
Novel IoT-based Health Monitoring [14]	2017	Portable system measuring heart rate and body fat	No ML technique applied, no alert system	Well-equipped for a doctor to examine the patients' data trends
IoT based system using NodeMCU[24]	2019	Monitoring of multiple physical signals	No diagnosis module	Economical solution for combating heart diseases
Edge Cognitive Computing [1]	2018	Healthcare system for addressing emergencies	No prototype	Cognitive analysis used to reallocate computing power for improved efficiency
IoT based Emergency System [10]	2020	Patient monitoring, data accessible to medical professionals	Lacks any way to efficiently deal with an emergency	Professionals can monitor, diagnose and advise patients remotely
IoT based Wearable System [8]	2018	Wearable system to track vitals & notify any anomaly	Limited sensor data	Decision making implemented using threshold values
Development of Smart Healthcare System [48]	2020	Monitoring patient' vitals & environmental conditions	Bulky, no ML technique or alert system	95% accuracy achieved between observed and actual data
Multiparameter Patient Monitoring [49]	2020	Prototype to predict patient's condition, SVM classifier	No webpage for viewing data trends	95% classification accuracy
System with Nested Cloud Security [50]	2018	Heart disease diagnosis system with cloud security, SVM classifier	No quantified result or accuracy	Patient confidentiality improved with security algorithm

the information and offer their diagnosis. Thus the advantages of Big Data management in cloud architecture are quite clear [9].

4.2. Data Processing

Since many healthcare monitoring systems consist of wearable devices which are usually battery powered with limited computational and storage capabilities, it is impossible for them to perform data analytics. However, employment of cloud services in these systems have brought different solutions to the table for accomplishing such tasks. The cloud offers computational offloading. This means that the resource intensive computational tasks would be assigned to cloud servers. Since cloud is an interconnected network of powerful servers, it can easily and efficiently perform the task of complex data processing. Numerous published studies in e-healthcare domain employ machine learning algorithms for data analysis. For this purpose, the raw data needs to be processed before training any machine learning algorithm. This is a computationally expensive task; hence the cloud's feature of computational offloading can help improve the efficiency of the system. The cloud can perform these tasks efficiently and at a faster pace due to its heavier processing power. This would not only extend the battery life of wearable IoT devices but also enable deployment of more complex algorithms in healthcare systems for higher accuracy in diagnosis [53]. The significance of computational offloading in healthcare is quite clear. By standardizing the huge chunks of data gathered by wearable sensors, machine learning algorithms can be trained more easily. Moreover, fast computational abilities of the cloud would result in lower latency in detecting patient health anomalies [9]. An overview of this system is shown in Fig. 9.

4.3. Cloud Types

The three types of clouds are: public, private and hybrid. In healthcare monitoring systems, the data collected is sensitive and private to a patient. The occurrence of any data leak is considered to be highly unethical. In light of this, Health Insurance Portability and Accountability Act (HIPAA) decided that public clouds are not suitable for healthcare applications [13]. In lieu of a public cloud, a private or hybrid cloud is utilized for remote healthcare

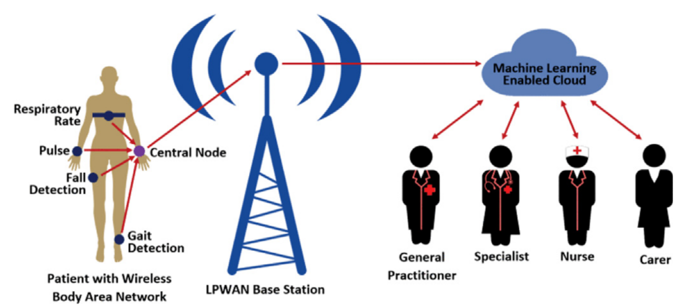

Fig. 9. Overview of the cloud based model proposed in [9].

services since it offers privacy, security and is HIPAA compliant. Private clouds function almost similar to public clouds with some differences. In a private cloud, the user or the owner must maintain the infrastructure at a highly secure location. This means that public cloud service providers such as Google, Amazon or Microsoft cannot view or legally own the data stored on the private cloud. Despite all these privacy and security perks of the private cloud, there is a major drawback to this system. Maintaining this infrastructure increases the cost of owning the private cloud for hospitals and medical clinics. More importantly the infrastructure is not elastic, which means that the system cannot adapt to changes in demand and resources. For instance, if there is a sudden huge need of more processing power, it would be utterly impossible to carry out cloud computing. In such a situation, servers may slow down or even crash which is dangerous and extremely undesirable in case of emergencies. A hybrid approach is most fruitful for remote health monitoring systems where the system primarily relies on its private cloud for the required services and processing. However, if more processing power is required it would seek the assistance of public cloud. This system would prevent overloading the private cloud and consequently would increase the cloud computing capability. (See Table 4).

4.4. Cloud Security

Cloud security has always remained a questionable issue in cloud based IoT systems. Privacy of health-related data is of utmost

Table 4
Literature Review Comparative Table.

Citation	Sensors						Edge Computing	Cloud Computing	Machine Learning	Web/ Mobile App
	Heart Rate	Body Temp	Blood Pressure	SpO2	ECG	Ambient				
Patient health monitoring [45]	✓	✓	✓				✓	✓	✓	✓
IoT based Patient Monitoring [46]	✓		✓				✓	✓	✓	✓
Wearable IoT Enabled Monitoring [47]	✓	✓	✓					✓	✓	✓
Medical IoT-based Framework [5]	The paper simply proposes an energy efficiency algorithm and does not discuss any prototype									
Novel IoT-based Health Monitoring [14]	✓	✓					✓			✓
IoT based system using NodeMCU [24]	✓		✓	✓	✓	✓	✓	✓		✓
Edge Cognitive Computing [1]	The paper only discusses the proficiency of an ECC based healthcare system, no prototype									
IoT based Emergency System [10]	✓	✓			✓			✓		✓
IoT based Wearable System [8]	✓	✓					✓			✓
Development of Smart Healthcare System [48]	✓	✓				✓				✓
Multiparameter Patient Monitoring [49]	✓	✓		✓	✓		✓		✓	
System with Nested Cloud Security [50]	✓	✓			✓		✓		✓	✓

importance, and therefore it must be safeguarded at all costs. Only authorized parties, which includes the healthcare professionals, should be granted access to the patients′ data. The data privacy rules should be approved by the patient to monitor who has access to their data. Medical data of any patient contains sensitive and private information, and in case it falls in the wrong hands, it can be used to steal their identity. Worse than that, the malicious attacker could change the medical health records which might put the patient′s life in danger. Therefore, safe guarding this data is vital and imperative in e-healthcare applications.[13] Certain measures have been taken for securing cloud based healthcare systems, which are discussed in the text below.

4.4.1. Access Control Policy

As the name suggests, an access control policy is responsible for granting data access to authorized users only as well as controlling the data that they are allowed to view. The implementation of the authentication mechanism by any access control policy requires the person who is attempting to access the data to verify their identity. The identity of a user can be authenticated by requesting the user to enter their valid credentials or using facial recognition software along with recording their biometrics. These techniques all together are used to identify and grant access to the user.

There has been recent research on further developing security protocols. Some of this research is focused on this specific application that includes granting complete control of medical data to the patient. After they have this control, the patients can enforce restrictions on the data displayed to medical health providers. The healthcare providers would have to login with their credentials to view the data. Another measure to address these cloud security issues is that if the healthcare provider takes a screenshot of the page or tries to copy it, the action is blocked. In addition to this, the patient is notified about this. In case the patient has granted such privileges to the health-care provider, they will be able to do this hassle-free, however the patient will still be notified. This would ensure complete transparency to the patients as they will be informed about any usage of their data. This seems like a great solution, but practically this is not as effective because any infiltrator may just take picture of the screen with a camera [13].

4.4.2. Data Encryption

Data encryption is a security tool for protecting and safeguarding a cloud database. It prevents any imposter or intruder from reading sensitive health information of any patient even if they have managed to hack into the database.

[9,51] implement data encryption by using nested server security protocols. Such protocols encrypt the received data of the cloud with AES encryption technique. The server side of such a security protocol decrypts the data and generates random keys for individual data packets. The data is again encrypted using the generated keys, and the cipher and keys are stored on the data server and the key server respectively. The keys are split into multiple shares by Shamir′s Algorithm and stored at the key server. Such security protocols are very efficient in securing the data sent to and from the cloud.

A review of various papers reveal that the most common encryption method used is AES, whereas other encryption methods like FHE are also employed. However, even with these encryption methods there remains a large research gap regarding security of cloud platform.

5. Machine Learning Techniques

The core responsibility of the medical sector is disease diagnosis and prevention to maintain health of patients. While remotely monitoring patients in an IoT environment, very large amounts of sensor data are generated. For decision making and diagnosis purposes, this data must be processed to extract useful information. Machine learning algorithms can be applied for this purpose. Machine learning can help make informed predictions and diagnoses of a patient's health status. Early diagnosis applications can benefit greatly from such technology since ML based diagnosis has proved to be an efficient application in smart healthcare.

In this section, different machine learning techniques used in various IoT-based healthcare systems have been discussed.

5.1. K-Nearest Neighbors

K-Nearest Neighbors (KNNs) is a very simple supervised learning algorithm in which data is classified according to predefined categories. In this paper [45], the authors have explored the role of IoT and machine learning in patient health monitoring. Their proposed system provides a platform for supervising the heath of patients. It includes a hardware section with blood pressure, heart rate, and temperature sensors interfaced with a Raspberry Pi board. The data collected from the sensors is stored in the cloud and analyzed for abnormalities. The analysis of the data is done by machine learning algorithms. The data and its analysis can be retrieved by the doctors. Moreover, the health state of the patient is made available on the hospital web page. The proposed system has three major parts: health monitoring, health state prediction and an emergency alert. The health state prediction module seems really promising, in which the data stored in the cloud database is subjected to a KNN classifier. A model is trained on a training data set and cross-validated for an optimum K value. The authors managed to achieve 98.02% accuracy on the test set. The initial training and cross-validation is performed using the UCI data set while the testing phase is carried out using the data collected from sensors. The use of KNN classifier seems to be a strong concept for a health state prediction module, but it poses a limitation on the model. KNN executes quickly on a small data set, but it can be computationally very expensive for a large data set.

5.2. Support Vector Machine

Support vector machine (SVM) is very powerful supervised machine learning classification model. It is used in different healthcare applications to predict whether a patient has a specific disease. In [50], the authors have presented a heart disease diagnosis system using SVM. For chronic heart illness, time is of the essence. The patient's previous history and current parameters (temperature, heartbeat and ECG sensors interfaced with raspberry pi) are used to diagnose a heart problem. This diagnosis assists the doctor in outlining an accurate treatment plan well in advance. A drawback of this research paper is that the authors have not discussed the accuracy of their proposed system.

In [49], an SVM classifier is employed since it is a fast and dependable data analysis algorithm. The project proposed by the authors consists of two parts. The first part deals with designing a prototype of their proposed system and the second part deals with the SVM classifier design. The system checks for four physiological parameters (heart rate, body temperature, ECG, blood oxygen saturation) and the sensors' data is transferred to the gateway using an ESP8266 microcontroller. In the second part, the machine learning algorithm is executed on the data to predict if the patient's health is normal or not. The authors managed to achieve an accuracy of 95% on their test data.

5.3. Ensemble Machine Learning

Ensemble machine learning methods use multiple learning algorithms to achieve better prediction accuracy instead of a singular algorithm. Some research has been conducted which compares the performance of different machine learning algorithms and evaluates against their ensemble counterparts. This [46] paper proposes an innovative model based on IoT and machine learning to monitor the health conditions of stroke affected elderly people. The authors highlight the importance of monitoring patients suffering from chronic diseases so that doctors can timely intervene with proper treatment. Stroke affected people are at high risk of dying because of delay in proper medical care. In the proposed model, the current health vitals of patients are measured by appropriate sensors and the data is sent to the cloud for storage. If the value of any of the parameters is not in the normal range, an emergency text and an email is sent to the doctor/caretaker. The prediction model is made using different classifiers and outputs whether the patient is at the danger of stroke or not. The authors perform a comparative study between different types of classifiers along with their ensemble classifiers to prove that ensemble learning works better. They compare different classifiers namely Naïve Bayes, Random Forest, KNN, Decision Tree and Bagging. The results show that the ensemble classifiers have a lot more accuracy than other algorithms. They choose the ensemble classifier called random forest for their proposed model with an accuracy of 93%.

5.4. Probabilistic Fuzzy Random Forest

In this paper[54], a system for smart disease prediction is proposed which is based on body sensor networks (BSN), IoT and machine learning. The system includes various sensors like pulse rate, temperature, and blood pressure. These sensors measure patient health parameters and send the data to the controller. Their proposed system offers the prediction of disease based on current patient reading using various supervised learning algorithms. The authors discuss and compare three supervised learning algorithms namely Probabilistic Fuzzy Random Forest (FRF), Linear Regression Classifier, and Q-Learning Algorithm. The different ML models are trained on data from an online repository while the testing is performed on real time data from an IoT based environment using a minimum of 6 body sensors. Different data mining techniques are applied to process the sensor data at the gateway. From their experimental study, they conclude that FRF works best for disease prediction with an accuracy of 93.57% while its false ratio is just below 5%. On the other hand, both the linear regression and Q-learning techniques have an accuracy of just 80%.

5.5. Deep Learning

Deep learning is a subset of machine learning that uses multiple layers to mimic the functions of a human brain and learn from large data sets. In recent years, deep learning techniques have been recognized as an exceptional tool in the field of artificial intelligence. In addition to a lot of different applications areas, deep learning has been widely adopted for medical diagnostics. Its capability to perform complex computations, extract meaning from lousy data, and perform well on large data sets distinguishes it from traditional learning techniques used in the healthcare sector. In [55], the authors have explored the feasibility of exploiting a deep learning based classification model for remote health monitoring and diagnostics. The authors use a 1D Convolutional Neural Network with three layers to classify abnormalities in incoming ECG signals. The initial training is done on an openly available data set. The authors argue that the accuracy of the model can be improved over time by adding the measured ECG signals to the training data set. The authors managed to achieve an accuracy of 96% with re-training their initial classifier model. Similarly, a fog-based model for heart health monitoring is proposed in [56] which runs a deep learning model for classification. The training and testing model of the application is shown in Fig. 10.

6. Fog/Edge Computing

We have already discussed the importance and advantages of employing cloud computing services in smart healthcare applications. The major drawbacks of these cloud based frameworks are; flexibility, network connection dependency, scalability and even security issues. In the IoT environment, the Internet and cloud are the key components for any application, but they pose a problem in latency-sensitive systems like health monitoring. Latest fog paradigms and edge computing technologies provide innovations in the cloud-based framework by bringing resources closer to the user and providing low-latency as well as energy-saving solutions. Therefore, a fog based architecture significantly improves quality of service of the system. A typical fog-based system's architecture is shown in Fig. 11.

Edge computing is a rising star in remote healthcare industry due to its efficient processing of voluminous healthcare data. This

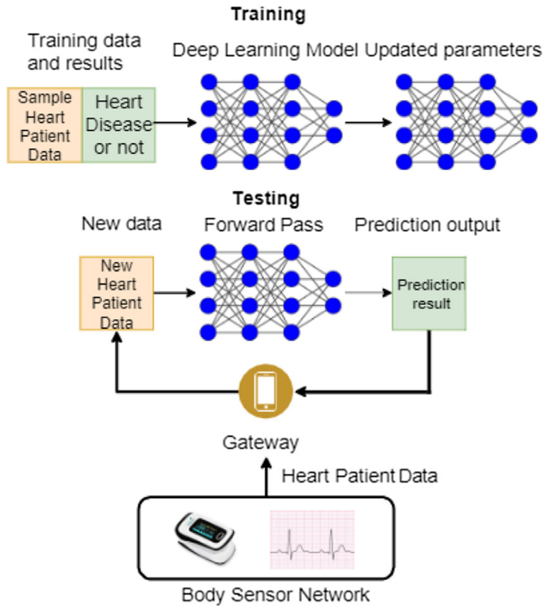

Fig. 10. Training and testing model of the application in [56].

[56] paper proposes a fog computing based smart healthcare system for automated diagnosis of heart diseases using deep learning and IoT. The system is called HealthFog. Since any smart cloud based framework is compute extensive, therefore the major drawback for these systems is the latency of results. This is where edge nodes provide a great advantage in reducing the response time of the system by handling the computation beforehand. Pre-processing of the data proves to be vital in catching any anomaly observed in the data. This also gives a new direction to research being conducted for integrating complex ensemble deep learning models with edge computing such that we obtain high accuracy results in real-time. The authors propose a generic system architecture for development of ensemble deep learning module on fog computing.

Edge computing acts as an architectural layer between the IoT devices and the Cloud platform, through which an added computing unit is available between them. In [57], the researchers have made the argument that the additional processing unit introduced by fog computing reduces latency, making systems more reliable and energy efficient, as well as with maintaining privacy of the system. Furthermore, it serves additional advantages over cloud computing through having computing power, storage capacity, networking capability and ability to analyze the data in real-time.

The main purpose of gateway devices in standard IoT frameworks is to provide a connection between the sensor network and the Internet or cloud. In [58], the authors have explored the extended role of a gateway device to become a fog enabler. This role is achieved by implementing some added features which include, but are not limited to, local data processing and analysis, adaptivity, local storage (repository), security, energy efficiency for sensor nodes, and latency. The authors discussed in detail a range of such services which can be offered by smart gateways. They also discussed an implementation of their proposed gateway device called UT-GATE which they used to demonstrate an intermediary processing layer.

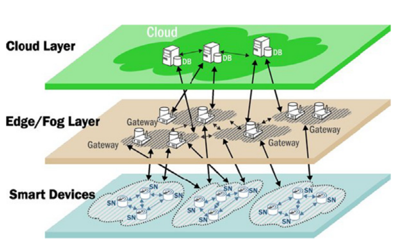

Fig. 11. Generic fog-based IoT architecture [58].

In [55], the authors propose a hierarchical computing architecture enabled by Convolutional Neural Networks. The proposed architecture assigns different tasks to different computing components. The edge computing component is assigned with two main tasks mainly Plan & Execute. The CNN classifier used in the proposed system is periodically updated at the cloud level and sent to the Plan which is located at the edge. This helps introduce a local decision-making component to the proposed system which can be personalized owing to the updates in the classifier. The data generated from the WBAN sensors are subjected to the classifier which makes a prediction about the patient′s health status. The second stage of the edge computing component is Execute wherein the prediction from the previous stage triggers an action response. It sends a notification to the users if an abnormality is detected at the Plan stage. It also forwards the data to the cloud and helps improve the classification accuracy by increasing the training data set. The proposed system is used for heart disease predictions based on ECG data. The authors conclude by testing their architecture against traditional cloud architecture and reveal that the response time of the system employing the edge computing node had a better response time, specially when the connection is poor.

7. Applications

IoT and Machine Learning technologies are being widely used in monitoring systems in various fields ranging from agriculture & smart homes to hospitals & home based health monitoring services. Internet of Medical Things (IoMT) has found various real life applications over the time. During the current pandemic of COVID-19, it has proven to be very valuable. The health monitoring systems of today have evolved from much simpler data collection systems to complicated ones that employ AI to make smart decisions. Such smart setups can even be even used to predict cardiovascular diseases [56] and human behavior [59]. Various devices & designs have been proposed by different authors which will be reviewed in the following section:

7.1. Remote Health Monitoring

In [10], the authors have proposed a system that collects data of three basic vitals (pulse rate, temperature and ECG) and displays it on the thingspeak server. In [8], Tastan took the system to another level by adding an emergency notification feature. The data collected from the sensors is sent to the blynk app. In case of an emergency, the system notifies the patients′ family and doctor through email and twitter and also sends the location of the patient by utilizing the GPS reading of the patient′s smartphone. However, this system lacks security of personal data. To counter the security issue, [60] uses a specific IP address to access the personal information along with user credentials. In another approach, [47] uses RFID reader for user authentication. In [61], the authors argue that in addition to a WSN (wireless sensor network), smartphones can also be used to collect human vitals. The paper presents a case study using an Apple watch. In today′s world, smartphones have well equipped features & modules that can be used to monitor patients′ heart rate and other important biological parameters that keep track of a person′s health. [62] has designed a monitoring system specifically for patients at risk of a cardiac arrest.It measures the three important vitals (blood pressure, body temperature and heart rate) through wearable sensors from which the data is extracted using a smartphone and is sent over to an online MYSQL server from SQL lite internal database.

7.2. Disease Prediction

The applications of smart healthcare are not only limited to monitoring of certain physiological parameters, but also to predict and prevent diseases using Machine Learning, Artificial Intelligence and other techniques. These modules lack research in medical applications due to the challenges faced which are discussed in [63]. Although smart prediction applications need more research, but some of the proposed solutions are discussed here. In [49], the authors have implemented a predictive system. The project consists of two parts. The first part deals with designing of a prototype and the other part deal with classifier design. In the first part the system checks for four physiological parameters (heart rate, body temperature, ECG, blood oxygen) whose data is transferred to a gateway node using ESP8266 micro-controller. In the second part, a machine learning algorithm called SVM (discussed above) is implemented on the data which predicts whether the patient′s health is normal. Using this designed system, classification accuracy of 95% was achieved. [50] addresses the security issue of such a system. This design is similar to the previous one, however it adds another stage to it. The author used a Raspberry-Pi to design a health monitoring. The first stage of the proposal consists of designing a prototype, the second stage with a classifier and the third with the nested security system as well as a last stage concerned with developing a Web application. In the first stage the system checks for four physiological parameters (body temperature, patient position, heartbeat and ECG). Once the data is collected, it is sent over to an open-source database (MySQL). The data obtained is then classified using an SVM algorithm. In the third stage, the patients′ information is secured by using Shamir′s algorithm. Shamir′s secret sharing algorithm deals with the encryption and decryption of data. The data is divided into various parts, encrypted and then a minimum value is set that is required to decrypt data which makes sharing of medical information reliable and secure. In the last stage, the Web app takes data from the patient & sends it to the doctor along with a suitable prediction about the heart disease.The feedback by the doctor is also displayed to the patient. In [46] a prediction model has been proposed which is constructed using different classifiers. It outputs whether the patient is at a high risk of stroke or not.

7.3. Human Behaviour Prediction

[59] proposes a research of a framework that supports behavior monitoring by employing noninvasive and privacy preserving sensing. The architecture of the system is shown in Fig. 12. The collected information by the sensors is transmitted, and henceforth analyzed with low richness in this proposed framework. For human behavior detection, various sensors tare deployed in the sensing space, which are all connected to a Wi-Fi enabled gateway that enables them to transfer the data to the cloud storage. The architecture has the capability to either store the collected data in the cloud or a local database. Once ample data is collected, the analysis stage are initiated which use classification machine learning techniques for trends and abnormality analysis in the human behavior. Through analyzing the video, which the system records initially using a camera, along with the collected data through body area sensors, the current human behavior can be predicted and label the privacy preserved data accordingly. The authors perform an experiment to test the validity of their proposed system. For the conducting this test, 5 sensors motes were installed in an office environment. The different sensors used were: PIR motion sensor, light sensor, infrared obstacle/ collision sensor, ultrasonic ranging sensor and microphone sound detector, all of which are connected to Arduino Industrial 101 board.

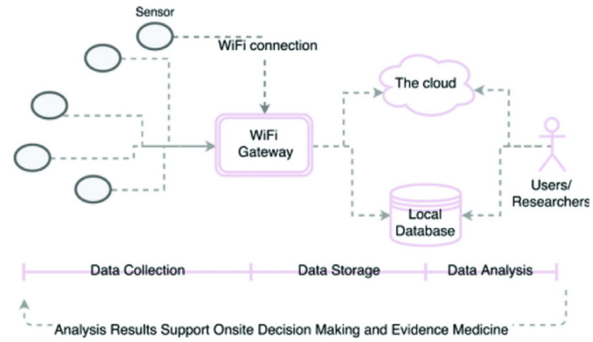

Fig. 12. The architecture of the system [59].

7.4. Automatic Insulin Injection

In [64], Raspberry-Pi 3 is being used in the proposed system which is not only cost efficient but also flexible. The data for four body vitals is collected and displayed on the web page along with a live streaming through webcam for continuous check. There are two login keys, one for the doctor & the second for the patients′ relatives for live monitoring purposes. If a sensors detects any instability or anomaly, a notification is sent to the doctor through GSM module. This project controls one physical parameter i.e. when the doctors observes a need to inject insulin, they can do so remotely from anywhere, The press of a button causes the solenoid valve to release a limited dose of insulin in the patient.

7.5. Intelligent Medicine Box

Timely intake of prescribed medicines is essential to keep the health of a patient intact. [65] has proposed a system specifically for old people and patients who do not have a caretaker available at all times. The system not only checks for the patient′s body temperature but also reminds them to timely take their medication. The working of the system is simple. There are three compartments with attached LED lights. When it is time to take a particular medicine, the respective compartment lights up. To increase the efficiency of the system & counter any human follies, a buzzer is activated if the wrong compartment is opened. All the prescription and timing information is stored in the android application which can be updated as required. Additionally, the system also enables patient access to the doctor through a unique registration ID. The patient can schedule appointments and consult with the doctor through their app. In case the temperature rises above a specified limit, the guardian or caretaker is informed. The proposed system is designed using Arduino Uno and a Wi-Fi shield for communication purposes.

In [66], the authors have designed a similar system using Arduino and stepper motors in which the patient is reminded to take medicine using notifications of an android app. A block diagram of this system is shown in Fig. 13. This system is almost similar to the last one, but instead of measuring body temperature, a heartbeat sensor is used that continuously records the heartbeat in a.txt file. If the vitals become unstable, a notification is sent to the emergency center which calls for an ambulance. The data is secured using mathematical part of elliptical curve cryptography which the authors argue is practically implementable. They have also upgraded the medical box using three LEDs; yellow, green and red. The box also keeps track of the medicines left in the box

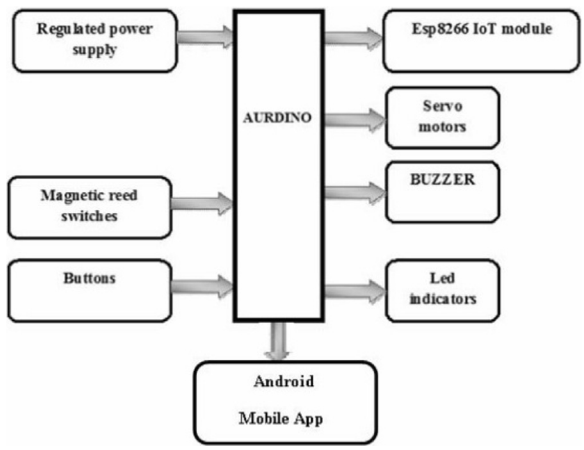

Fig. 13. Proposed intelligent medicine box with magnetic reed switches [66].

to ensure that the patient is not skipping the use of their medicine. The system uses the Arduino clock to keep track of time. As the time for taking the medicine approaches, a red flash blinks along with the green LED for a reminder.

7.6. Mental Health Monitoring

With the focus of medicine shifting towards mental health in this era, researches are exploring the use of machine learning and artificial intelligence techniques to sense patients' emotional health, monitor stress levels and predict any possible disorder. [67] has proposed a model to monitor a person's stress levels. It uses photoplethysmographic (PPG) signal that is calculated three times a day by the participants using E4 wrist band by Empatica. Linear regression model is used to predict stress level. The data collected at night time was found to be up to 90% accurate which is then further used to predict heart rate variability (HRV). The stress level is calculated by the ratio of low frequency power to high frequency power of HRV power spectrum. However, due to the limited number of participants (only eight), it is not yet viable and needs more research. [68] has developed a system based on Galvanic Skin Response (GSR) which is considered to be the most accurate in sensing emotional excitation. It uses an inbuilt accelerometer to minimize the effect of physical movement. The recorded signals are sent to the server through wireless radio transmission. The participants of the experiment are shown a clip of 5 to 8 min to sense four emotions; amusement, fear, sadness and relaxation. The signal produced by each emotion is different. Each signal is rescaled, resampled and filtered and finally classified using an emotional classifier which was the KNN classifier in this particular model. Using GSR sensing, the authors were able to achieve accuracy of 80%.

[69] provides a detailed discussion of different behavioural, physiological and social signals that can be monitored using various technologies to predict mental illnesses and disorders. The reason for the limited research in the mental health is due to rapid development in the technology and limited data of patients. Patients are usually reluctant to take part in such experiments owing to privacy concerns. However, if all three parameters (behavioural, physiological, social) are sensed while monitoring mental health, accurate results can be obtained which can help development in the mental healthcare sector.

7.7. Non-Invasive e-medical care

The advantages of non-invasive medical care are limitless as compared to traditional medical care since they can be inconvenient and uncomfortable for patients. Although certain medical treatments require surgery and contact, but non-invasive care can help reduce the incision area by pin pointing the place of infection. All in one, the pain and discomforts of a patient can be significantly reduced, and it also aids in minimizing wounds & scars on the body due to the treatment. Typically, any non-invasive health monitor uses IR thermography. On the other hand, there is a lot of on going research using radar systems to monitor and measure vital signs of the patient. In [70] a smart IoT based risk management system for neonatal incubator is developed which alerts the medical staff in case of any anomaly, such as hypothermia andor hyperthermia, concerning the temperature of the newborn. The system is shown in Fig. 14. The system uses an IR-thermography sensor placed at the top of the incubator to investigate the emission of infrared electromagnetic radiation spectrum. The collected data is sent to a local processing node, where the data is processed and checked for any abnormality. If the data is within the nominal range, it is transferred to the cloud for storage. Another paper [71] discusses and proposes a non-invasive system that measures human blood pressure. PPG sensor along with pressure sensors are used to sense the bio-signals of the patient. The signals are processed and operated on by a microcontroller specifically implemented for Signal Processing. To find the blood flow, PPG signal is analyzed using FFT to surface the underlying characteristics of the signal and extract the required information. [72,73] propose another non-invasive vital signs monitor, which has the ability to monitor the heartbeat and respiration rate. The framework consists of optical-fiber interferometers, which are embedded inside a mat on which the patient can lie on or sleep on. The change in breathing (breathe in and breathe out) as well as the heartbeat results in slight strain changes on the mat which effects the light entering the mat. Therefore, waveforms for the heartbeat and breathing rate are generated by analyzing the light reflected out with signal processing. The data is then stored remotely on a cloud to perform health analysis and monitor the vital signs of the patient. Another approach to measure arterial pulse non-invasively is discussed in [74,75]. The papers propose an antenna and radar system which is employed to monitor and sense the cardiac motion as the patient walks. The approach uses a millimeter-wave radar system that is incorporated into a wearable device which is worn on the wrist. Hence, the radar is near the artery without any contact with the pulse. This allows close range measurement of pulse of the patient without actually touching the skin. The measurement is in fact in an analogue signal form, which is then fed into a signal processing unit and analyzed for the vital signs.

7.8. Sleep Monitoring

Sleep disorders are common in humans and hence monitoring sleeping patterns is the key to treat and diagnose such disorders. To develop an efficient sleep monitor, it is imperative to understand sleep physiology and pathophysiology [76]. There has been increasing research in developing portable sleep monitors. In

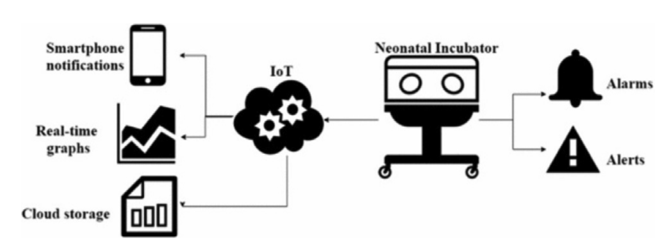

Fig. 14. Non-invasive IoT sensing and monitoring system for neonatal care [70].

[77], the proposed system architecture monitors obtrusive sleep apnea by measuring four different categories of parameters: Sleep, Physiological, Physical activity and Air Quality. The data collected is analyzed in a fog-computing based architecture to improve the quality of service and latency, specially in case of an emergency. Another study in [78] develops a sleep monitoring system where RFID tags are embedded inside a bed cloth which are responsible for monitoring breathing rate and body movement. Moreover, a Convolutional Neural Network is deployed to predict the movements of the person. [79] adopts a similar approach to observe sleep information by recording breathing rate during sleep. Force sensitive resistors (FSRs) are installed under a pillow, and to manage data acquisition a small mini computer is used where the collected data is uploaded to a server for analysis and processing. In case an abnormality is detected in the breathing rates, the medical health providers are notified. This helps in timely diagnosis of a sleep disorder. [80] proposes a Seismometer based sleep monitoring system given its robust and stable performance. The bed-mounted Seismometer system is used to monitor the heart and respiratory rates, body movement and posture during sleep. [81] studies the sleep performance of a user using their polysomnography (PSG) signal which is regarded as the gold standard for diagnosing sleep disorders. This technique records brain waves using EEG sensors, along with other important human vital parameters that include blood oxygen saturation, heart rate, respiration rate etc. The researchers implement a novel radar-based contactless breathing monitor that predicts sleep stages. The monitor utilizes an ensemble approach of machine learning algorithms trained on PSG data. The authors were able to achieve 75%, 59.9%, 74.8% and 57.1% accuracy in predicting Deep, Light, rapid eye movement (REM), and Wake stages respectively. In [82], the authors develop an IoT powered sleep monitoring pillow (Fig. 15), that uses force sensitive resistors (FSRs) to collect respiration rate data. The raw data is transferred to a cloud database, where it is processed and analyzed for detecting different breathing patterns such as hypopnea and apnea. These parameters are then utilized to administer the quality of sleep. Another novel approach for studying stress related sleeping habits is investigated in [83], where the authors have used a Blockchain-Integrated IoMT based framework to develop a smart-yoga-pillow (SaYoPillow) which analyses physiological changes that occur during sleep. These changes are used to form a correlation between stress and sleep, which then allows the system to accurately predict stress levels for the following day. Integration of blockchain technology enhances the security features for this system. The authors have used a fully connected neural network to achieve stress prediction accuracy of 96%. It is observed that significant research is going on for more efficient ways of monitoring patients/ sleep.

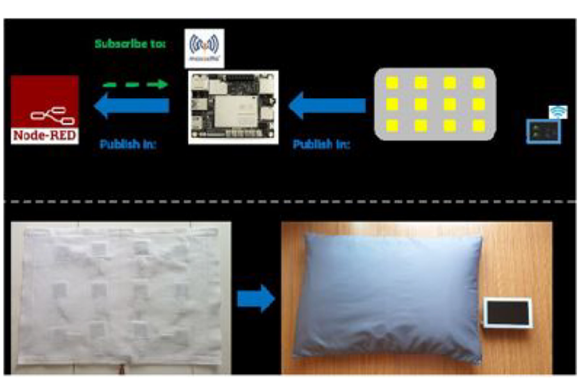

Fig. 15. Proposed smart pillow prototype [82].

7.9. Fall Detection

People of old age suffer from various health related diseases that renders them physically weak and exposes them to fall accidents. These accidents may cause fatal injuries in some, while others manage to recover given timely treatment. Many scholars are carrying out novel research to prevent this injury in elderly by using real-time sensing or monitoring technologies to detect or predict this event. A recent published study offers smart real-time camera-based surveillance for fall detection [84]. The authors in this paper accomplish this by training a Support Vector Machine (SVM) classification algorithm on falling video segments, extracted from surveillance video tapes to form a dataset. Their experiments offer promising results although the exact accuracy as well as real-time implementation of the system is not mentioned in the paper. However, the authors believe that improvement of their algorithm will certainly increase feasibility and efficiency of their fall detecting system. Researchers in [85] propose a patient specific system for fall detection that uses tri-axial accelerometer attached to a patient's thigh. The collected data from this sensor is used to distinguish between daily activities and fall events using state-of-the-art machine learning classification algorithms. The proposed system has support for two modes of operation. The first mode of operation has a low response time (300-700msec) in predicting a fall event and alerting relevant caretakers. This mode is termed as Fast Mode Fall Prediction (FMFP). Tthe latter is termed as Slow Mode Fall Detection (SMFD) which has a 1 s latency in detecting fall events. The two modes of operations differ in sampling rate, since for continuous and regular monitoring having a high sampling rate will consume more power and introduce a computation overhead on the proposed system, therefore, to increase the practicality of this system the authors have integrated these two modes. The study performs experiments on 20 different subjects aged over 65 years. FMFP achieves sensitivity and specificity of 97.8% and 99.1%, while the SMFD obtains 98.6% and 99.3% respectively. [86] also uses a tri-axial accelerometer in implementing a fall detection system for the elderly. Their approach, however, consists of using Sum Vector Magnitude (SVM) and Activity Signal Magnitude Area (ASMA) for analysis of data acquired from the accelerometer. The authors claim that their experimental results provide accurate results but the exact figure is not mentioned. The proposed system features low computational cost and real-time response, and can easily be integrated to a telemedicine ecosystem for monitoring or predicting fall events in the elderly folk.

7.10. Seizure Detection

Technological advancements in the field of IoMT have provided considerable opportunities in healthcare such as reducing cost of service, out-of-hospital monitoring, and real-time anomaly detection. These state-of-the-art approaches also encompass management and monitoring of acute disorders. Epilepsy is a common neurological disorder that leads to recurrent seizures, which is a sudden electrical disturbance in the brain. Hence, it is of utmost priority to detect/predict it timely so that proper care and treatment can be given to the patient. Authors of [87] propose an IoMT-based solution that can predict onset of seizure using the electroencephalography (EEG) signal of a patient. The system analyzes neurological signals acquired from an EEG sensor and processes it continuously to extract the hyper-synchronous pulses from the brain. This feature-set is then used to detect occurrence of a seizure. The implementation was achieved using a voltage level detector along with a signal rejection algorithm (SRA) which is used to eliminate unwanted signal artifacts such as noise. The seizure onset is detected by defining a threshold number of hyper-synchronous pulses within a time frame. In case a seizure is detected by the system the concerned caretakers or doctors are immediately notified. A basic overview of the system is illustrated in Fig. 16. Experimental results report that the seizure detector achieved a sensitivity of 96% and specificity of 97.5%. In [88] the same group of authors of [87], investigate epileptic seizure detection using discrete wavelet transform (DWT). The proposed system is based on the IoMT framework, where IoT nodes record the EEG signal and process it using DWT. The signal is decomposed into sub-bands, and each sub-band is further processed for feature extraction such as activity, signal complexity and standard deviations. Next, these extracted features are fed to a deep neural network (DNN) classifier to predict whether the EEG signal is normal, interictal or ictal. The experimental results report an accuracy of 100% for two classes; normal and ictal, while 98.6% accuracy was achieved for normal, interictal and ictal classes. The dataset used for this study adopted an ensemble approach of using multiple open source databases for EEG. The final dataset consisted of 5 datasets, where each dataset contained 100 EEG segments, and each segment of 4097 data points. This system features remote monitoring since it offers real-time alerts to doctors and caretakers. Another published study [89] investigates epileptic seizures by proposing a deep learning powered IoT based framework for continuous monitoring and prediction. The wireless EEG headset sends the raw data to a FPGA, where it is preprocessed for extraction of vital spatiotemporal features, and then fed to the embedded deep convolutional neural network (DCNN) on the FPGA. The prediction result from the CNN model along with the EEG data is transferred to raspberry pi, where real-time notifications are integrated in case a seizure is detected. The EEG signal is also uploaded to a cloud, for periodic evaluation by the doctor. Experimental results of the proposed system acquire 96.1% prediction accuracy. Most of the published studies regarding seizure detection use EEG based monitoring to analyze and predict the onset of seizure, however, the authors of [90] propose yet another approach. Their proposed system consists of IoT-based heart rate monitoring for seizure detection, where the main feature under observation is heart-rate variability. The study is designed for children aged 15 years or below that are suffering from neurological disorders. The authors achieved this objective by designing a wearable prototype for monitoring heart rate and sending the data to a cloud database for analysis. However, this research study is still under progress and the results have not yet been documented.

7.11. Stress and Anxiety Monitoring

Stress and anxiety disorders have become a common occurrence in today's life. Due to this, ineffective stress management can lead to stress disorders, psychological distress, and physical ailments. Preliminary research reveals that people who recovered from COVID-19 increasingly suffered from anxiety disorders and various other mental diseases. [91] proposes an IoT based low-cost anxiety disorder monitor, which derives emotion features based on physiological parameters in a semi-immersive environment. The IoT node records heart rate and physical activity data and sends this data to a Raspberry-pi 3 where the data is pre-

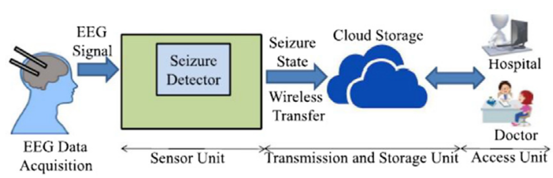

Fig. 16. eSeiz architecture overview [87].

processed and uploaded to the IoT cloud. The validation results of this system revealed an overall accuracy of 90% in detecting anxiety disorders. Another paper, [92] proposes an EEG powered smart emotion-aware IoMT based framework for health monitoring. The system uses a two-layer architecture, where the first layer records EEG and feeds it to the devised hybrid classifier for determining the emotion status of the user. The second layer consists of analyzing the user's touch behavior on their smart-phones using TMguard scheme [93]. This approach is adopted to increase classification accuracy of the proposed system. The validation results of the proposed system reveals that this ensemble approach for detecting emotions of the user increases the classification accuracy of emotion-aware IoMT based architectures by 7–9%. In another research [94], an IoMT-based novel system has been proposed for chronic stress management in women and the elderly. The authors have devised a functioning edge device powered by IoMT technology and integrated with deep learning models for stress management. Physiological data is used to not only detect stress levels at the edge but is also uploaded to the cloud for a detailed and systematic analysis of the physiological data using deep learning theory. The authors have designed a wrist band integrated with sensors (contact-temperature sensor, humidity sensor, and an accelerometer) for detecting stress patterns in users. The Stress-Lysis sensor data is used to generate discrete stress values i.e., Low, Normal or High, by using a deep neural networks (DNNs) algorithm. The authors have performed different validation tests to verify the accuracy of the proposed system by applying their algorithm on different datasets and verifying it's efficiency using real-time metrics. The results of their analysis show that their proposed model is accurate in a range of 98.3% to 99.7% in determining the stress levels of a user. Similarly, in [95], the authors have proposed iMirror, which is an ML-based smart device that detects stress levels in users to aid the IoMT framework of smart cities and offices. This device aims to reduce stress levels ultimately leading to less chronic diseases caused by various stressors. The proposed system utilizes a camera attached to a mirror which detects the face of a person, captures images for stress analysis and then updates the stress level on a mobile application. The captured images of a person (based on a unique ID) are processed by an automatic data processing unit which extracts features for applying an ML model which will classify the stress level of the user. The 4 features extracted from the image are: eye redness, eye bags, pupil dilation, forehead frown and facial sweat. These features are fed to a stress analysis unit which characterizes the stress level by using an ML model (a light & optimized version of SSD Mobilenet) and updates the status on the mobile app. The system is useful for allowing a customized experience to the users by providing control remedies based on the user's data. Experimental data proved that the model has an accuracy of approximately 97% and a precision score of 81.2%. The research is a potential candidate for enabling smart stress management and reduction of mental health illnesses worldwide. Stress-eating is a common term used for people who undergo considerable weight-gain during a difficult period of their life. For stress monitoring purposes, it is important to understand a person's food intake and utilize the extracted eating behaviour patterns to determine if the person is suffering from a stress disorder. Such work is highlighted by [96] that features an ability to automatically log the food-intake of a user by either using a smartphone's camera, or a camera mounted single board computer, to determine the stress state of the user. iLog, the proposed system, is a deep learning model for edge computing devices which enables automatic detection, classification and quantification of objects from the plate. Based on the data gathered from the plate of the user, iLog can determine their stress state. The novelty of the authors' approach lies in automatic food quantification and identification, along with forming a co-relation between calorieintake and stress. This IoMT based approach takes pictures from iLog glasses, developed for capturing continuous pictures, and then sends them to the edge computing device. The edge computing device then segments the images and uses the TensorFlow Object Detection API to identify the objects in the images. A ML model, namely Single Shot MultiBox MobileNet, is used to classify these identified objects into food. The collected data is compared with a nutrition database to determine calories. In order to determine stress-state of the user multiple features are extracted and the data is analysed. The features are type of food, amount, time at which food was being consumed, and the gender of the user. Experimental results reveal that the proposed system accomplished an overall classification accuracy of 98% with an average precision of 85.8%.

8. Conclusion

In this paper, a detailed review of several papers discussing smart & remote healthcare monitoring systems has been presented. The state-of-the-art-work published in the e-healthcare domain has been discussed. In Section 3, an analysis of several wearable as well as non-wearable sensors, particularly for monitoring vital signs of the patient such as blood pressure, and blood oxygen levels etc, has been portrayed. A detailed assessment of different machine learning algorithms employed in recent research of health monitoring systems is covered. The machine learning techniques are used to classify the patient′s health status. It is suggested that any system designer should look into different machine learning models and compare their performances since they may or may not work for their application. It is imperative to determine which algorithm has the most desirable accuracy & characteristics for a given framework because there is not a generic machine learning algorithm that works best for every remote healthcare system.

Moreover, recent works are studied which utilize cloud technologies for data storage. The importance of cloud in any IoT based system, specially healthcare, is also highlighted. A cloud based framework proves to be vital for big data management as well as data processing in e-healthcare systems. Several works also recommended that significantly better data processing can be achieved on a cloud platform with its high computational ability as opposed to the wearable devices with their limited processing capability. Heavier tasks, such as training machine learning algorithms on archived data, are allocated to cloud platforms in order to improve quality of service of the system. However, these works also highlight the potential security risks of the cloud platform, and many papers proposed light encryption mechanisms to address them which have been presented in Section 5. Lastly, this study analyzed the Edge computing platform integrated within the IoT systems and concluded that its impact is huge. Edge computing not only improves quality by reducing response time, but it also offers many other complex services such as data filtering, data preprocessing, user privacy, energy conservation and a local database. Edge or Fog computing can also be utilized to employ local decision making modules which alert the patients and caretakers in case of an abnormality.

The detailed literature review reveals that the Machine Learning and Edge Computing aspects of IoT-based smart healthcare have the most significant impact, and also the most room for research and further improvement. The security issues of the cloud platform are also being improved in order to make them compliant with healthcare systems. The machine learning and edge computing aspects of IoT-based smart healthcare systems are the most important, and yet the most under researched in this sector. Future researchers are urged to improve these modules so as to facilitate the ever growing population. Hence, it can be concluded that IoMT provides better real time management of persistent diseases with lower cost; improving patients′ and elderly care wellness programs and providing improved and better quality of life.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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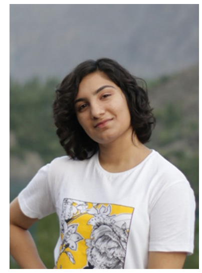

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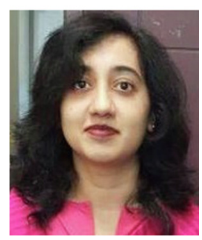

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