# IoT-Enabled Remote Monitoring Techniques for Healthcare Applications – An Overview

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*IoT-enabled remote healthcare monitoring applications have surged against countless other technologies to assist patients. Recently, the healthcare sector has sought a devastating escalation in augmenting appropriate monitoring technologies for effective remote monitoring and improved diagnostics during the pandemic era – i.e., the existing methods need to be revamped with sophisticated technologies. In this paper, remote monitoring techniques proposed for healthcare applications and their challenges are surveyed. In addition, a healthcare architecture for effective remote monitoring is explored. It was observed that most of the solutions focused on the application of edge analytics and deep learning mechanisms. The review aimed at guiding healthcare practitioners and developers to understand the pitfalls of existing approaches and to innovate solutions in newer dimensions.*

*Povzetek: Podan je pregled IoT sistemov za pomoč v zdravstvu.*

# 1 Introduction

As the COVID-19 pandemic goes ahead offering limited access to hospitals, there is a near certainty among patients that they would be proactively prevented from diseases. The pandemic created direct and indirect impacts on chronic patients who visit hospitals. However, it ignited innovations in the existing aid approaches – i.e., the growth in the healthcare industry has recently magnified.

Several healthcare applications evolved to address the needs of the patients by evaluating the sensor values mounted on the body, in the home, or in environments. For instance, mobile applications that advise proper diet or telemedicine [76, 10], IoT-enabled sensor applications that monitor the health status of patients or remind appropriate medicines [23, 48, 70], AI-assisted applications that check the sleep issues of patients, online counseling, and so forth have marked upgraded functionalities in the recent past.

In spite of inviting improvements and enabling strong technical requirements, the ICT solutions of the healthcare sector have not become mature to experiment with them on patients/individuals. A few notable challenges that exist in the domain include:

1. *Patient Data security:* Data theft, hacking, and the other security breaches in the patient data [5, 41] hamper the realization of remote patient monitoring.

2. *Availability:* Most remote patient monitoring IoT-enabled applications utilize cloud databases or service-oriented infrastructures. Availability of these compute resources is challenged due to the emergence of modern execution models such as serverless compute environments.

3. *Device inter-operability:* There are several proprietary sensor devices involved in accomplishing healthcare applications. Managing the data transfers and connecting them using appropriate communication protocols are challenging aspects for researchers and industry practitioners.

4. *Cost/Performance efficiency:* The cost and performance of applications grow into a tradeoff that needs to be elegantly handled in healthcare applications. For instance, scaling applications, enhancing privacy [27], or improving the reliability of applications could directly or indirectly influence the operational costs of applications.

A few researchers have implemented healthcare applications using IoT, blockchain, and hierarchical-computing technologies. However, there exist several limitations and research gaps to be fulfilled for improving the diagnostics for real-world scenarios.

The major contributions of this article are listed as follows:

1. To illustrate a remote IoT-enabled health monitoring architecture that details the inner functional details;

2. To critically review on the existing remote monitoring healthcare techniques; and,

3. To study the impact of datasets, devices, and IoT-enabled applications.

The rest of the article is organized as follows: in Section 2, survey works related to the healthcare domain are discussed; in Section 3, a generic IoT-enabled healthcare application architecture is revealed; in Section 4, a few available remote monitoring techniques and their challenges are presented; Section 5 reveals a few applications that are widely utilized in the market; and, finally, research directions and conclusions are expressed in Section 6, the last part of the article.

# 2 Related work

Remote monitoring of the health status of patients has heightened the utility rate of healthcare applications since the inception of technologies such as IoT, serverless, edge, blockchain, and so forth. For instance, an increase in the number of filing patents and publications manifests the growth pace of healthcare applications [22, 42, 10].

The techniques involved in the remote monitoring of patients or individuals have expanded in various implementations – for example, telemedicine, clinical trials, online counseling, psychological monitoring [43], and so forth, have diverged the markets using wearables, mobile phones, or implantable sensor units. Particularly, the focus on the remote monitoring of the health status of patients/individuals involved elderly [61, 75], chronic patients, or preventive care individuals such as working professionals. Unique methods need to be adopted for the efficient handling of healthcare applications.

In the past, a few survey works were carried out by researchers to study healthcare applications. For instance, authors of [35] have surveyed the healthcare applications such as emergency monitoring, gesture determination using mobile phones, knowledge-based decision support systems, and so forth. Similarly, researchers of [9] have explored the available communication protocols and technologies for healthcare applications. However, these survey works did not focus on remote monitoring health applications.

The need for delving into the remote monitoring techniques that have been practiced in recent years is multifaceted:

1. To suggest the directions of research and the possible improvements in the existing monitoring techniques;

2. To promote newer insights while designing remote monitoring healthcare architectures incorporating technologies such as serverless or AI methods;

3. To provide the amount of works/developments or competitors before investigating time for their innovations; and, so forth.

This work focuses on investigating the remote IoT-enabled health-monitoring techniques and available solutions.

# 3 IoT-enabled healthcare architecture

This section explains the generic remote health monitoring healthcare architecture and the significance of the components involved in it. Figure 1 illustrates the architecture and the functions of components. In addition, the section highlights a few notable existing healthcare monitoring architectures/frameworks.

## 3.1 Major components

The major components involved in the architecture and their functionalities are listed in the following paragraphs.

### 3.1.1 User-interface

Users, mostly patients and their well-wishers, are prompted with ease-to-use interfaces. The major features that an interface includes are:

- *Seamless Responsive Designs*: The users or patients prefer to utilize multi-size screens of varying gadgets such as mobile devices, laptops, or servers. The GUI design of remote monitoring systems, in general, includes a unique design with minimal variations to have a flexible layout of visibility features at the end devices.

  In doing so, the contents and visual representation of patient information are scalable with respect to the contents and screen size of the gadgets involved in the application.

- *Automated Bots*: The web designs of the remote monitoring healthcare applications involve automated software robots named bots. Bots are, in general, a piece of software instance that performs automated execution of tasks [63]. In healthcare applications such as smart e-consulting or e-counseling, AI-assisted software robots are implemented to simplify the processes involved in performing tasks. These bots quicken the processes such that registration of patients to appropriate hospitals and suitable available doctors happen in a short span of time.

  In the past, authors of [67] have studied the importance of chatbots in assisting patients. These authors have studied the input data formats such as voice, text, or video of chatbots while interacting with patients; also, they have identified the requirements of natural language processing, reasoning, and so forth for elegantly automating the assisting processes.

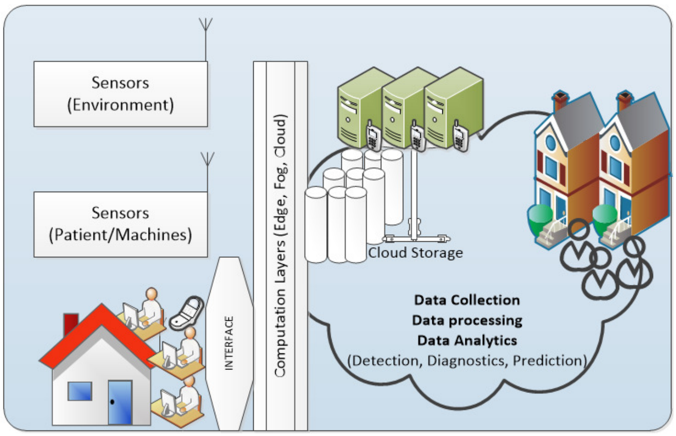


Figure 1: Generic IoT-enabled Healthcare Monitoring Architecture.

- *Multi-factor Authentication*: The privacy of medical data or personal records is crucial in healthcare applications [27, 65]. This feature prevents users' data from being protected from hackers or malicious suspect devices. It is very unlikely that multiple pieces of programs that are responsible for independent authentication mechanisms such as username/password, iris recognition, biometric sensor units, and so forth, will be trapped by the hackers.

  In a few IoT-enabled remote monitoring healthcare applications, a single sign on (SSO) feature is implemented to improve the user-authentication experiences by seamlessly connecting with multiple cloud-enabled healthcare services.

- *Virtual Reality*: The user interface of healthcare applications needs support for virtual reality. In short, virtual reality incorporates human senses such as touch, sight, hearing, taste, and smell into programs and supportive hardware devices to provide a virtual environment. Applications such as remote monitoring and counseling require a realistic environment of patient diagnostics involving doctors from varying locations. The user interface of such applications, therefore, shall include these features for robustness and liveliness.

### 3.1.2 End devices

Increasing the number of end devices and sensor units for continuous medical diagnostics or disease detection has prompted for delivery of superlative care by doctors to patients in recent years.

In fact, the detection of diseases evolves based on the screening processes of healthy or non-healthy individuals. It requires skillful listening to abnormalities if any. The major purpose of detecting diseases is to identify the risk indicators concerning diseases or probabilistic diseases. By doing so, individuals could reduce the long-term risk factor that might arise in the future. Whereas, diagnostics is the confirmation of the availability/non-availability of a particular disease.

IoT-enabled systems require real-time sensed data from different patients/individuals to detect diseases. By this, the spread of the diseases is prevented. More importantly, in order to perform diagnostics of diseases, IoT devices require more prominent authenticated accurate data for confirming the diseases that are often represented in a layered structure[69]. In the past, researchers have utilized biomarkers to dictate the confirmation of diseases.

Recently, researchers have coined the term Internet of Medical Things (IoMT) to establish connected IoT medical devices by extending the internet to tiny sensing objects. The end devices that are utilized in the healthcare application domain for remote monitoring the health status of individuals can be classified into 6 categories as discussed below:

1. *In-body devices*: Implanted sensors or medical things constantly monitor and add value to remote monitoring health applications. Many actuating things are often implanted in human bodies to stimulate near-failure organs. For instance, devices such as neuro-stimulators, cardiac defibrillators, insulin pumps, cochlear stimulators, and so forth are implanted to the patients for stimulating chemical actions for medical benefits. In recent years, the utilization of insulin pumps has tremendously increased as diabetic patients are prone to reach an uncontrolled augmentation of insulin.

2. *On-body devices*: The majority of the devices under the category of IoMT are wearable devices. These devices are attached to a human body in the form of wristwatches, dresses, rings, or adorable devices to frame wireless body area network (WBAN) [26]. These devices follow communication protocols such as IEEE802.15.4, which has a short-range communication medium, to emit less energy. Most commonly available on-body devices include accelerometers which are designed to measure acceleration

forces; gyroscopes which measure the angular rate or orientation angles; GPS sensors that sense the latitude/longitude of locations; heart-rate sensors which measure the heart rate of humans; and pedometers that count the steps taken by patients or athletes while running or walking.

3. *Portable devices*: Medical things that are mobile in nature are termed portable devices. These devices are often directly connected with cloud server instances or fog nodes. Devices that constantly monitor the blood pressure or insulin level of patients are examples of portable sensor devices.

4. *Static devices*: Devices such as temperature sensors or air pollution sensor nodes [64] that are attached to environments such as smart homes/cities are denoted as static nodes. For instance, sending alarms or short messages to doctors/relatives of patients for detecting pneumothorax in X-rays is fixed to x-ray devices. The connectivity of these devices is much more reliable when compared to portable devices. Besides, the inherent accuracy of these devices is stable in healthcare applications.

5. *Ambulatory devices*: IoT-enabled devices fitted to mobile vehicles such as ambulances are peculiar as they have to consider the real-time delivery of data to the hospital clouds servers. In spite of being error-prone due to the frequent hops in communication channels, the devices should deliberately handle switching-on stations without errors. Reliable measures need to be practiced so that patients could be saved due to the right medical prescriptions based on the sensor data.

6. *Hospital devices*: IoT has been utilized in hospitals not only to detect and monitor patients' temperature, blood pressure, and so forth, but also to locate medical kits. For instance, a 1000 bed hospital usually has over 200 wheelchairs. It is also mandatory to locate patients considering the safety measures of patients – i.e., an asthma patient needs pollution-free environment; or, patients wanting for medical equipment such as defibrillators, nebulizers, oxygen pumps, and so forth, have to be guided to the nearest available wards in the hospital. Clearly, IoMT is beneficial to quickly identify the location of medical devices and serve patients/hospitals. Figure 2 pictorially represents the devices utilized in the remote healthcare applications.

The most commonly available IoT-enabled sensor devices for measuring health-related parameters include i) glucose monitors, ii) temperature sensors, iii) heart-rate monitors, iv) oxygen pulse monitors, v) electromyography sensors (ECG) for heart-care checks, vi) wheeze anomaly detection sensors, vii) movement disorder checks, viii) stress indicator, ix) posture indicator, x) lung status indicator, and so forth.

#### 3.1.3 Edge/fog layers

Edge and Fog nodes increase the capability of user experience in the healthcare sector. These networked nodes provide text, video, or image analytics with the help of robust AI mechanisms and sensor devices. For instance, monitoring patients in ambulances using edge devices or mobile devices assist technicians to deliver first-aid services with the advice of remotely available doctors before the patient was reached in hospitals; virtual reality enabled operating rooms are becoming a new normal for practicing edge supported operations to patients.

Edge and fog nodes reduce latency when compared to cloud-level analytics. This real-time delivery of findings is one of the major characteristics of healthcare applications.

#### 3.1.4 Cloud services

A large volume of scalable computations and analytics of healthcare data is possible in cloud infrastructures. In fact, the recent newer cloud computing execution model such as serverless clouds has manifested the feasibility of providing reduced cost to the users. Typically, in healthcare applications, periodic monitoring of health-check devices is practiced. The frequency of remote monitoring is lower in some applications where the patients involved in the processes are quite normal. If a serverless execution model is not provided for such applications, the user could lead to huge costs due to the utilization of cloud server instances.

In addition, the sensor data could be of higher size ranging from terabytes to zettabytes in healthcare applications, especially when video analytics of operations were involved. Obviously, there is a dire need for an automated scalable environment for healthcare applications.

It could be noticed that to improve the prediction accuracy in remote health monitoring applications cloud services requires long-term analytics obtained from a larger dataset. For instance, bots increase accuracy by improving text analysis strategies; analytics of images is required for classifying, learning, or predicting health-related symptoms such as tumor analysis, cancer analysis [50, 21], eye-retinal failure detections, and so forth; analytics of videos is required for learning the emotions of patients, neurological disorders, and sleep disorders.

#### 3.1.5 Hospitals and doctors

Remote healthcare monitoring architectures enable an active involvement of doctors or hospitals. For instance, mobile phones engage doctors and individuals; and, associated servers involve hospital authorities for decision-making processes. These mobile devices and gadgets connect doctors/hospitals in a remote fashion to strengthen the assurance of patients.

Observing the most existing remote monitoring applications, doctors and hospitals are connected for providing online prescriptions/diagnostics [18], scheduling doc-

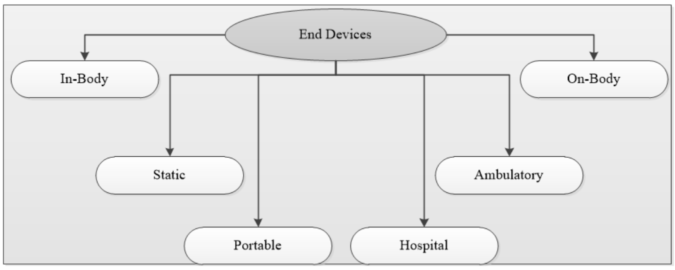


Figure 2: Devices Utilized in Remote Health-care Applications.

tor appointments, sharing files/videos, communicating effectively, and so forth.

### 3.2 Existing architectures and future insights

Most of the existing architectures/frameworks developed for monitoring patients has shown similarities with the generic architecture. Table 3.2 reveals the key components of generic architecture adapted in the existing architectures and the uniqueness found in them. For instance, authors of [49] developed healthcare monitoring system for Saskatchewan, a specific region in Canada; authors of [62, 16] included alerts, notifications, or early warning systems for agile operations. In the table, “Y“ resembles “YES“. A few architectures submitted medical data to cloud services using publish/subscribe approaches ([56, 29]). There exist a few works in the healthcare monitoring domain that improved the security aspects of medical data using blockchains ([59]); and, the data analytics of healthcare data using novel deep learning algorithms ([33]). Additionally, frameworks that improve the human behavior/attitude by assessing the mental states had opened a novel research dimension in the healthcare sector.

Apart from the existing healthcare monitoring frameworks/architectures, the following modules or techniques could be incorporated in the near future architectures of the remote healthcare monitoring systems:

1. Serverless-based cloud execution model – It is a known fact that cloud services or the associated resources are not required throughout the entire period of healthcare applications. For instance, a few applications might only update the health status of remote patients on cloud storage devices once in a week. Considering the infrequent utilization of the services, it is sufficient to adopt serverless-based based cloud execution models for these applications;

2. Blockchain-enabled medical data protection systems – Tampering medical data or records is not tolerated in many countries or policies. Blockchain-enabled frameworks/architectures could solve these underlying issues by involving multi-party stakeholders;

3. End-to-End auditing framework – A very few efforts have been attained in the past to audit the functions or applications at end-to-end level. The remote monitoring healthcare applications execute logics that are computed on multiple nodes or servers of varied computational capabilities. By diligently auditing the services, the optimization of resources or efficiency of computations could be improved.

## 4 Remote monitoring techniques – taxonomy

The remote monitoring techniques could be classified depending on several factors, as follows: i) based on the utilization of different computing systems, ii) based on importance to serve tasks (priorities), iii) based on communications involved, iv) based on accessibility features, v) based on level of intelligence, vi) based on specified metrics, and vii) based on focused delivery. This section explores the most available IoT-enabled remote monitoring techniques and their characteristics in detail.

### 4.1 Computing continuum assisted techniques

Remotely monitoring the health-related parameters of healthcare applications involves varied computing devices surpassing from battery-operated sensor devices to scalable clouds. Depending on the utility pattern of computing nodes, the remote healthcare monitoring applications could be either performance-efficient or cost-efficient.

In most healthcare applications, edge nodes are predominantly applied for the immediate analysis of sensor data. Authors of [14] have applied edge devices to register patients, authenticate them, and raise alarms using blockchains. Similarly, in [51], authors have designed a BodyEdge platform that connects most of the patients’ sensor data with edge nodes for improving the scalability; authors of [47, 73] have studied the impact of energy efficiency, and so forth. These edge devices are often battery-operated with limited processing capabilities. Edge nodes, in fact, deal with decentralized medical data obtained from the nearby sensor modules.

In recent years, a few implementations including containers such as docker containers in edge nodes have been

Table 1: A Comparison of Existing Healthcare Monitoring Architectures.

| Components | [49] | [62] | [56] | [16] | [50] | [29] | [73] | [59] | [33] | [38] |
|---|---|---|---|---|---|---|---|---|---|---|
| **UI** | Y | Integration Units | Y | Y | Integration Units | Y | - | Integration Units | Y | - |
| **End Device** | Y | Y | Sensors (Wearables) | Sensors (Wearables) | Y | Sensors (Wearables) | Y | Y | Y | Y |
| **Edge/Fog** | Hierarchical (Mesh) | Fog | - | Fog | Y | - | - | Y | Edge | - |
| **Cloud services** | Y | Y | MQTT | Y | Y | MQTT | Y | Y | Y | Y |
| **Hospital/ Doctors** | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| **Uniqueness** | Saskatchewan (Canada) | Alerts | Publish/ Subscribe | Early Warning | Cancer care | Elderly | ECG Compression | Blockchain security | Deep Learning | Persuasive Technology |

adopted to improve the lightweight migrations and executions. For instance, authors of [34] have utilized raspberry pi-based architecture to execute containers on edge nodes for enabling the visual representations of healthcare applications. Additionally, RFID clusters placed in the edge layer improve the connectivity of sensor nodes in some healthcare applications. Authors of [3] have utilized active RFID devices to establish RFID clusters and monitor patients at home.

Compared to Edge nodes, Fog nodes handle a large volume of data collected from multiple sensor modules of the vicinity [8]. Typically, fog nodes are responsible to process sensitive data and autonomously decide on performing certain actions without the knowledge of the entire status of applications available in the cloud.

Clouds, on contrary, are often utilized by many healthcare applications. They are highly scalable with the capability to adapt to the increasing data size and computational requirements – i.e., the storage space for handling a large volume of data in the cloud is very high. Clouds are also capable of quickly processing/transferring the analysis observed from the large sensor data. In the recent past, authors of [52] have applied a cloud ecosystem to provide health diagnoses among students. Similarly, authors of [15] highlighted the importance of cloud services for analyzing health data in a hierarchical fashion. Obviously, clouds, due to the capability of their larger processing power, remote diagnostics within a limited time frame is possible. However, clouds are powered on for the entire duration of the remote monitoring healthcare applications.

Overriding the continuous execution of cloud instances, serverless cloud environments spawn compute nodes based on the trigger received from sensor nodes. Serverless doesn't mean that the computations are performed without servers. Rather, it is an execution model of clouds where the users are benefited from the limited utility of servers. Depending on the availability of servers, the serverless framework could either power on and boot up the machines or it could utilize the available idle server instances.

The scalability component of the different continuum of computational units involved in the remote monitoring healthcare applications varies – i.e., increasing the number of server instances and cloud-enabled services, scales the spanning of applications across the globe. Similarly, it could be noticed that the cost of including only serverless functions for healthcare applications would drastically reduce their operational/infrastructural costs of them. On contrary, this method reduces the serviceability when compared to involving the combination of edge, fog, cloud, and serverless environments.

## 4.2 Priority-enabled remote monitoring

Remotely monitoring the health status of individuals is clouted by the priority in attending tasks/requirements. For instance, a healthcare monitoring application should prioritize the monitoring features involving healthcare workers such as doctors and monitoring patients – i.e., in a healthcare remote monitoring system, monitoring the health status of healthcare workers, especially in isolated wards, is quite important than serving the other devices or individuals.

Also, cloud services have to be prioritized with sufficient intelligence in an automated fashion. In general, the requests are served on a first-come-first-serve basis. However, policies and protocols need to be provided in the remote healthcare monitoring applications so that notified prioritized activities are executed.

Depending on the tasks specified in Figure 4.7, priorities could be set up for remotely monitoring the healthcare applications, as follows:

1. *Critical Tasks* Availing a secured data channel to express the health status of patients to hospitals/doctors is one of the crucial tasks in remote monitoring healthcare applications. Healthcare applications have to prioritize these tasks and execute them within the limited computational node availability.

2. *Periodic Tasks* There exist tasks in the remote healthcare sector to pursue routine checks and monitoring mechanisms. Routine checking is not only specific to the patients but also to the machines involved in sending data. For instance, monitoring the patient's temperature, pressure, glucose, and so forth is a common practice in the health sector domain. However, monitoring the health status of the robotic machines involved in the operations or learning the failure cases of machines using IoT-enabled systems are crucial tasks.

3. *Preventive Tasks* A few healthcare tasks are preventive in nature. Mechanisms involved in preventing medi-

cal failures or diseases require lots of artificial intelligence embedded in the system [28, 46]. For instance, learning algorithms such as random forests, support vector machines, linear regressions, deep learning models, and so forth could be applied to preventing the patients from severity in the impacts. A few algorithms such as convolutional neural networks are applied to early detect cancer symptoms from images relating to skin, lungs, and brain.

4. *Federated Tasks* In remote monitoring, collaborative engagement of multiple peers or medical things is involved. Examples such as analyzing the patient similarity or emotion analysis require collaborative learning involving sensors from various hospitals and organizations. A federated learning mechanism needs to be incorporated into these systems. In federated learning processes, the global learning models are refined by the distributed local learning models. This way, a robust process of targeting multiple machines and organizations is possible for healthcare applications. Applications such as collaborative drug discovery with the involvement of sensor data and machines from multiple organizations are carried out using federated mechanisms.

5. *Alarming/Actuating Tasks* Healthcare monitoring also involves tasks to send notifications or alarms by actuating appropriate actuators. Hospital beds might have to be tilted to 60 degrees to comfort patients, especially for patients with Parkinson's disease. Similarly, eye-related operations are supported with laser positioning equipment in eye hospitals. Based on the feedback given by the doctor, the position of the lasers has to be accurately organized in real-time.

6. *Educational Tasks* Providing training or awareness often prevents the spread of diseases such as malaria, COVID-19 [54], and so forth. Tasks relating to awareness have increased due to the inclusion of mobile devices and mobile health applications in recent years. Although these tasks are not crucial to execute in real-time, they have to get a wider reach with minimal costs and failure rates. Additionally, these tasks have to support multiple formats such as audio, video, or texts that choose the most appropriate protocols. These tasks have to increase the public reach in the form of successful campaigns incorporated in wearable gadgets.

Table 2 reveals the comparison of tasks in the remote monitoring healthcare domain. The importance of certain characteristics is specified in the star ratings for tasks. It could be observed that the periodic tasks have to be cost-efficient whereas critical tasks must be completed within a specific time-bound. The critical tasks have to provide more priority to performance efficiency than cost efficiency as they are crucial life-saving tasks. Similarly, educational tasks or alarming tasks aim at reaching a larger mass of connected people or automated systems for delivering messages.

### 4.3 Communication-specific RM

The remote monitoring of health applications requires an apt selection of communication protocol standards for connecting sensors. IoMT devices are connected using WIFI, Bluetooth4.0, GPS, infrared, Zigbee, and so forth (see Figure 4.7).

High bandwidth requirements are often the scenario in healthcare-related applications, especially when operations were held by doctors using videos or robotic engines. To compensate the high-speed bandwidth requirements, 5G, NB-IoT [12, 57], or similar connections are often set up in the modern hospital premises. The utility of 5G is immense: for instance, authors of [11] have studied the importance of 5G and the design criteria such as channel selection options, bandwidth efficiency, and so forth, in the healthcare applications. Particularly, narrow-band communications for healthcare have profoundly been utilized in the healthcare sector. The main reason is that the NB-IoT communication medium could provide low-energy support to sensors. However, due to the limited bandwidth support and security breaches [59], 5G overrides NB-IoT. There exist a few works relating to NB-IoT in the past. For instance, the authors of [31] studied the uplink/downlink transmission efficiencies of healthcare sensor nodes when NB-IoT was applied as communication links. A few researchers have improved the transmission efficiency of communication links by designing software-defined networks. In the work by Farag et al. [58], the authors have designed an SDN approach to channelize sensor nodes for efficient communications with limited traffic delays.

In addition, ISO/IEEE 11073 protocols are imposed on healthcare devices for establishing efficient secure communications and the delivery of data over these secured connections. Authors of [79] implemented the IEEE 11073 protocol to integrate tiny biosensors to the cloud using Constrained Application Protocol (CoAP).

The important features of the communications involved in the remote health monitoring applications include:

1. *Unique identification*: Several devices might intend to connect to each other or the cloud using various means of connectivity options such as wifi, Bluetooth, or infrared. A unique identification mechanism is required in healthcare applications to avoid the wrong delivery of insights to medical practitioners or users.

2. *Interoperability feature*: The devices manufactured from different vendors such as Samsung, OPPO, cisco, intel, and so forth, might need robust interoperability features [55] so that the healthcare applications are effectively laid in a vicinity. To ensure interoperability, the exchange of data in a specified format and the conversion of protocols are mandatory processes. There exist a few protocol conversion mech-

Table 2: Comparison of Priority-Enabled Tasks – Characteristics.

| Tasks | Time/Speed | Cost Efficient | Performance Efficient | Wider Reach |
|---|---|---|---|---|
| **Critical** | ***** | * | **** | *** |
| **Periodic** | * | **** | ** | ** |
| **Preventive** | ** | * | **** | *** |
| **Federated** | * | *** | *** | **** |
| **Alarming** | *** | ** | *** | ***** |
| **Educational** | ** | **** | ** | **** |

anisms which could be incorporated into the gateway devices or edge devices for solving the interoperability issues.

3. *Cooperative Aspect*: In some cases, cooperative decision-making features and collaborative involvement of devices are required to accomplish the remote healthcare monitoring of patients. For instance, studying the behavior of patients could be analyzed by sensing data across hospitals. Here, an inter-hospital communication system that augments the collaborative learning of patients is desired.

   Similarly, sharing the findings of patient information across multi-specialty hospitals also claims for a cooperative mechanism in the healthcare sector.

## 4.4 Accessibility-specific RM

Access to healthcare services is bound to financial capabilities. Accessing international medical equipment or hospital facilities requires uninterrupted services with the ability to audit the necessity of facilities/equipment. In addition, healthcare services should automatically assign scalable computational units or storage units for the delivery of medical assistance.

Depending on the accessibility feature of remote monitoring assistance, the healthcare services could be classified into local or global remotely accessible monitoring services. In local accessibility setup, the underlying medical services comprise intra-hospital medical things such as oximeter measurements, blood pressure monitoring services, and so forth. In a global accessibility set up, the services involve inter-hospital services and doctors for monitoring the health status of patients. In general, the global accessibility services are meant for collecting the health status of pandemics such as COVID-19, examining infectious diseases, analyzing the causes of deaths across countries, and so forth.

## 4.5 Intelligent level specific RM

Associating artificial intelligence to the internet of medical things is quite important for automating processes and equipping with more accurate results – an option to deliver proactive healthcare to patients/users. An array of applications have evolved in the recent past with the inclusion of AI methods for assisting healthcare services. For instance, predicting the hospital risks in a remote fashion or developing AI-powered robots to assist patients have been well appreciated among the healthcare communities.

Technologies such as computer vision, which embodies AI into it, obtain information from images or video frames to provide meaningful insights. For instance, performing remote clinical trials could be effectuated using computer vision. Similarly, AI-driven big data processing of medical machines [33] or patients encourages multi-specialty hospitals or concerned doctors to proactively strengthen the prescriptions with utmost accuracy.

Multi-label classification-based AI methods, which utilize robust learning algorithms, improve the decision support systems. These approaches promote automation in remote health monitoring applications.

Additionally, tailor-made solutions could be adopted using ontologies [2] and semantic technologies [68, 78] for enabling health successes. For instance, suggesting the timing and duration of regular exercises, closely monitoring the performance of healthcare, and so forth.

The incorporation of AI in remote health monitoring applications increases the revenue due to the involvement of many doctors or hospitals. In addition, it improves the cost and accuracy efficiency of patients/users. For instance, authors of [72] provided an approach to handle the trade-off between sensing health details and advising remedies irrespective of the less availability of health datasets using adversarial sensing method.

## 4.6 Performance metric-specific RM

Remote monitoring of patients can be fine-tuned based on the metrics applied. For instance, the metrics such as makespan of healthcare applications, availability of service requests, scheduling features of applications, and so forth, could be improved by skillfully choosing the metrics in algorithms or implementations.

The most common metrics that typically improve the performance of healthcare applications are listed as follows:

1. *Round-Time*: This metric determines the time taken for delivering the service requests. This round-time metric involves time to select the doctor, choose the right services, and so forth. In [36], authors have simulated a case study to manifest the importance of responsiveness metrics while designing healthcare applications in cloud environments. The authors revealed the scalable feature of clouds which improved

the round-time of sensor applications. Also, authors of [45] discussed how low-latency could be improved in healthcare applications when edge devices were included in the monitoring system.

2. *Reliability*: Reliability metric checks the availability of services or medical things for processing applications. It includes features for evaluating the availability of services. A few researchers have studied the reliability feature of healthcare applications. Notably, authors of [44] designed oneM2M protocol that included a fault-tolerant algorithm for increasing the reliability in the gateway layer of sensor networks.

3. *Energy consumption*: As similar to the performance of services, this metric, if fine-tuned, attempts to reduce the energy consumption of applications. In fact, the energy consumption of applications has to be diligently handled, especially for executing applications in power scarce locations or power-constraint devices. This metric is one of the most crucial ones for assessing healthcare applications. Authors of [18] proposed energy-efficient optimization-based clustering approach for connecting sensor nodes of the patient monitoring system. Their results, when applied with the Particle Swarm Optimization (PSO) technique have manifested to diagnose diseases with a minimum energy value.

4. *End-to-end encryption*: Providing end-to-end encryption for healthcare applications could improve their security and privacy features of them. Blockchain features are incorporated in some healthcare applications to improve security aspects of them [30, 40]. A few authorization approaches are studied in [74]. However, a tradeoff exists between the performance and security aspects of applications.

5. *Inter-operability count*, The inter-operability feature specifies the number of sinking devices of a medical thing. A higher number of interoperability metrics reveals the capabilities of the device to connect to more healthcare applications.

## 4.7 Focused delivery-specific RM

The mechanisms applied for healthcare applications could be focused on solving specified objectives – i) Emergency purposes [39], ii) Elderly Care, iii) Disability Care [60], and iv) Behavioral/Mental Care [37, 38, 81]. The mechanisms implemented to solve these specified objectives are unique. For instance, focused delivery of healthcare services to elderly people requires specialized care for bathing, fall detection, medicine reminders, personal hygiene, and emotional care. Most preferably, these elderly people staying in old-age homes are depressed due to emotional avoidance from family or relatives. IoT-enabled systems could drive them to play comforting music or their preferred games, protect them from more-likely falls by actuating airbags, warm up them during winter seasons using heat-actuated jackets, and so forth. Researchers have started to work on these focused deliveries of medical assistance in recent years. For instance, authors of [29] proposed a three-tier framework involving medical centres to care the elderly people; authors of [13] investigated the procedure to handle older adults considering scheduled medical consultations.

Authors of [37, 38] introduced a novel persuasive technology approach for improving the behaviors or mental states of human beings. The persuasive technology, associated with IoT-enabled wearable gadgets, could improve the cost involved in hiring mental healthcare professionals. For instance, AI-assisted chat bots could control the suicide attempts of young minds if they are semantically designed to tailor the needs of defaulters.

# 5 Remote monitoring healthcare applications – discussions

Remote monitoring healthcare applications are drastically shaping the future, especially during the post COVID-19 pandemic era. These healthcare applications modernize the approach of living standards as appropriate management procedures, sensor nodes, communication methodologies, detection/diagnostic algorithms, tools, and datasets have been evolved in the recent past.

## 5.1 Applications – categories

Establishing an intuitive understanding of the characteristics or requirements of the existing remote monitoring healthcare applications is an initial primordial step to deliver newer techniques and innovations. In fact, a few orthogonal research dimensions were identified based on i) applying managerial techniques, ii) addressing specific health concerns, and iii) utilizing assistive technologies.

### 5.1.1 Management-oriented

The involvement of IoT sensors and associated technologies has fixated in a few healthcare applications for remotely managing hospital premises or knowledge acquisition. Mechanisms need to be channelized to manage sectorial growth in healthcare.

**Hospital management** Clinical trials, especially during the post-COVID era, have seen a shift of focus in managing hospital premises with the advent of IoT technologies. The most diverse remote monitoring which manages hospital premises involve:

1. organizing medical equipment and devices based on the knowledge shared by the IoT gadgets;

2. optimizing the location layout of medical equipment such as wheelchairs, oxygen defibrillators, and

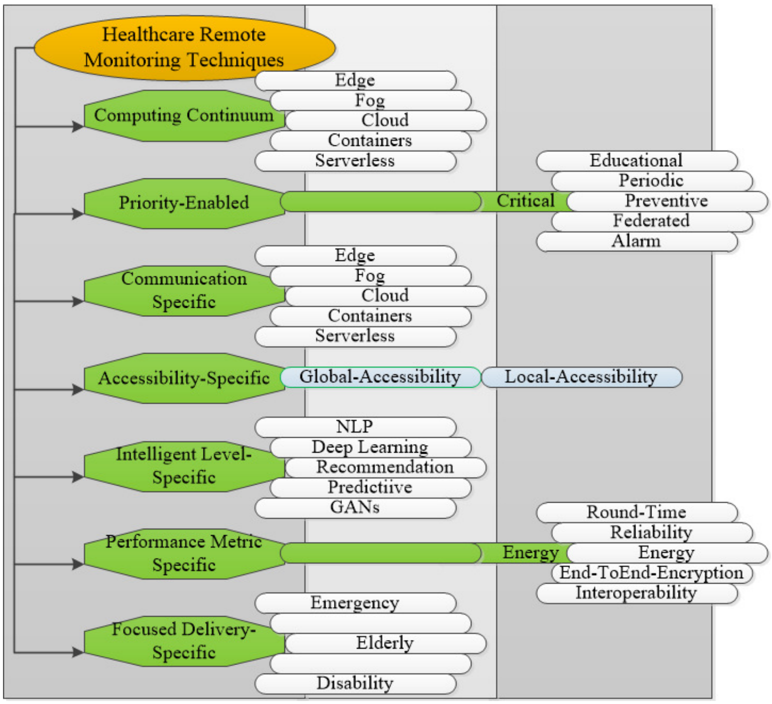


Figure 3: Taxonomy of Remote Healthcare Monitoring.

so forth, for distributing them across the hospital premises;

3. designating manpower such as doctors, nurses, cleaning staff, and security guards considering their willingness to serve wards and overseeing the need of departments;

4. automatizing the collaborative involvement of machines and sensors to coordinate the out/in patients during the stay in hospital premises;

5. managing assets in pharmaceutical department of hospitals, and, so forth.

**Drug management** In addition to managing hospital premises, IoT sensors and remote monitoring solutions are often utilized to trigger the well-being of patients by managing the drug delivery processes. There exist a few drug management solutions as listed below:

1. Drug Reminders – Solutions and medical kits were developed to constantly remind patients of the intake of drugs. In doing so, chronic patients are benefited at large. There have been several cases of deaths or medical emergencies as patients such as diabetes consume overdose or low dose insulin owing to repressing the consumption of drugs.

2. Drug Identification – In some situations, it is required to identify the complications due to drugs. Particularly, the previous history of patients with respect to the drugs has to be evaluated based on IoT systems or medical records. Investigating the real-time effect of drugs using IoT-enabled applications has bolstered the reduction of side effects to patients.

3. Drug Governance – Pharmaceutical companies and drug delivery units of countries require a machine-assisted system that senses and administers optimal supply chain management. Appropriate communication technologies and processing of data have to be handled in these machine-enabled applications for providing better logistics.

**Data management** One of the key points to converge IoT and healthcare applications is data management – i.e., a clear plan to perform data acquisition from sensor nodes considering geographical locations or large-scale data. Healthcare applications need to consider the continuum of computing devices located in edge, fog, or cloud environments [49]. Handling data in edge nodes based on the latency and real-time requirement of applications has to be automatized in the data-related IoT healthcare applications. There exist a few data management tools for healthcare applications such as Enterprise Data Warehouses (EDWs) for processing data collected from diverse sensor nodes in real-time. A few companies such as SnapLogic have delivered a platform-as-a-service model to elastically scale data integration services.

#### 5.1.2 Health-specific

IoT-enabled healthcare applications that target addressing health issues could be classified depending on i) chronic diseases, ii) Disease-specific or iii) Preventive care diseases.

**Chronic Diseases** Remotely monitoring chronic diseases with the intention of reducing the death rate and improving cost efficiency is one of the most awaited purposes of applications in this pandemic era. Chronic patients such as diabetic Mellitus, cardiovascular diseases, respiratory diseases, malignant neoplasms, cancer patients, and so forth, have to periodically visit hospitals if remote monitoring was not extended to the patients. It is to be noticed that over 85 percent of elderly people are prone to at least one of the above-mentioned chronic diseases. Obviously, the costs involved in the patient monitoring processes have been reduced due to the IoT-enabled healthcare system in such situations.

**Common Diseases** The majority of the diseases relating to general infections or deficiencies could be remotely assisted using IoT-enabled healthcare systems. The solutions are most welcomed by individuals, including transnational healthcare aspirants owing to the following reasons:

1. Avoidance of hospital appointments,
2. Mobile-assisted interactions,
3. Frequent virtual meetings with doctors or hospital administrations, and,
4. Tailor-made solutions, including robotic solutions.

In fact, home assistance in a remote fashion plays a vital role in specific health-conscious diseases. In the past, a home nurse would be appointed to monitor the vital signs and administer medicines. With the advent of IoT-enabled mechanisms, home-based medical assistance is enthused for these specific-category patients. For instance, patients belonging to traumatic brain injury (TBI) or spinal cord injury prefer home assistance as traveling to hospitals for visiting the doctors is sometimes dangerous, especially for patients living in crowded societies. Tailor-made robots for home-assisted medical delivery are often practiced to provide therapy such as speech therapy or physiotherapy.

**Preventive Care** Preventive healthcare or prophylaxis is introduced decades ago to avoid potential risk factors of the living. IoT-enabled systems are designed and innovated to consider the sector of people requiring preventive care through appropriate remote healthcare monitoring mechanisms.

It is also important to advise concerned patients to avoid their routine habits such as improper dietary, chewing tobacco, smoking, consuming alcohol, and so forth, by understanding the level of glucose, blood pressure, and body mass. In succinct, IoT-enabled devices and frameworks could automatically guide the patients and prevent them from many of the diseases with limited visits to the concerned hospitals/doctors.

## 5.2 Tools, libraries, and datasets – remote monitoring mechanisms

Connected IoT devices and hospital premises have to include sophisticated tools, including AI tools, to collect the right sensor data and prevent or diagnose diseases in a remote fashion. The most commonly utilized tools, libraries, and datasets for predicting diseases are discussed based on the remote monitoring techniques discussed earlier.

### 5.2.1 Tools for computing continuum

The computing continuum consisting of edge, fog, cloud or serverless containers has most commonly utilized in IoT-enabled healthcare applications. It is often crucial to understanding the most available tools that enable the right computing continuum for executing applications. For instance, offloading sensor data from medical things to edge or cloud or fog-connected cloud should be automatized in the healthcare application framework.

The important functions for establishing similar tools to enable the computing continuum of IoT healthcare applications are listed as follows:

1. *Dynamic Configurations* – Setting configurations that switch between edge or fog or cloud for executing healthcare tasks is required for incorporating computing continuum in applications. For instance, the configurations could be set up using YAML files and processed at runtime using programs written in nodejs or golang.

2. *Flow-specific Representations* – The tool that provides computing continuum in an automatic fashion needs specific tools to represent tasks and subtasks in a flow model. Obviously, workflow-specific tools such as kubeflow or workflow-description language-based tools will be utilized for specifying the flow of tasks.

3. *Reliability Features* – One of the crucial ingredient for developing tools that promote a continuum of computing in healthcare tasks is to provide reliability features. Reliability measures ensure the consistency delivery of computing resources to complete the assigned tasks.

4. *Statefulness* – Stateful services, including the health status database, are important for completing workflow tasks or for recreating container instances during failures. In IoT-enabled healthcare applications, there is a high possibility that the applications fail due to connectivity failures or the non-availability of appropriate resources. Most importantly, a healthcare application that requires a cold-start computing instance could take a long execution time than executing it in a warm-start instance.

#### 5.2.2 Tools for prioritizing tasks

Healthcare applications could easily lead to delayed responses owing to the increasing number of remote monitoring requirements and decreasing number of available resources, including hospital accessibility or doctor availability. Patient prioritization is, therefore, a crucial component of healthcare tools. There exist tools to prioritize tasks for delivering a fair prioritization of tasks. For instance, Clinical Priority Assessment Criteria (CPAC) is followed in New Zealand, Australia, and a few other countries to prioritize the need of outpatients. This approach is transformed to IoT-enabled healthcare applications for servicing the requests of online patients based on the availability of resources, including doctors.

#### 5.2.3 Tools for communications

As discussed earlier, several sensor nodes or wearables are involved in submitting the sensor data over a secured channel to edge, fog, or cloud compute instances. These sensor nodes communicate to the higher-level device or peer nodes using various communication protocols such as WIFI, Bluetooth4.0, LoRA, Infrared, LiDR, and so forth. 4G/5G/NarrowBand technologies are involved to connect the communication medium of devices.

Tools are often required to automatically suggest connecting to devices within hospital premises and outside hospital premises. For instance, the data rate outside hospitals could be very less when compared to the hospital premises. Obviously, the teleconference approach, especially in video mode, to remotely monitor the health status of individuals has to be diligently handled by applications. Similarly, the devices are prone to electromagnetic interference. Hence, tools need to assist the application to utilize appropriate communication links.

#### 5.2.4 Accessibility features

Accessibility in healthcare applications has two dimensions:

1. *Interface* – The framework should involve interfaces to provide feasible and effective communications to patients/individuals. For instance, a patient might not have the strength to type in available gadgets to communicate to doctors; the patient might find it difficulty to infer the suggestions delivered by doctors. In such a scenario, multiple assisting technologies should be combined to enable efficient communication and accessibility of end devices or doctors/hospitals.

2. *Device Accessibility* – In addition, accessibility of different connected medical things that follow different standards or protocols to collect data or deliver data is a challenge. Tools should enable the best possible approach to efficiently access devices or actuators belonging to the application.

#### 5.2.5 AI-enabled tools

The inclusion of AI techniques in healthcare increases the detection accuracy or assisting nature of applications. However, appropriate tools and techniques have to be integrated into the system for achieving better results and experiences. The most notable approaches of utilizing AI techniques for healthcare applications could be listed as follows:

1. *NLP-assited interfaces*: Natural Language Processing (NLP) methods are required in healthcare to deal with the large volume of healthcare records or datasets. NLP algorithms could parse the text messages from a large volume of data and extract the significance of the context for representing them through interfaces. The programs or algorithms associated with these methods have to become robust and error-free – i.e., careful handling of the dataset is required for the NLP logic to represent the intended content of doctors or patients.

2. *Deep-Learning or Models for inferences*: Deep learning or similar neural network-based learning models have manifested in the healthcare sector for their fast predictions or inferences without compromising the expected accuracy.

   The applications of deep learning models in healthcare are immense. For instance, deep learning models are utilized to detect anomalies in X-ray images, CT scans, MRI scans, and so forth; to analyze documents or health records and predict diseases; and, so forth. For instance, authors of [15] have proposed deep learning-based hierarchical learning approach to improve the response time of sensor-enabled classification problems; also, authors of [53] applied neural networks to classify diseases.

3. *Recommendation systems*: AI is most commonly utilized as recommendation system in healthcare applications. Several recommendations for providing appropriate diets or awareness about the spread of diseases are carried out using recommendation systems. In addition, drug recommendation is also carried out from the perspective of doctors to patients. These recommendation systems have to collect sensed data in a secure fashion [19] from various sensors or medical records and reason recommendations depending on the presented contexts. Recently, in [24], authors have proposed a word similarity measure method using learning algorithms which improves the recommendations of selecting online IoT-enabled medical services.

4. *Predictions and Classifications*: AI embodies several statistical and optimization techniques to predict health conditions or classify diseases. There exist several prediction and classification problems in the past: for instance, the application of decision trees, support

Table 3: Remote Monitoring Techniques in Healthcare Applications.

| No | Focused | Perf. Metrics | Computing | Priority-level | Comm. Protocols | AI/ML |
|---|---|---|---|---|---|---|
| [77] | Tele ECG (Heart Rate) | * | Cloud | Periodic | WIFI | * |
| [71] | Elderly | * | * | Periodic | WIFI | * |
| [16] | * | Exec. Time CPU Load | Fog | * | WIFI | * |
| [25] | Disability (Speech Disorder) | * | Mobile/ Edge | Periodic | WIFI | NLP |
| [20] | Heart disease | * | Android/ Edge | Continuous | WIFI, Bluetooth | * |
| [31] | Heart disease | Throughput | * | * | NBIoT | * |
| [50] | Cancer care | * | Cloud, Hadoop | * | WBAN, WIFI, Zigbee | ML/DL |
| [32] | Cancer care | Sensitivity | Cloud | * | WIFI | ANN/PSO |
| [1] | Diabetes care | Accuracy | Cloud/ Fog/Edge | Periodic | WBAN | Decision Support |
| [6] | * | Energy | Simulation | Critical | RFID, WBAN IEEE802.15.4 | * |
| [4] | Cancer care | Security | * | Critical | WIFI | Kernels/ ML |
| [15] | * | Response Time | Edge, VMs | * | Hierarchical | DL |
| [34] | * | * | Container Edge | Periodic | WIFI, Zigbee, Bluetooth | * |
| [80] | Chronic Diseases | Energy harvesting | Edge, Cloud | Periodic | Bluetooth4.0 | * |
| [3] | * | Round Time Energy | WBN cluster Simulation | * | RFID, WBN | * |
| [7] | * | Reliability, Response Time | Fog, Edge | * | 5G, Fibre/xDSL | * |
| [17] | Non Focused | Latency, Computation Cost | Cloud | Periodic | WIFI, 5G | RS |
| [39] | Emergency | * | Hadoop, Cloud | Critical | 6LoWPAN, RFID | * |

vector machines, K-nearest neighbor algorithms, linear regressions, and so forth, were quite common in the healthcare domain. In addition, several unsupervised learning algorithms such as reward-based agent systems and reinforcement learning methods were incorporated in the applications.

In a few medical diagnosis approaches, researchers have proposed federated learning mechanisms to protect the privacy of patients by protecting the data within local compute resources. By incorporating federated learning models, fine-tuned local learning models were updated in global models for fast predictions. In fact, these learning mechanisms are beneficial for mobile-assisted learning systems [66] where the local models are executed in battery-powered mobile devices.

5. *Generative Adversarial Networks (GANs)*: In a few cases, the electronic medical records could not be exposed to the public for exploration which keeps the supervised learning models such as Convolutional Neural Networks (CNNs) a failure. GANs, an unsupervised AI learning model, support the learning process in such cases. GANs, in general, involve both the generator model and discriminator model for the learning dataset to increase the positivity of the predictions. For instance, the electronic medical records for Zika, a mosquito-borne virus infection, in Kerala are very rare. In such situations, GANs could produce some additional datasets without compromising the accuracy of predictions.

### 5.3 Comparison of remote monitoring applications

Table 3 illustrates the remote monitoring healthcare applications that were developed by researchers and practitioners in the past. It highlights the target groups such as the elderly, common diseases addressed, and so forth; the performance metrics analyzed in the applications such as execution time, CPU load, energy, round-time, and so forth; the computational units involved in the applications such as containers, VMs, Edge, Fog, Cloud, serverless, or hierarchical compute instances; the priority-level initiated in addressing the tasks; the communication protocols which connected sensors with gateways or healthcare applications/services; and the intelligence level incorporated in the applications.

The notable observations from the existing remote monitoring healthcare applications are listed as follows:

1. Majority of the applications utilized WIFI-based communication protocol to connect sensor nodes or hospital devices;

2. Among the available AI-assisted healthcare applications, deep-learning algorithms, and their variants were incorporated in the solutions for better accuracy and resolutions;

3. Almost all applications that were not simulated included a compendium of computing instances such as edge, fog, cloud, or VMs in a hierarchical fashion for pursuing the detection of diseases or providing remote medical assistance.

## 6 Conclusions

The prevalence of IoT-enabled healthcare applications has urged the inclusion of novelties to support individuals and doctors during the pandemic era. Investigating the remote monitoring techniques in the healthcare sector is a vital role in delivering superlative care by doctors to patients. In this paper, the most predominantly applied remote monitoring techniques were studied. Based on the findings, a generic remote monitoring healthcare architecture was elaborated and the taxonomy of remote monitoring techniques was illustrated. Additionally, techniques practiced in the existing remote monitoring healthcare applications and associated research directions were enlightened for the researchers.

## Compliance with ethical standards

– Funding: This study was funded by IIIT-Kottayam Faculty Research Fund.

– Conflict of interest/Competing interests: The author declares that he has no conflict of interest.

– Ethics approval: This article does not contain any studies with human participants or animals performed by any of the authors.

– Consent to participate: Yes

– Consent for publication: Yes

– Authors' contributions: The corresponding author did the entire survey work.

– Informed consent: Informed consent was obtained from all individual participants included in the study.

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