# The Future of Healthcare Internet of Things: A Survey of Emerging Technologies

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***Abstract*—The impact of the Internet of Things (IoT) on the advancement of the healthcare industry is immense. The ushering of the Medicine 4.0 has resulted in an increased effort to develop platforms, both at the hardware level as well as the underlying software level. This vision has led to the development of Healthcare IoT (H-IoT) systems. The basic enabling technologies include the communication systems between the sensing nodes and the processors; and the processing algorithms for generating an output from the data collected by the sensors. However, at present, these enabling technologies are also supported by several new technologies. The use of Artificial Intelligence (AI) has transformed the H-IoT systems at almost every level. The fog/edge paradigm is bringing the computing power close to the deployed network and hence mitigating many challenges in the process. While the big data allows handling an enormous amount of data. Additionally, the Software Defined Networks (SDNs) bring flexibility to the system while the blockchains are finding the most novel use cases in H-IoT systems. The Internet of Nano Things (IoNT) and Tactile Internet (TI) are driving the innovation in the H-IoT applications. This paper delves into the ways these technologies are transforming the H-IoT systems and also identifies the future course for improving the Quality of Service (QoS) using these new technologies.**

***Index Terms*—H-IoT, WBAN, machine learning, fog computing, edge computing, blockchain, software defined networks.**

## I. INTRODUCTION

THE rise of the Internet of Things (IoT) in recent years is leading to a paradigm shift in all the areas of human-machine interaction. From the manufacturing industry to healthcare, from governance to infrastructure management and from consumer services to defense, IoT has seen massive adoption in a span of a few years. The projections from the McKinsey Global Institute show that the IoT applications in multiple domains will have an annual economic impact of USD 3.9 trillion to 11.1 trillion across the globe [1]. The integration of IoT in the manufacturing and consumer goods sector has ushered in the fourth industrial revolution or Industry 4.0. Whereas the integration of IoT in the healthcare sector is dubbed as Medicine 4.0, also referred to as Health 2.0. Health 2.0 follows the age which saw an exponential adoption of diagnostic tools in the healthcare sectors. Health 2.0 marks a transition towards ubiquitous monitoring of the patients, which aids in the early detection of disorders and the implementation of a proactive treatment plan. The IoT focused on medical applications is also termed as Healthcare Internet of Things (H-IoT).

The key features of IoT include limited power nodes connected over a network which aid in the data sensing and collection. An informal description for the phrase "IoT," as put forth by IEEE, is *"a network of items each of which is embedded with sensors and these sensors are connected to the Internet"* [2]. IoT essentially refers to a network of ubiquitously connected smart devices that are deployed to perform a plethora of tasks like environmental sensing, health monitoring, industrial process monitoring, and smart city applications. The most important underlying technology for IoT is Wireless Sensor Networks (WSNs), while the major underlying technology for H-IoT is the Body Sensor Networks (BSNs). A BSN is a network formed by deploying sensors in and around the human body [3]. The current widespread use of H-IoT is in the form of fitness tracking using smart wearables [4]. Apple, Fitbit, and Xiaomi held the major share in the majority of 115.4 million units of wearable devices shipped out in the year 2017. This figure shows a growth of 10.3% from the total 104.6 million units shipped in the previous year 2016 [5]. These figures indicate the popularity and the massive adoption rate of H-IoT technology in the consumer space. However, this massive adoption for early detection of diseases and diagnostic purposes is still underway.

H-IoT is continuously evolving according to the advances in the underlying technologies in WBANs. This evolution aims at achieving the salient features of WBAN based H-IoT. These features include (a) compact form factor for sensors, (b) data security, (c) fault tolerance, (d) Quality of Service (QoS), like low latency with high

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data integrity, and (e) interoperability. Additional features include easy deployment, real-time processing, and ease of mobility [6].

With the introduction of new technologies to improve the above-listed individual features, the overall performance of H-IoT is improving. Introduction of Machine Learning (ML) at multiple layers of IoT protocol stack optimizes the entire system. ML is used at the application layer for security, error correction, and signal processing. At the Data Link Layer (DLL), ML predicts traffic, allocates channel resources, and evaluates the link quality. Several routing protocols efficiently find optimum routes at the network layer using ML. At the higher layers of the protocol stack, ML performs tasks like resource management, data processing, and application optimization [7].

One of the most important features in H-IoT is low latency. The transmission time between the nodes (sensors) and the sink (processing unit) has to be reduced to fulfill this requirement. It can be done either by shortening the distance between the nodes and the sink or by speeding up the transmission. Edge Computing is one such platform that can do both. Edge Computing provides computation power locally in the network. It is highly essential as the nodes are conventionally low power in terms of energy and computational resources. The time for transmission between the edge devices and the processing units reduces significantly, as the processing unit becomes the part of the network. The data is either processed at the edge or pre-processed at the edge and then offloaded to the remote processing unit. In both cases, the network performance in terms of latency enhances considerably. Additionally, edge computing helps in providing interoperability between multiple devices by isolating the edge devices from the core network [8].

The sensors deployed in the H-IoT generate a large volume of data every second. The processing of this continuously generated streams of data is virtually impossible to process using traditional data processing techniques. Thus, big data is an important aspect of healthcare systems and needs specialized techniques for processing. Cloud and Edge computing are two systems that can support Big Data analytics in the H-IoT environment [9]. The requirements of data storage are munificent. Apart from the high volume, there is a large number of data types that are generated by a number of different device types. The issue of data interoperability is a major challenge in H-IoT implementation. The integration of data analytics and IoT is enabling the real-time analysis of data with mobility and context awareness [10].

The applications of blockchains are no longer limited to cryptocurrencies. Blockchains are finding themselves in many new application scenarios. In the context of H-IoT, blockchains can provide solutions to many critical challenges. The blockchain, by its design, is transparent and secure, the features that are characteristic to H-IoT. The advantages of blockchain in H-IoT are not limited to secure sharing of patient data across platforms, enhancing interoperability of data, and removal of third-parties for access control. Thereby creating an efficient, fast, and secure system [11].

SDNs are making a huge impact on network management, especially in IoT systems. The implementation of SDNs is shifting IoT from application-specific systems to a more programmable ecosystem. SDN essentially decouples the network control and data plane. This decoupling allows for the dynamic and flexible configuration and management of data-forwarding rules in the network [12]. It is achieved by virtualization of network device functions to suit the requirements of the network in real-time. Therefore, leading to efficient energy utilization, improved resource allocation and management, and enhanced security and privacy [13].

*Motivation:* The statistics point to an explosive proliferation of devices that will connect to the Internet. The studies show that the number of devices connected to the Internet would reach a staggering 20.8 billion devices by 2020 [14]. Healthcare is projected to be the most dominant application of IoT systems [15]. New paradigms are explored for H-IoT implementation and massive adoption. The requirements of H-IoT differ from the IoT systems in several key aspects. ML and AI are transforming the entire H-IoT system design and architecture. SDN has revolutionized the network management and implementation framework. The big data analytics are helping in creating more and more accurate mathematical models and feature points for fast and efficient diagnosis. Blockchain is enhancing data management and privacy features of H-IoT. There are a number of comprehensive surveys that explore these technologies as standalone systems. However, this study aims at integrating all the emerging technologies and presenting a review of their use in H-IoT. Table I is the compilation of the abbreviations frequently used in this paper.

*Contribution:* This paper targets to present an in-depth survey and analysis of future technologies for H-IoT. As H-IoT is transforming with the advances in complementary technologies, there is a need to accumulate the works in these different fields and create a unified repository. We can summarize our contributions as follows,

1. We provide an overview of the H-IoT structure, its requirements, and its relevance. The relevance of the H-IoT is justified by the use cases and applications of H-IoT in the current state-of-art.
2. We introduce the features of H-IoT based on the distinctions from the generic IoT systems.
3. The various architectures based on the use cases are presented.
4. Our main contribution lies in exploring and analyzing the complementing future technologies in H-IoT. The literature on ML, edge computing, blockchain, big-data, and SDN is analyzed. The advantages that these technologies impart are discussed. We introduce the significance of the Internet of Nano Things in the future H-IoT systems.
5. Finally, we identify the future research directions in the healthcare industry that exploits the advantages of the novel technologies presented in the discussion. Additionally, future directions based on TI and IoNT are also introduced.

TABLE I
LIST OF ABBREVIATIONS

| Abbr. | Full Form |
|---|---|
| 5G | Fifth Generation |
| AAL | Assisted Ambient Living |
| AES | Advanced Encryption Standard |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Networks |
| AR | Augmented Reality |
| BAN | Body Area Networks |
| BCI | Brain Computer Interfacing |
| BSN | Body Sensor Networks |
| CHF | Congestive Heart Failure |
| CNN | Convolution Neural Networks |
| CVD | Cardiovascular Diseases |
| DBN | Deep Belief Network |
| DL | Deep Learning |
| DQN | Deep Q-Networks |
| ECG | Electrocardiogram |
| EEG | Electroencephalogram |
| ER | Emergency Room |
| ETE | End to End |
| H-IoT | Healthcare Internet of Things |
| IDS | Intrusion Detection Systems |
| IEEE | The Institute of Electrical and Electronics Engineers |
| IoBNT | Internet of Bio Nano Things |
| IoNT | Internet of Nano Things |
| ITU | International Telecommunications Union |
| kNN | k-Nearest Neighbour |
| KPI | Key Performance Indicators |
| LTE | Long Term Evolution |
| MAC | Medium Access Control |
| MC | Molecular Communication |
| MEC | Mobile Edge Computing |
| MEMS | Micro Electro Mechanical Systems |
| ML | Machine Learning |
| MQTT | Message Queue Telemetry Transport |
| NFV | Network Function Virtualization |
| NOS | Network Operating System |
| OS | Operating System |
| PHY | Physical Layer |
| PoCD | Point of Care Devices |
| QoL | Quality of Life |
| QoS | Quality of Service |
| RSA | Rivest–Shamir–Adleman Algorithm |
| SDN | Software Defined Network |
| SVM | Support Vector Machines |
| TI | Tactile Internet |
| VR | Virtual Reality |
| WBAN | Wireless Body Area Network |
| WSN | Wireless Sensor Network |

We present a case for the H-IoT in the current medical systems. The advantages of H-IoT are numerous and can alleviate a great degree of the load from public health institutions. We have aimed to provide a unified state-of-the-art survey for the research community that provides a systematic review and analysis of future technologies that would be instrumental in the large-scale deployment of the H-IoT systems.

*Paper Organization:* The paper organization is as follows. Section II gives a brief comparison with the related work. Section III describes the basics of H-IoT systems. Section IV discusses the application-based frameworks used in H-IoT systems. Sections V through IX discuss the implications of ML, edge computing, big data, blockchain, and SDNs in H-IoT, respectively. Section X identifies future research directions, while Section XI presents the conclusion. The paper structure can be visualized as Fig. 1.

## II. RELATED WORK

The Point-of-Care Devices (PoCD) working group of IEEE was approved in September 2018 to standardize the architecture, communication, and QoS for service-oriented point-of-care medical devices and medical IT systems [16]. The current literature explores the many facets of H-IoT in detail. However, breakthroughs are made every day in the IoT technology, particularly in the healthcare sector. In the surveys [17], [18], various aspects of H-IoT are reconnoitered. A majority of these surveys explore the various individual objectives and functions, but the surveys [19] and [20] also review the associated technologies and aspects of H-IoT.

Alam *et al.* [17] review the various communication protocols and standards applicable to H-IoT. The paper explores the state-of-art pertaining to five application scenarios in which H-IoT can be instrumental. An introduction to the various communication technologies is presented along with the identification of challenges and future technologies in healthcare. This survey doesn't cover a key aspect of security and privacy, which is a major part of H-IoT. It also fails to cover the use of emerging technologies such as ML in Medium Access Control (MAC) and PHY layers. Additionally, this survey does not present any recent advances or contributions in mitigating the drawbacks and challenges in H-IoT. The survey [21] provides an insight into the application of fog computing in H-IoT. As low latency has been described as one of the basic requirements of H-IoT, fog computing is providing a solution by bringing the computational power closer to the network. The paper discusses the various fog-based frameworks and models in addition to subsystems that include the use of fog paradigm in the H-IoT architecture for a wide range of functions. The paper covers a diverse set of objectives, such as reducing latency, improving data security and interoperability, and data processing in real-time. The discussion could have been enriched with the inclusion of application-specific fog computing implementation. Moreover, it does not explore the complete potential that fog computing has to offer in terms of network management, especially routing functions and autonomous network management. The discussion of network function virtualization was not included in the survey. The survey [22] is a detailed overview of the sensors deployed in healthcare IoT. The paper delves into the sensor devices, their working principles, and operations. The detailed

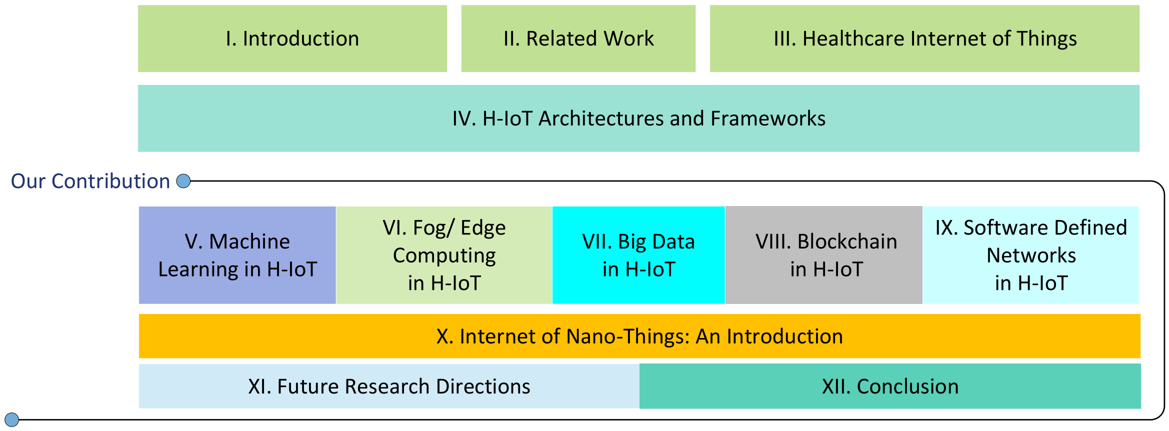


Fig. 1. Structure of our Survey.

study of the application-specific sensors is undertaken. The paper also explores the power systems in the sensor nodes, the on-sensor pre-processing capabilities, and wireless communication systems. The paper, however, does not include the study of commercially available solutions and prototypes that can be readily implemented for H-IoT system at the sensor level. The authors do not discuss the implementation of energy-saving or power optimization methods that can be implemented at the device level. The discussion on security aspects is not found in the paper. The paper suffers from a deficiency in terms of its discussion of network-layer protocols, which are limited to the legacy protocols and techniques. The paper fails to include emerging technologies such as ML and edge computing in its discussion.

The survey [19] is an overview of the architecture, constituents, and applications of H-IoT. It proposes a model for H-IoT implementation. The survey covers the application-specific wearable sensors, communication technologies, applications of cloud technology, and big data in H-IoT. Since the survey aims to provide a comprehensive survey of each component, it leaves out many aspects such as data privacy, device and network layer security, and data processing techniques. Important aspects of H-IoT such as ML, network management are excluded from the discussion.

In contrast to [22], [23] takes an in-depth look into the wearables for medical applications. The paper discusses several proprietary devices that are either commercially available or as research prototypes. The survey includes new frontiers such as smart garments, patches, and jewelry. Additionally, it explores the security threats at the communication levels and the energy aspects of these wearables. Additionally, [23] distinguishes itself by addressing the on-device computing capabilities of the wearables. Although the discussion is highly detailed, the discussion on communication systems and protocols optimized for these devices and the functional use cases is not included. Even though it discusses the security threats for short-range communication systems such as Bluetooth Low Energy (BLE), but fails to address the issues of security at the network layer for long-range communication protocols. No discussion on the data management front was presented. The issue of interoperability is an essential challenge at the device layer, which was excluded from the paper. One of the functions of the H-IoT is to generate feedback from the sensed data after processing. The survey [24] attempts to bridge the gap in the literature for the same. The paper touches upon the architectures, components, and use-cases of the biofeedback systems in H-IoT. The critical aspect of the feedback generation is maintaining data integrity, which was not discussed. The paper is limited in its scope by leaving out the data processing literature, which forms the basis of generating feedback. The survey includes a discussion on the feedback control mechanism but does not venture into future technologies and vast application areas such as Brain-Computer Interfacing (BCI) and prosthetic limbs. The survey [20] deals with the implementation of IoT from the healthcare perspective. The survey covers architecture, applications, security, and IoT policies worldwide. The paper proposes an H-IoT architecture and a security model. The survey focusses on the security of the IoT network but does not comprehensively cover the security risks, mitigation methods, and evolution of the security risks according to the new paradigms. This survey does not feature any discussion on cloud computing, big data, and network management functions.

In [25], a brief overview of routing protocols optimized for H-IoT is presented. The survey is limited in its scope, mainly discussing only the routing protocols optimized according to energy consumption. The current H-IoT networks take multiple metrics under consideration for path selection, such as QoS and shortest path, yet no discussion was present. The survey is a very brief introduction to the classification of the routing protocols for the WBAN environment. Another survey [26] extends the coverage of the routing protocols designed for WBANs. It covers the routing protocols based upon the underlying methods. A small number of proposed methods are included, which do not include future technologies. A discussion on autonomous network management and path selection is left out. The survey [18], attempts to identify the security at three levels of H-IoT, i.e., device level, network level, and data level. The survey is aimed to identify the potential risks at multiple levels, but in essence, does not provide solutions to mitigate these security risks.

TABLE II
THE COMPARISON OF THE STATE-OF-THE-ART FOR H-IOT

| Reference | Use Case Architectures | Machine Learning | Edge/ Fog Computing | Big Data | Blockchain | Software Defined Networks |
|---|---|---|---|---|---|---|
| Alam *et al.* [17] 2018 | ✔ | ✖ | ✖ | ✖ | ✖ | ✖ |
| Mutlag *et al.* [21] 2019 | ✔ | ✖ | ✔ | ✖ | ✖ | ✖ |
| Baali *et al.* [22] 2018 | ✖ | ✔ | ✖ | ✖ | ✖ | ✖ |
| Baker *et al.* [19] 2017 | ✔ | ✔ | ✖ | ✔ | ✖ | ✖ |
| Senevirante *et al.* [23] 2017 | ✖ | ✔ | ✖ | ✖ | ✖ | ✖ |
| Li *et al.* [24] 2017 | ✔ | ✔ | ✖ | ✖ | ✖ | ✖ |
| Islam *et al.* [20] 2015 | ✔ | ✖ | ✖ | ✖ | ✖ | ✖ |
| Kurian *et al.* [25] 2017 | ✖ | ✖ | ✖ | ✖ | ✖ | ✖ |
| Jijesh *et al.* [26] 2017 | ✖ | ✖ | ✖ | ✖ | ✖ | ✖ |
| Sain *et al.* [18] 2017 | ✖ | ✖ | ✖ | ✖ | ✖ | ✖ |
| Qi *et al.* [27] 2017 | ✔ | ✔ | ✖ | ✔ | ✖ | ✖ |
| Aceto *et al.* [28] 2018 | ✔ | ✔ | ✔ | ✔ | ✖ | ✖ |
| Dhanvijay *et al.* [29] 2019 | ✔ | ✖ | ✖ | ✖ | ✖ | ✖ |
| This Work | ✔ | ✔ | ✔ | ✔ | ✔ | ✔ |

Legend: (✔) Discussed in the cited work (✖) Not discussed in the cited work

### A. *Comparison With Our Work*

From the discussion of the state-of-the-art, we can identify the various aspects of H-IoT. We can identify the areas which are covered by the current surveys. ML is an important aspect of H-IoT. It is applicable at the device layer, communication layer, as well as data processing layer [23], [27]. We have undertaken a detailed discussion of ML at the different layers of H-IoT, which is not present as per our best knowledge. The detailed discussion about fog computing is present in [21] but remains deficient in covering application-specific fog systems. Additionally, we also cover network management literature based on the edge paradigm. This paper presents a unique discussion on blockchain in H-IoT, which is not currently available in the literature. The implementation of SDN is new to the H-IoT systems, and therefore, we include literature based on SDN in our discussion. Even though [28] covers a wide range of Information and Communication Technology (ICT) paradigms, the literature included has been published before 2016. Another comprehensive survey has been presented in [29]. The work in [29] presents a systematic review of works focusing on the various aspects of an H-IoT system, such as enabling communication technologies, security issues, and application cases. In contrast, this paper is focused on the emerging technologies supporting future H-IoT systems. The literature under consideration is published prior to the literature considered in this work, and more importantly, this work focusses more on the new technologies that are revolutionizing the IoT for the healthcare industry. To the best of our knowledge, this work primarily includes the state-of-the-art literature published from 2016 to the time of submission of the manuscript. The comparison of the different works is tabulated in Table II.

## III. HEALTHCARE INTERNET OF THINGS

One of the major applications of IoT is in the field of healthcare. The H-IoT is, therefore, the IoT system deployed for healthcare applications. The H-IoT is a subset of a generic IoT system. The major underlying technologies for IoT and H-IoT are WSNs and BSNs, respectively. The IoT and the H-IoT systems can be identified from their underlying technologies. The differences between IoT and H-IoT are summarized in Table III. Table III highlights the main contrasts between the two systems [30]. The introduction of IoT in healthcare is a recent trend. There has been a massive surge in the use of fitness trackers or wearables in the past few years, and the market data is indicative of the same with the

TABLE III
CHARACTERISTIC FEATURES OF GENERIC IoT AND H-IoT [30], [257]

| | Generic IoT | H-IoT |
|---|---|---|
| 1 | It is usually deployed over a large geographical area and serves a single purpose | Usually deployed in a closed or small geographical area, either in and around the human body or in a healthcare facility |
| 2 | Energy sources can include solar and wind energy. In case of stationary nodes, the nodes maybe powered continuously | H-IoT nodes can also harvest energy from human body using heat, stress and motion |
| 3 | Monitor environment, used in defence applications, industrial monitoring | Used to monitor human body vitals |
| 4 | Desirably small nodes but node size vary according to environment and application | The nodes are miniaturized to be unobtrusive |
| 5 | Usually these are stationary | Essentially mobile as associated with human body |
| 6 | Deployment of sensors is comparatively easy | Deployment is a difficult particularly in case of implants which mostly requires a surgery |
| 7 | Data integrity is tried to maintain. The redundancy compensates for errors | The data must be preserved and transmitted with utmost integrity |

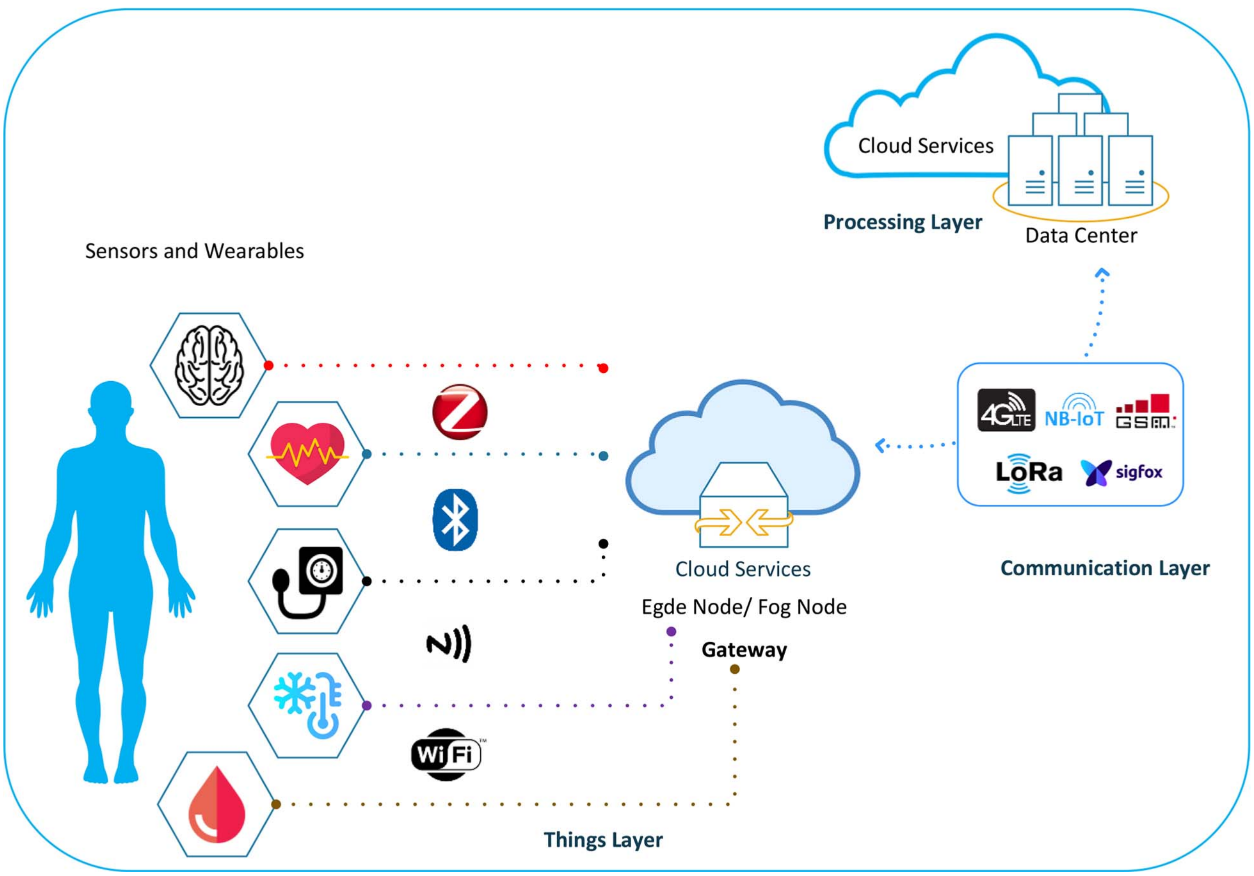


Fig. 2. The three-tier Architecture of the H-IoT systems. The communication technologies used at the different layers are identified. The interaction between the different layers is indicated.

projected increase in the use of these in the future [31]. The evolution of smart health monitoring devices added with improved connectivity to the IoT communication infrastructure has led to the development of a healthcare-oriented system called IoThNet [32]. There is a massive potential for these IoT systems to track the health progress of the users. The patients that are connected to the network can be tracked for the change in their health parameters such as vital signs

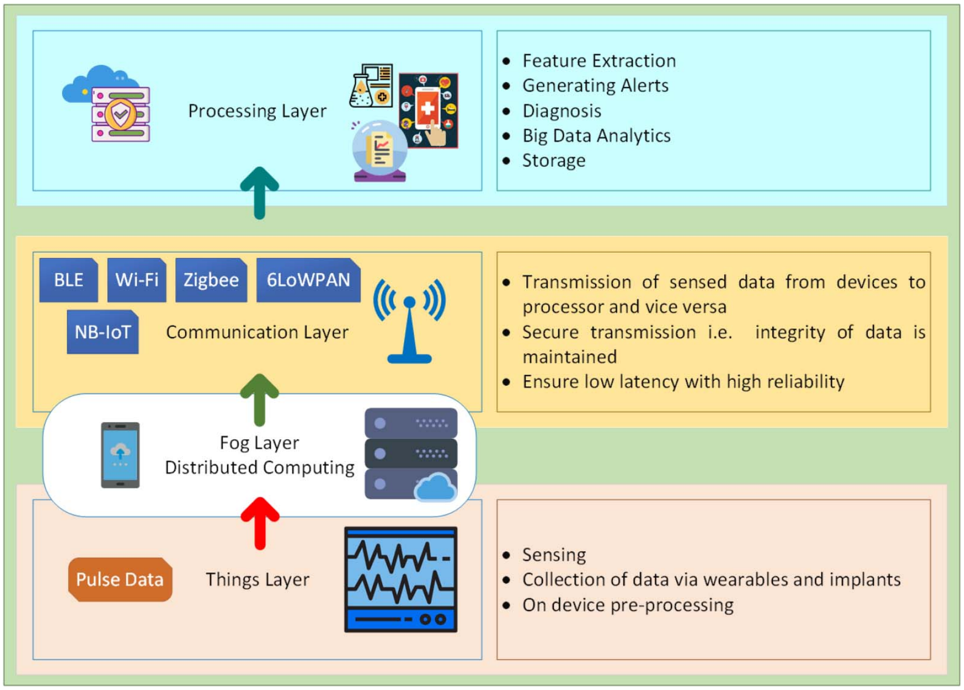


Fig. 3. Illustrative Description of an H-IoT system.

and biometric information for better diagnosis and quality of delivered medical care [33], [34]. It raises a need for the development of a standardized architecture to facilitate the exchange of information between the various participating entities. A standard or a reference architecture would be a key enabler of the widespread adoption of H-IoT. Multiple standard architectures are being established by numerous consortiums and commercial entities for the implementation of various IoT applications [35]. The IEEE Standards Association has established a working group for the standardization of the service-oriented distributed Point-of-Service healthcare devices. It defines the node setup, discovery, and communication in the H-IoT scenario along with the Quality of Service parameters [36].

A three-tier structure, composed of the sensor or things layer which corresponds to the open end of the network, communication layer, and server or processing layer, is a widely adopted architecture followed in H-IoT systems. Fig. 2 represents the popular three-tier architecture that is followed in H-IoT. The H-IoT things are sensing systems that record the different indices based on the application. The "things" may also refer to the application service provider or an actuator that conveys the output to the user after the analysis. Sometimes, the data can be pre-processed before being transmitted to the processing layer at the edge node. The communication system ensures that the sensed data is transmitted to the processing layer, where the big data is analyzed. Yin *et al.* [37] discussed the IoT based telerehabilitation systems, their enabling technologies, and implementation. In some cases, [38], a fourth layer is created by separating the sensing systems from the end service providers such as hospitals, ambulances, or medicine supply chains. Furthermore, H-IoT systems are able to monitor the patients accurately and update the health status in real-time, improve the quality of life for the seniors in assisted living facilities, predict forthcoming health issues, assist in healthcare services in hospitals and ER's [39], [40]. We can understand the basic working of an H-IoT system by using a cardiac monitoring system as an example [41].

The heart rate variability (HRV) is an indicator of the health of the heart. It indicates the time intervals between the heartbeats and can indicate the presence of a heart attack or a myocardial infarction. In order to estimate the HRV, a pulse sensor is used. This layer containing the sensor is termed as the *things layer.* The sensor records the heart rate that is transmitted to the data processing unit. In an H-IoT system, the sensed data is wirelessly transmitted to the *processing layer*. The processing layer is connected to the *things layer* via a *communication layer*. The wireless technologies used at this layer are low power consuming technologies such as Bluetooth, ZigBee, radio-frequency identification, and Wi-Fi. The processing unit for extracting the useful features from the collected data can be implemented either on local hardware or remote cloud system. Since the amount of data generated by the sensor is substantial, a cloud-based solution is more feasible. However, the delay induced by transporting the data from the sensor to the cloud is significant than the delay incurred by processing the data at a local processing unit. It is called an *edge node*. The basic structure of the H-IoT system remains more or less the same, but sometimes an additional layer of distributed computing resources is included in the structure. The *fog layer* constitutes this additional layer. The advantages of the fog layer include reduced latency, improved data processing, enhanced security, and increasingly interoperable. Fig. 3 tries to exemplify the H-IoT system and its constituents.

There are a set of key performance indicators (KPI) that grade the performance of an H-IoT system such as latency, security, reliability, and efficiency. However, many different performance-related challenges are faced by the current H-IoT systems, and they present a roadblock in their massive deployment. Some of these challenges are presented and characterized based on their effect on the H-IoT system. In the following sections, the contribution of the various authors is analyzed in mitigating these challenges using future technologies. These challenges are classified into two prominent groups

A. QoS Improvement Challenges
B. Scalability Challenges.

### A. QoS Improvement Challenges

The various QoS parameters or the KPI have already been identified in the earlier discussion. The H-IoT is characterized by low latency and low power operation, and high reliability and security. Numerous opportunities can be explored to improve the performance of H-IoT systems by utilizing new technologies. The solutions for the following stated challenges are discussed in the upcoming Sections V through IX.

*1) Low Latency:* The QoS parameters defined for the H-IoT system includes minimal latency due to its time-critical nature. The H-IoT system incurs delays during end-to-end transmission and processing. The total delay is reduced by minimizing the transmission delay by exploring communication technologies with high bandwidth and availability. Employing ML algorithms for routing and channel access can significantly reduce the end-to-end delay. While the inclusion of fog and edge paradigm demonstrates advantages in terms of reducing the network delay. Additionally, combining AI with fog and edge computing is highly effective in reducing the processing delay.

The advantages of combining multiple technologies have demonstrated significant improvement in system performance, as demonstrated in [42] and [43]. The Deep Learning (DL) techniques improve the big data analytic systems that handle a colossal amount of information, but the limitations of the current algorithms hinder the extraction of all the useful information from a dataset. Therefore, algorithms for exploiting the complete information from the datasets are required. The main advantage of the fog/edge scenario is the reduction of delay. The inclusion of the computing resources near the edge of the network reduces the transmission delay as well as processing delay. Utilization of the distributed computing platforms offered by fog paradigm can ensure the QoS compliant latency in the time-critical H-IoT systems [44].

*2) Low Power Operation:* The energy constraint is among the primary challenges of the IoT systems. The deployment of the sensors in the H-IoT is in the form of wearables as well as implantable devices. The wearables can, however, be recharged after a period of operation, but the implants require a long-lasting battery power to sustain their long-term operation as the batteries of these sensors cannot be frequently replaced or recharged. Therefore, a host of solutions have already been proposed in the reviewed works. There are breakthroughs in the battery technology that can solve the energy storage problems. The development of battery sources for implantable sensors is a very lucrative research area, especially the development of new materials safe for use within the body. Novel solutions for minimal foreign intervention in the body are required, as demonstrated by [45]. This approach helps in avoiding the development of harmful side effects.

The efficient utilization of the existing power resources is equally necessary. There is a need for lightweight operating systems (OSs) for the operation of the power-starved WBAN systems [46]. Similarly, efficient resource management is necessary to enhance the lifetime of the network. The management of limited power, limited processing capability, and limited memory is required for the optimum working of IoT sensors [47]. Additionally, ML algorithms can easily optimize the computing processes to conserve energy usage in an H-IoT system further. Therefore, the development of lightweight algorithms for the optimization of the performance of the H-IoT system is utterly necessary.

The advantage of having a distributed architecture as in the case of fog and edge system includes conservation of energy as the power consumption for short-range transmission is lower than the long-range transmission. It becomes imperative to design a network that is served by distributed power resources to optimize energy usage as well as maintain availability and security.

Currently, some solutions offer battery-less operation utilizing the features of human anatomy to power the sensors and transmission modules as in [48]. There are many energy harvesting solutions for deriving energy from the human body itself for the operation of the implantable sensors. An array of methodologies can be implemented for generating energy for the operation of the sensors implanted in the body [49]. These solutions can prolong the life of the nodes in the H-IoT ecosystem. There is a need for low-cost solutions to implement efficient harvesting methodologies without causing any harm to the user. Efficient and fast charging methodologies are also required to complement these solutions.

*3) Security:* The security of patient-generated data is paramount in an H-IoT system. The misuse of user data has serious legal and safety implications. Guarding the privacy and maintaining the anonymity of the user is an essential aspect of healthcare data management [50], [51]. The guarantee of patient data security, as well as the patient's identity, is directly associated with the adoption rate of H-IoT. The secure data access for the authorized users can be ensured by employing cryptographic techniques [52], [53]. However, many threats exploit unorthodox methods to compromise patient data and privacy. Thus, new approaches to mitigate the threats of new attacks should be adopted. To learn the threats and devise a countering methodology, AI can provide a feasible and effective solution. But, most of the H-IoT systems are resource-constrained; therefore, it becomes imperative to devise lightweight algorithms. The application of ML in mitigating the security threats in H-IoT is demonstrated by [54]. The threats at various levels of the IoT systems, from sensor level to the application layer, in the front end, and at multiple layers in the back-end, can be mitigated by using

ML and DL. The resource-constrained nature of the H-IoT system calls for the utilization of algorithms that are capable of lightweight operation. The H-IoT is ideally a distributed system, where several collaborating nodes interact; therefore, it is necessary to authenticate the identity of the nodes. Key sharing algorithms perform this task, but they are energy-intensive [55]. Therefore, lightweight and energy-efficient key sharing algorithms are required for a massive deployment of H-IoT systems.

Fog and edge systems also provide a platform for securing the data collected by the sensors. The computational capabilities introduced near the devices can help in securing the user-generated data beginning from the things layer. Securing the data by adopting a distributed system instead of a federal system is achieved by the use of fog paradigm. This strategy is particularly helpful in the mitigation of Distributed Denial of Service (DDoS) attacks [56]. Additionally, the DDoS attacks caused by botnets are a critical threat to an IoT system Malwares such as Mirai flood the network with a massive amount of data, therefore rendering the system unresponsive [57] Securing the sensor devices acts as the first line of defense against the security threats as the access to the sensor allows an attacker many possibilities to exploit the system and threaten the security of the critical user data. The work [58] introduces a scheme for securing the monitoring data by encrypting it before transmission to the cloud. This added layer of security can be implemented using the edge node also.

Blockchain is contributing to securing the H-IoT systems by providing a transparent system of data storage and leveraging smart contracts to secure the services. The work [59] identifies the scope of blockchain in securing the various components and layers of an H-IoT system. The use of smart contracts can ensure the services offered by service providers are securely and fairly compensated.

The softwarization of the IoT systems by the utilization of SDN and NFV can be leveraged to enhance the security and privacy of the user data. The inclusion of SECaaS, which stands for security as a service in the current H-IoT systems, can solve a host of security problems faced by H-IoT systems at different levels of network protocol stack [60].

Securing the medical data and ensuring the privacy of the users is exceptionally essential for the widespread adoption of the H-IoT systems. The use of novel technologies can enhance the security features, but the different technologies can be effectively used only at specific layers. The resource-constrained nature of the H-IoT systems calls for the development of lightweight algorithms to counter the security threats to the data as well as preserving the privacy of the users while sharing the data over the network.

*4) Real-Time Operation:* The data collected by the sensors is processed to obtain insights about the health status of the user. It is notable that the amount of data generated during the sensing process is substantial and requires specialized processing algorithms for extracting useful information. However, the current algorithms are incapable of processing all the data that is generated by the sensors. There is a need for designing algorithms to extract all the useful information in real-time to generate alerts as well as generating trends. The DL algorithms enhance the processing performance of the data to generate alerts and diagnosis of diseases in real-time [61]. However, a significant challenge that is identified in the processing algorithms is that of extracting all of the useful information that a dataset contains. Therefore, there is a need for efficient data processing algorithms that can identify multiple features and combine the redundant features in a dataset during runtime.

### *B. Scalability Challenges*

The vision for the H-IoT calls for high scalability. Therefore, a number of contributing factors are to be optimized for a large-scale deployment of the H-IoT systems.

*1) Scalable Deployment:* The implementation of the H-IoT systems is aimed to be ubiquitous, like all the other IoT systems. The multifold increment in market penetration of the wearables from 80 million device shipments in 2015 to 200 million shipments in 2019, indicates the positive potential of H-IoT in the current market environment [23]. Therefore, personal wearable based monitors are bound for a large-scale deployment of H-IoT systems. It is possible by providing interoperable platforms for the devices and the underlying communication technologies. Standardization of communication technologies for wearable devices and implantable sensors to provide seamless connectivity is extremely important. The significance of standard data format across the various hardware platforms, as well as application layers, is paramount. The proposed work in [62] demonstrates the integration of heterogeneous communication technologies for the deployment of the H-IoT scenario at multiple network layers. The data traffic generated should be processed without incurring additional computational delay and cost.

Additionally, the fog computing paradigm can extend the computational power to the network allowing more nodes to access the computational resources and maintain an acceptable QoS for H-IoT systems [63].

The contribution of innovative use of the electromagnetic spectrum by convolving multiple communication technologies is highly significant in the massive deployment of H-IoT. The 5G wireless technology has the ability to increase the current network capacity by a thousand times while providing a tenfold improvement in energy efficiency. In [64], the potential of LTE WLAN aggregation (LWA) in large scale adoption of IoT is identified. It lays down a framework for the coexistence of LTE and WLAN and hence, for expanding the deployment scenarios for wearables and WBAN sensors.

The widespread adoption of the H-IoT systems demands compliance with the standard QoS parameters in terms of latency, accuracy, and availability. Scalability challenges will have to be addressed to support the large-scale deployment of the H-IoT. The support for a large number of users in a system is to be complemented by an increased network capacity and efficient use of the network spectrum. The commercial rollout of 5G can significantly support the ever-increasing devices joining the H-IoT ecosystem. Cognitive radios (CRs) can further help in the efficient use of the existing network spectrum.

Furthermore, it is vital to develop a standardized format for sharing the data between the multiple systems. It will allow the current systems to scale up the current systems by a significant factor.

*2) Networking Solutions:* The channel access mechanisms for the nodes in the network should be fast and fair, which is demonstrated in the ultra-dense WLAN environments by [65]. However, the WBANs are resource-constrained, and the access mechanisms are power consuming. Therefore, it is enormously essential to design low-power consuming channel selection mechanisms that are fast and collision-free. Since the data delivery is crucial in the H-IoT QoS, access mechanisms should ensure that no packet drops occur. The applications of ML are immense in this regard. There are several AI-based solutions in the IEEE 802.11 MAC layer. However, the current standards for H-IoT, like the IEEE 802.15.4 and IEEE 802.15.6, can also exploit the RL based algorithms for a distributed channel selection mechanism. RL algorithms are lightweight and do not require memory and computational resources like other ML classes.

Additionally, decentralization is a potential solution that can be explored for achieving the required QoS. Some novel solutions based on edge and fog computing can be implemented to achieve a fair and secure use of the network resources. The application of blockchain in this area is in its infancy. The suitable consensus mechanisms are required, but at the same time, the QoS parameters are required to be respected.

The routing protocols in the IoT systems are becoming resource-efficient, which is suitable for the majority of IoT systems. However, IPv6 routing protocol for low power and lossy networks (RPL), which is the most popular routing algorithm, has an unsatisfactory performance to support the dynamic nature of the H-IoT systems. Therefore, it is essential to design the routing protocols that are efficient in operation along with support for mobility in the real scenarios. The latency is very critical in the H-IoT systems, which makes it essential for the routing algorithms to be robust and fast at the same time. Besides, the delivery of data should be ensured in H-IoT systems as any data loss can potentially lead to harm. These requirements are the underlying conditions for the design of future routing protocols. In this regard, the use of learning algorithms can be pursued. Learning the traffic patterns and resource consumption to design a more efficient routing protocol can be achieved by using ML, and it is an enticing research area. Moreover, high energy efficiency in these routing algorithms should also be ensured.

*3) Service Availability:* The issue of mobility is a critical challenge in IoT based systems. The sensors are placed on the human body that causes degradation of network performance as soon as the user moves from its location. The services must remain available in spite of the mobility of the user.

The introduction of IPv6 in the BANs is effective in providing pervasive availability of the network services. The architectures for the IPv6 based systems need to be refined to reduce the handover times from one network coordinator to others.

However, there are issues of localization and coverage. Additional challenges include issues with calibrating the network as nodes are continually changing. There should be provision for robustness to deal with the dynamic nature of the network, which calls for reprogramming the network. All these challenges have given birth to a host of research frontiers [66]. The improved support for an ever-increasing number of devices in the 5G scenario is groundbreaking for H-IoT. Additionally, the advances in the CRs will be helpful in the support for mobility.

SDN's can provide a solution for enhancing mobility support by distributing control and improving the programmability of the system. The increased programmability can enhance the ability of a network to adapt to the changing topologies and addition of heterogeneous devices.

ML algorithms can be used to learn the mobility patterns of the network to provide proactive solutions to the changing network dynamic while fog computing can enhance the computational capabilities to support the varying loads throughout the network lifetime.

The novel inclusion of the human body in the network has already been envisaged. The greater integration of the human in the network can be exploited to enhance the scalability of the H-IoT systems as well as solve the mobility challenges.

Therefore, the H-IoT system is deeply affected by the mobile nature of the participating nodes. Therefore, it is imperative to counter this challenge by employing solutions that involve enhancing network availability as well as coverage. The use of ML in determining the mobility patterns can optimize the handover procedure. While introducing the SDN based architecture can solve the programmability constraints. The distributed computing paradigm can mitigate the load balancing issues due to the dynamic nature of the network.

*4) Interoperability:* The H-IoT systems are envisioned to be deployed massively. It requires the inclusion of devices and services from many original Equipment Manufacturers (OEMs) and service providers. As already discussed, there is a requirement for standard data formats to fully integrate the systems and achieve an interoperable massive H-IoT system. The SDN frameworks can offer a scalable platform for a massive deployment of H-IoT systems. Additionally, SDN can address the heterogeneity challenges in the massive H-IoT deployment [67]. The separation of the control plane from the data plane can enable the creation of several sub-networks that can maintain a requisite QoS by utilizing a distributed computing resource for each subnetwork. Hence, providing scalable solutions for challenges like data handling, security, and network management.

The heterogeneous devices connected over the Internet generate and transmits data structured in several proprietary data formats. Therefore, a collective effort from the regulatory and industrial organizations is required for agreeing upon a unified data format.

*5) Regulatory Policies:* Many laws in effect are protecting the users of different services against the breach of trust and protection against hazards. For the adoption of H-IoT, there should be clear guidelines for the protection of data and privacy of the users. There should be safeguards against the exposure to the electromagnetic radiations connecting the sensors to the network. There is a need for such legislation and

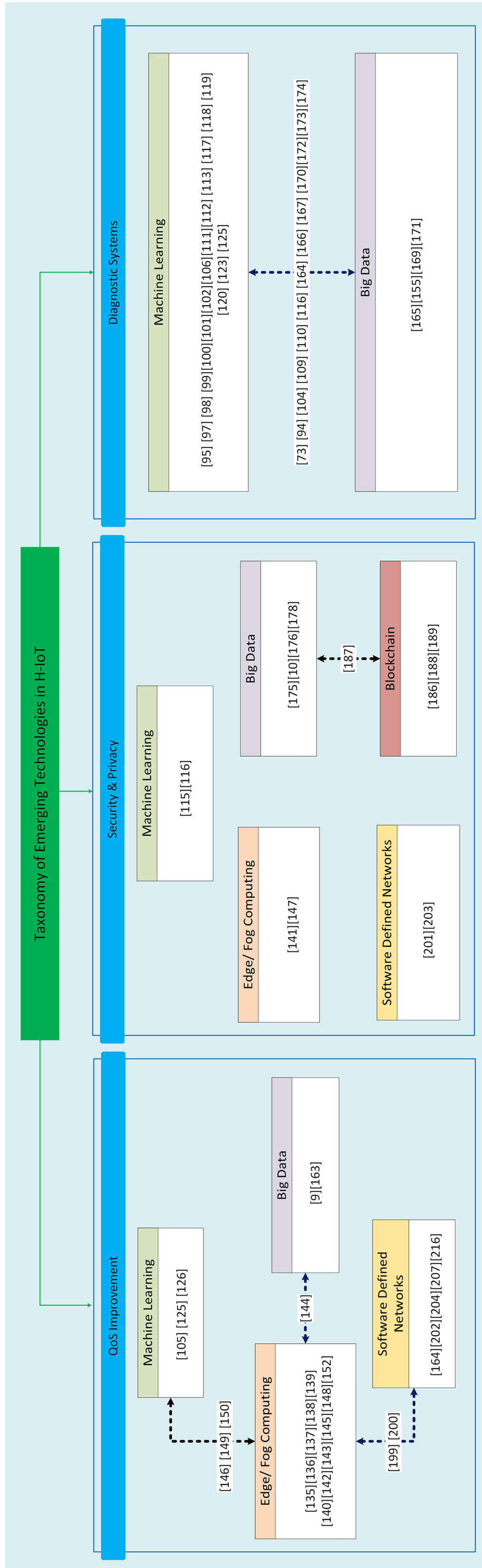


Fig. 4. The Taxonomy of this Survey Paper.

devising the policies to guide the large-scale deployment of H-IoT systems. This involves a close co-operation between the research community and the legislative bodies.

These solutions to the above-stated challenges are a vital step in the mass adoption of the H-IoT system. Therefore, many approaches in mitigating these challenges are proposed.

In the following sections, the analysis of these proposed solutions is presented. The proposed solutions are based on technologies like AI, edge computing, big data, blockchain, and SDN. Some of the solutions use a cross-dimensional approach utilizing more than one of these underlying technologies. Fig. 4 presents an overview of the taxonomy of this survey. The multi-technology approaches exploit the advantages of these techniques to enable a QoS compliant H-IoT system. From the figure, it is clear that multiple technologies collaborate (denoted by dotted lines) to fulfill the high QoS requirements and deliver high performance while maintaining network security and data privacy.

## IV. Healthcare Internet of Things Application Frameworks

The H-IoT systems are designed based upon the target application and defined QoS. Therefore, to match these requirements, the authors have proposed multiple architectural frameworks. This section reviews these frameworks and organizes them in accordance with their application areas.

We can identify the applications for the H-IoT systems based on the vitals or indices tracked by the sensing system. We discuss some of the state-of-the-art use cases that are implemented either commercially or as working prototypes. Fig. 5 illustrates some of these applications diagrammatically. The applications can be classified into the following broad areas:

A. Cardiovascular Diseases
B. Neurological Disorders
C. Ambient Assisted Living
D. Fitness Tracking

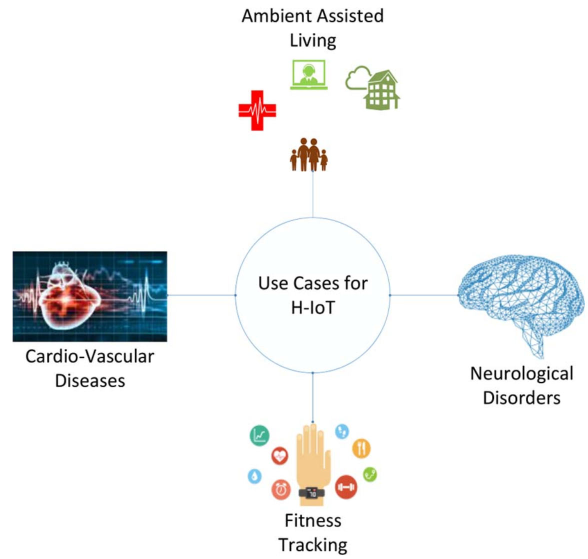


Fig. 5. Broad Categories of H-IoT Applications.

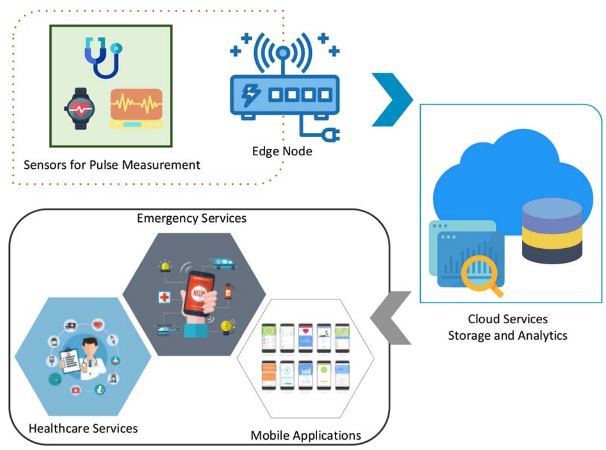


Fig. 6. Generic Architecture for Detection of CVDs.

### *A. Cardio Vascular Disorders*

Cardiovascular Diseases (CVD) are a class of diseases that affect the heart and blood vessels. Some common CVDs include hypertension or high blood pressure, a cerebrovascular disease which is known in the common parlance as stroke, coronary heart disease, or mostly known as heart attack [68]. Some of the risk factors associated with the CVDs are smoking, increased cholesterol, and triglycerides levels in the blood, hypertension, sedentary lifestyle, diabetes, and obesity [69]. Some of these life-threatening diseases can be predicted by the use of IoT based health monitoring systems. The risk factors associated with CVDs can be monitored for their prevalence. There are several use cases discussed in the literature which follow different architectures. However, most of these architectures are based on the widely accepted three-tier structure. The input for the detection and analyzing the CVDs is the electrocardiogram (ECG), which is the electrical activity of the heart. Fig. 6 gives a general idea about the architecture of these systems. A system for determining the HRV is proposed to majorly predict the occurrence of myocardial infractions (Heart Attacks) [41]. The body temperature is also measured along with the pulse that gives a better estimate of the health status. A four-layer architecture is taken as a reference, and based on this; a five-segment methodology is formulated. The four segments are serviced by an IoT Platform Manager, which is the fifth segment. It manages the collected data from the sensors. The sensors are supported by virtual sensors that contain the programmable construct for the deployed sensors. The mobile applications are the interface for the user to the system. The healthcare services are managed according to the IoT platform manager. The communication between the segments and the manager is done via a Representational State Transfer (REST) API.

The use of fog computing in the IoT has significantly improved the performance of IoT networks by reducing the response time between the IoT network and the IoT services, less delay, and jitters [70]. This advantage of fog computing has been exploited to create a system to predict the occurrences of hypertension attacks. The hypertension attack prediction can be carried out by analysis of the data captured by the sensors at the fog layer of the proposed three-tier architecture. The utilization of Artificial Neural Networks (ANN) to monitor the multiple risk factors helps in generating an alert for immediate medical assistance. The cloud layer stores the long-term data, including the alerts that are generated and to facilitate the universal availability of the data.

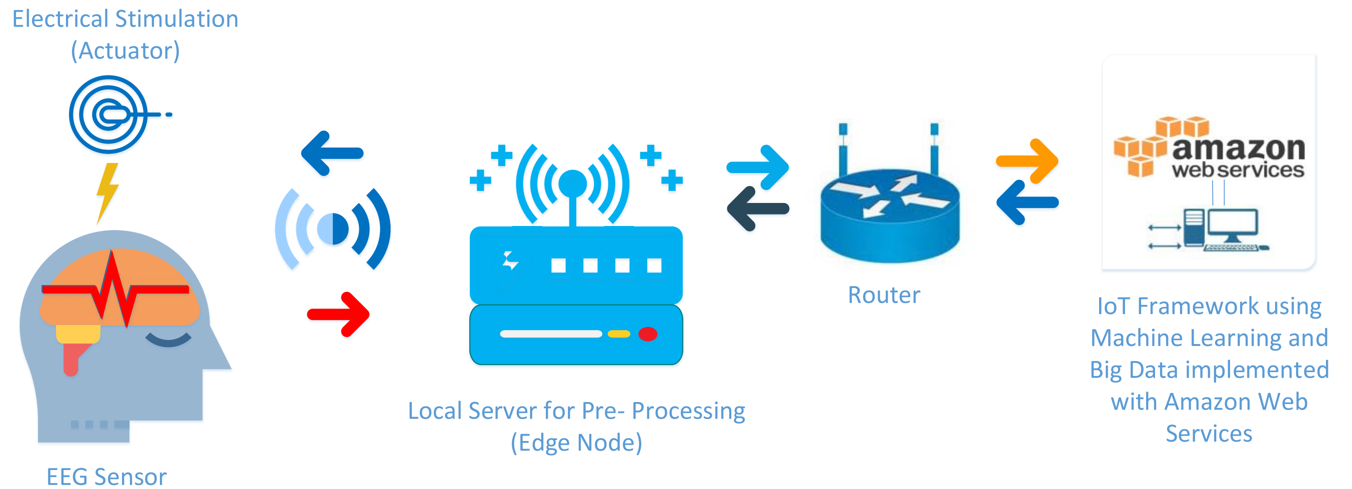


Fig. 7. The Architectural Framework for Real-Time Sensing and Seizure Suppression Systems for Epilepsy.

A federated approach is adopted [71] to provide scalability, energy efficiency, and flexibility in the monitoring of the cardiac condition for patients suffering from Congestive Heart Failure (CHF). The federated system is divided into three subsystems that share common resources. The collected data is processed locally using the personal server, which is essentially a low-power processing device located in the collection station. The cloud system carries out heavy calculations and big data storage. The analysis of the large volumes of data provides a better classification. The observation station consists of the healthcare providers on the ground. Different services can access the data; therefore, extending the interoperability among many platforms.

### *B. Neurological Disorders*

One of the major application areas of the H-IoT is the diagnosis of neurological diseases such as epilepsy, Alzheimer's disease, and Parkinson's disorder (PD). The patients are monitored for the electrical activity of the brain, called the electroencephalogram (EEG) and gait patterns to help in diagnosing these problems. EEG is a standard tool used for the detection of neurological disorders [72]. The IoT systems continuously monitor the body movements, body temperature, sounds to detect the presence of an epileptic seizure [73]. In [74], the authors provide a framework for predicting the occurrence of seizures using a combination of feature extraction and classification algorithms. The authors propose the classification algorithm based on the features of each patient to enhance the accuracy of the algorithm. A similar approach is taken up for the detection of the tremors and gait patterns, which can help in the diagnosis of PD. A framework for the detection of epilepsy has been implemented by the use of EEG capturing sensor-equipped headband that is connected to an intermediary device that acts as a gateway as well as an edge node in an IoT based architecture. The captured EEG data is processed at the gateway, and emergency alerts are generated to alert the caregivers. The intercessor transmits this data to the cloud, where it is stored for the long-term analysis and precision diagnosis by healthcare professionals [75]. The use of big data and convolution neural networks (CNN) can also predict the occurrence of the seizures by analyzing the pre-ictal EEG. The convolution of cloud computing and the pre-processing at the network level provides the capabilities not just to predict the seizures but can also be used to generate a stimulus signal to suppress the seizure [76]. The framework for such applications can be depicted in Fig. 7.

Tremors are a major symptom of PD and can be quantified by using a combination of a gyroscope and an accelerometer. Proprietary sensors are available that can record the body movements, and from the generated data, the condition of the patient can be determined for treatment. The collected data is pre-processed at the device level. The pre-processed data is transmitted to the diagnosis level via a gateway. The diagnosis system is accessible by an interface such as a mobile application [77]. Along with the tremors, freezing of gait (FoG) is another symptom of PD. An inertial sensor can be used along with a commercial smartwatch equipped with health tracking sensors that can track multiple vitals and body movements. The architecture followed is a three-tier architecture with the sensors constituting the device layer. A smartphone acts as a gateway for the sensors. The collected data is finally transmitted to the cloud layer, where it is analyzed for developing a real-time detection of FoG events and sleep diseases [78]. It causes highly adverse effects on the quality of life (QoL) of the patients. The basic activities, like feeding and picking up objects, become virtually impossible due to tremors. A framework based on ML and IoT is proposed to enable the patients to self-feed. The role of IoT and ML is to track the health status of the patient and to help in the calculation of the counter forces to balance out the tremors. Most importantly, this system helps in the determination of the rate of deterioration of the patient's condition as PD is a neurodegenerative disorder. Alerts can be generated based on the patient's condition. The architecture followed includes a sensor layer that collects the data from the self-balancing spoon. The data is processed at the Proportional, Integral, and Derivative actions (PID) controller that transmits the long-term data to the cloud. The PID controller provides immediate feedback to the spoon for balancing [79]. Another major health challenge that is mostly faced by developed countries is Alzheimer's disease (AD). It is characterized by dementia that makes independent living virtually impossible. Therefore, an ICT based solution for the monitoring of the patients suffering from PD and AD has been proposed. The architecture consists of three sub-systems. The low-level subsystem is responsible for the detection and tracking of abnormal behavior and condition. The high-level subsystem is responsible for decision making based upon the input from the low-level subsystem and medical data stored. The top layer is an interface for the patients and caregivers that allows entering the data and its manipulation for aiding the decision-making process [80]. For the management of patients who have dementia, the use of ML algorithms and data analysis algorithms on the sensor collected data is enabling the caregivers to obtain alerts in case of any mishaps or emergencies [81].

The work presented in [82] presents a multi-modular input for studying the effect of virtual reality (VR) on the ability to relax or meditate. The effect is studied by using EEG, ECG, breathing levels, and body motion as input and applying real-time analysis.

### C. Ambient Assisted Living

The population aging is a global phenomenon where it is predicted that 10% of the population in the Organization for Economic Co-operation and Development (OECD) countries will be more than 80 years old. Overall, the population will age rapidly in non-OECD countries also but at a slower rate [83]. Therefore, dependency on healthcare facilities will grow exponentially. *Wan et al.* [84] present an overview of the Assisted Ambient Living (AAL) systems based on IoT. Their analysis suggested a class four-layer architecture for implementing AAL systems with capabilities for remote monitoring of users, detection of emergencies such as falls and behavior monitoring. Fig. 8 summarizes the architecture presented in [84]. The sensing layer comprises the sensing systems that include the sensors and trackers. The networking layer is composed of communication networks like Wide Area Networks (WAN), Internet, and Personal Area Networks (PAN). The data processing system is the third layer in the architecture with faculties for multiple approaches. The fourth layer, i.e., the application layer, utilizes the former layers as support systems as it defines the use cases for AAL.

The AAL system performance can be amplified by the inclusion of cloud technology in the architecture. An architecture with cloud capabilities is proposed. The use of cloud provides the capabilities for data analytics, interoperability with multiple systems and mobility. The proposed architecture in [85] is a three-tier architecture with a perception layer, a network, and gateway layer, and an integrated application layer. The Perception layer includes the data collecting faculties and short-range communication systems with the gateway. The gateway in the proposed work is based on Raspberry Pi that utilizes the Message Queue Telemetry Transport (MQTT) protocol for communication. The Integrated Application represents the backend or the IoT infrastructure for analysis of

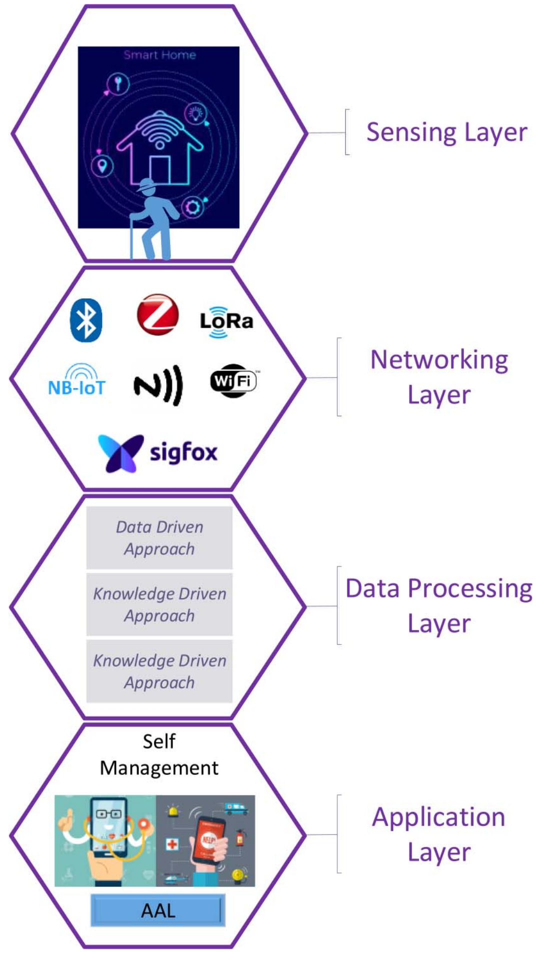


Fig. 8. Architecture of Ambient Assisted Living Systems with IoT.

collected and user interface for healthcare providers, emergency services, and the patients. The European project called City4Age amplifies the scale of this proposed architecture. It is a part of the H2020 research and innovation project [86] that expands the AAL capabilities from smart homes to smart cities. The proposed method is focused on the detection of geriatric conditions and Mild Cognitive Impairment (MCI), which are associated with increasing age. The bottlenecks in the implementation of such systems include low throughput, secure economic and rapid sharing of information, relevance, and accuracy of detection algorithms that require a suitable baseline, which is developed based on reference datasets. The proposed architecture includes the creation of a shared repository of data that is collected unobtrusively via the smart city sensing infrastructure. The authors have developed a REST-application programming interface (REST-API) to manage the database. Fig. 9 summarizes the proposed method in [86], [87]. Another European project called the "NOt Alone at Home" (NOAH) presents a platform for end-users and caregivers. The solutions are proposed for the analysis of streamed data and data access methodologies on the cloud [88]. The proposed architecture enables the user to access the cloud-based data analytics services via a mobile application. The backend support is provided by the IBM Watson and Data Science Experience, which are

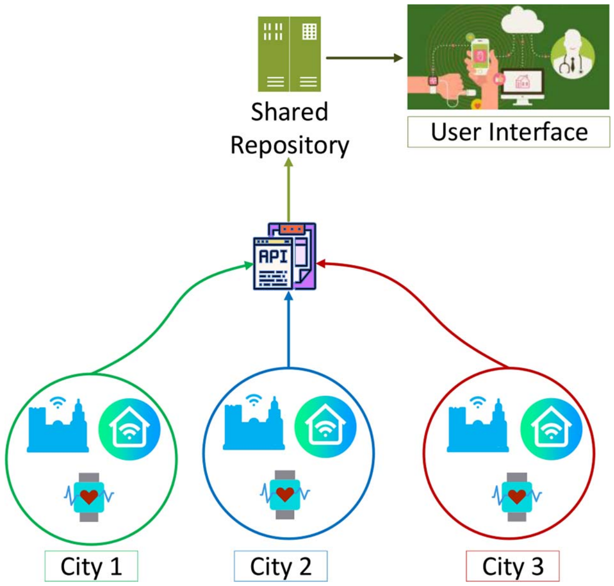


Fig. 9. AAL System Supported by Smart City Infrastructure.

cloud-based services data analysis of International Business Machines (IBM). The entire system mimics the three-layer architecture with a user-accessible mobile device layer, and Internet supported cloud services layer and the third back-end layer that comprises of the internal network. A novel application of wearable glasses is presented in [89], which allows the people with Disabilities of Arm, Shoulder, and Hand (DASH) to establish their identity by vocally inputting the passcodes on the computer terminals, thereby creating a hands-free authentication system. The proposed system uses off-the-shelf Google Glasses.

## D. Fitness Tracking

The major application of IoT in healthcare is fitness tracking using wearables that are available in the consumer electronics domain. The domains include smart wrist bands that track motion and pulse and smart clothing that can monitor cardiac activity. The overall data collected is used to determine the fitness levels of the user, particularly sports persons [90]. The use of an array of sensors to measure the overall fitness of the user is proposed in [91]. The device layer is an input interface between the user and the local processor in a three-layer architecture. The locally processed data is sent to the database server for storage. The database is remotely accessed by the user to keep track of health parameters. The sensors considered in this work include pulse sensors, temperature sensors, and accelerometers to track the moment and a Grove GSR sensor that analyses body sweat. All the sensors are attached to the commonly available fabric that emulates a smart fabric. For determining the effectiveness of gym training, a user-tailored workout plan determination system is proposed [92]. The proposed system uses proprietary *Apple Watch* and to access the data, Apple's health application is used. A system to track the fitness of a bike rider is proposed in [93]. Besides, it also detects the bike theft. The system architecture is two-pronged based on the application sharing a common backend

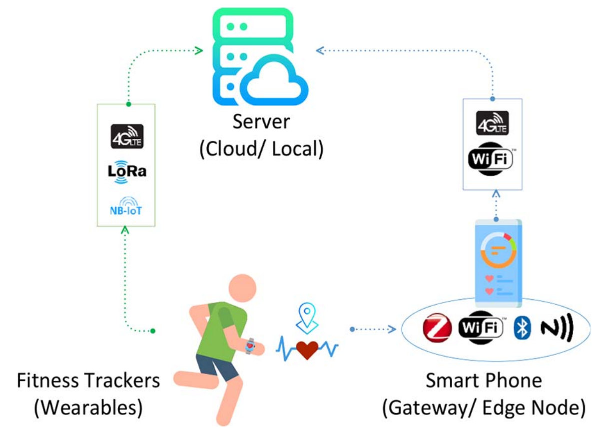


Fig. 10. An Overview of Fitness Tracking System.

system and communication system. The three-stage architecture has a sensing module and bike safety module at the user end. The heart rate is the main input for the detection of health parameters, while the bike safety system depends upon readings from an accelerometer. These two systems work in synchronization, and the collected data is sent to an android app where the user can monitor the health parameters and bike lock status. A comprehensive system of tracking human fitness is proposed that is aimed at the recognition of physical activity like running, walking, and resting [94]. The architecture is divided into three layers, a BSN layer that contains the sensors. The BSN is connected to the processing block, the cloud-assisted layer that is implemented using MATLAB, and an IoT analytics tool called ThingSpeak. The analyzed data is accessible to the user via the third layer, an application for PC and mobile. A mobile phone acts as a gateway between the BSN and the Cloud Assisted layer. Fig. 10 summarizes the fitness tracking systems deployed using IoT.

*Summary of the Section:* In this section, an overview of the use cases of H-IoT is presented. Using the QoS as a basis, architectural frameworks are proposed to optimize the said QoS. Based on the requirements like low latency in stroke detection, an edge node is introduced [70]. For the sharing of data among the various authorized parties, cloud architecture is proposed [41]. Table IV highlights the various works analyzed in this section. From the discussion, it is clear that a three-tiered architecture is adopted by the majority of the works cited in the section. The application determines the sensors selected in the things layer. The various specialized sensors are used to collect the data from organs like the heart, brain, or skin. The collected data is an accumulation of useful data and noise signals. Among the many advantages of edge computing, the sensed data signals are de-noised before its transmission at the device itself, if the sensing device can support edge computing. In the opposite case, the signal can be de-noised and pre-processed at the gateway. The gateway devices are usually more capable than the sensors in terms of processing and energy resources. Efficient and secure transmission protocols like the NB-IoT and BLE are used for the communication between nodes and gateway. The processing of the collected data is supported by AI algorithms such as ANNs and CNNs. The ANN and CNN are

TABLE IV
SUMMARY OF THE USE-CASES AND THEIR ARCHITECTURES IN H-IOT

| Reference | H-IoT Framework | Use Case | Underlying Technology |
|---|---|---|---|
| Yin *et al*. [37] | IoT based rehabilitation system formed around a three-tier architecture | Assistive Healthcare System | Big Data for rehabilitation |
| Kaleem Ullah *et al*. [38] | Four-layer architecture for patient health data management | Assistive Healthcare System | ML for alert generation |
| Gardašević *et al*. [39] | Architectural standardization of IoT for multiple domains | Messaging Protocol for IoT | Evaluation of network layer protocols |
| Kamaruddin *et al*. [69] | Detection of CVDs using machine learning | Cardio Vascular Diseases | ML for arrhythmia detection |
| Singh *et al*. [41] | IoT Framework for health monitoring system supported by cloud | Cardio Vascular Diseases | Cloud services for alert generation |
| Abawajy *et al*. [71] | A cloud supported IoT based pervasive patient health monitoring system for patients with congestive heart failure | Cardio Vascular Diseases | ML for ECG classification |
| Jagtap *et al*. [73] | IoT based epileptic seizure detection system using temperature, motion and sound sensors | Neurological Disorders | Online databases for EEG classification |
| Nassralla *et al*. [74] | A Patient-aware epileptic seizure detection using spatio-temporal feature identification and classification | Neurological Disorders | ML for EEG classification |
| Lin *et al*. [75] | Cloud supported IoT epilepsy detection system using EEG | Neurological Disorders | Cloud Computing |
| Hosseini *et al*. [76] | IoT and deep learning-based seizure detection and localization system | Neurological Disorders | Big Data for seizure detection |
| Vijay *et al*. [77] | Detection of Parkinsonian tremors using wearable based IoT | Neurological Disorders | MEMS based IMU solution for PD classiication |
| Šatala *et al*. [78] | IoT systems to study the sleep patterns and FoG for Parkinson's patients | Neurological Disorders | FoG pattern classification |
| Baby *et al*. [79] | Anti-spill spoon for detection of Parkinson's tremor's and improving QoL of the patients | Neurological Disorders | ML and Cloud based feedback |
| Alvarez *et al*. [80] | An IoT platform for monitoring patients from Alzheimer's and PD using sensor fusion and cloud computing | Neurological Disorders | ML for activity recognition |
| Enshaeifar *et al*. [81] | A technology Integrated Health Management System based on IoT architecture for management of geriatric population especially for dementia | Neurological Disorders | Big Data assisted with cloud based system |
| Wan *et al*. [84] | A four-layer IoT architecture for AAL systems | Ambient Assisted Living | Review work of AAL supporting technologies |
| Rashed *et al*. [85] | An integrated three-tier system for monitoring patients in an AAL environment supported by big data analytics | Ambient Assisted Living | Big Data based AAL system |
| Mulero *et al*. [86] | An EU project for AAL supported by smart city infrastructure called City4Age | Ambient Assisted Living | Big Data based AAL system |
| Almeida *et al*. [87] | City4Age project for detection of Mild Cognitive Impairment using IoT | Ambient Assisted Living | Big Data assisted risk analysis |
| Moraru *et al*. [88] | A smart home based AAL system supported by cloud storage | Ambient Assisted Living | Cloud based AAL system |
| Damopoulos et al. [89] | A hands-free voice enabled authentication system called Gauth for patients suffering from DASH using Google Glasses | Ambient Assisted Living | ML and Cloud based authentication system |
| Kansara *et al*. [91] | Development of a smart fabric for monitoring multiple vital signals | Fitness Tracking | Smart fabric and Cloud based H-IoT |
| Ferreira et.al [92] | Generation of a personalized workout plan for fitness using wearable generated data | Fitness Tracking | Wearable based health tracking |
| Nath *et al*. [93] | IoT based analysis of fitness data for the monitoring the health and safety of bicycle rider and security of the bicycle | Fitness Tracking | Cloud based data repository |
| Santamaría et al. [94] | Use of fuzzy logic on IoT data for monitoring the health | Fitness Tracking | Sensor fusion and fuzzy logic |

relatively resource-intensive algorithms. Therefore, fog computing is highly significant in H-IoT for providing support in improving the latency and processing delay. The data for the long-term storage and generating trends is sent to the cloud. Therefore, the interaction between the various technologies enables a seamless and ubiquitous H-IoT that can diagnose

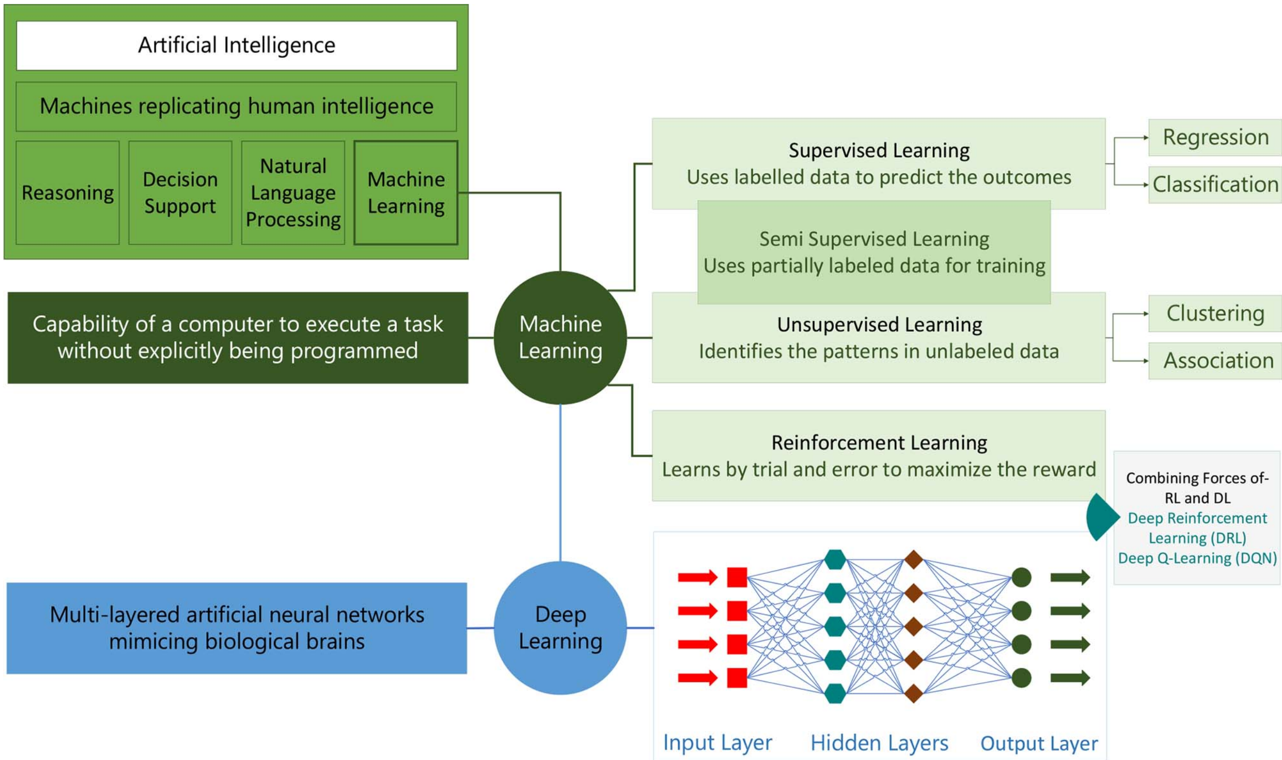


Fig. 11. Relationship between AI, ML and DL.

and predict medical emergencies and help in long-term care. However, the challenge for the research community lies in seamlessly integrating these diverse set of technologies. Thus, improving the reliability of these systems. The solutions to these impeding challenges can elevate H-IoT systems as the primary healthcare measure.

## V. Machine Learning in H-IoT

The application of ML is taking the lead in all the research fields as well as the industry. At the Consumer Electronics Show 2019, an annual event that gives an insight into the technological trends for the upcoming year, artificial intelligence (AI) has been called the next chapter in human progress [95]. A large number of consumer devices, especially in the healthcare sector, were unveiled, of which the majority is powered by AI. Wearables, lifestyle, and assistive devices for rehabilitation, body care, and disease diagnosis are becoming increasingly ubiquitous [96]. In this section, we explore the use of ML in H-IoT. AI empowers the machines with human-like intelligence. AI is a term that encompasses ML. AI includes capabilities like natural language processing, perception, and knowledge-based decision making. ML enables the machines to learn without any explicit programming. The ML algorithms can create models from the labeled or unlabeled datasets for making predictions. The ML algorithms can also learn from itself without using any previous datasets. It helps in classifying the ML algorithms into three classes, supervised, unsupervised, and Reinforcement Learning (RL). Some of the examples of ML algorithms are K-Means, support vector machines (SVM), and Naïve Bayes. The semi-supervised learning algorithms are an intermediary class of ML, where the majority of the training data is unlabeled, but a small part of the data set is labeled. Deep learning (DL) is also a sub-class of ML that tries to mimic the decision-making process of the human brain. It is a multi-layered system with higher capabilities. Some of the standard DL algorithms are CNN and deep belief networks (DBN). The collaborating DL and RL algorithms exploit the advantages of both the approaches, yielding high-performance algorithms like Deep Q-Networks (DQN) [97]. Fig. 11 shows the relationship between AI, ML, and DL [98].

ML is having a revolutionary impact on all the scientific areas, including IoT. The use of AI is transforming the healthcare applications of IoT. The significant impact of AI has been on the detection and prediction of disorders that required complex medical tests. The use of ML can help in the diagnosis of the disorders in real-time and provide personalized healthcare. The applications of ML in H-IoT is in three major areas to provide personalized healthcare [99],

1. Diagnostics.
2. Assistive Systems.
3. Patient Monitoring and Alarm Systems.

ML can help in the remote diagnosis as well as real-time diagnosis of disorders in the absence of established healthcare services. Assistive systems contribute to the rehabilitation of patients after trauma or treatment procedures. As discussed in the preceding section, AAL is supported by the monitoring systems for the elderly and the immobilized patients. However, it is seen that the deployment of H-IoT in the diagnosis and treatment of CVDs is a very practical approach. The early prediction of cardiac arrest using IoT systems is proposed in [100]. The collected ECG data is processed for the removal of the high-frequency noise components. The prediction algorithm is implemented in two stages where the first stage compares the features of the heart activity and the body temperature with the threshold values. If the thresholds are violated, the fluctuations in the cardiac activity is predicted, and an appropriate alert is generated. The continuous monitoring of the ECG via the wearables can yield the HRV value. The HRV can, in turn, be used for the prediction of arrhythmias. The use of the k-Nearest Neighbors (kNN) classifier has resulted in a high accuracy of 97% in detecting the arrhythmia of the heart in real-time [101]. In the proposed methodology in [101], there is a provision for uploading the data to the electronic health records (EHR) for future references. It is noteworthy that the ECG waveforms are inflicted by noise and artifacts by body movements and interference. Therefore, it becomes necessary that these artifacts are removed, and only true ECG signals are processed. Therefore, [102] provides a signal quality-aware system for the detection of CVD's using ML. The proposed technique evaluates the signal quality by the implementation of an ML-based Signal Quality Assessment (SQA) algorithm. The result of this evaluation decides if the signal is going to be processed for further analysis. If the signal quality is unacceptable, the data is discarded; otherwise, it is sent for storage and analysis. This ML-based approach helps in improving the energy efficiency of the system by saving the resources from being utilized by preventing the noise infested, and low-quality data from processing and transmission. This also helps in providing better mobility and freedom of movement for the user without hampering the accuracy of the system as the system has been tested for various scenarios. Stroke is one of the most common CVD that renders limbs paralyzed in many cases. Therefore, IoT has been used for the rehabilitation of the limbs after a stroke. For this purpose, an armband with the sensors for the detection of the surface EMG signals (sEMGS) is designed. The data collected by these variables is processed by ML-based classification complexity estimating algorithms (CCEAs) and principal component analysis (PCA). This system can identify the gestures from the sEMG signals with an accuracy of about 97%. The results are verified by the real-time control of a 3D printed robotic hand that is controlled by the processed sEMG signals [103].

The impact of H-IoT is immense in AAL applications. ML is enabling a myriad of applications in the AAL domain. The use of ML in the detecting patient's fall is implemented in a cloud and edge-based architecture. The ML-based approach for analyzing the video feed from a camera in the smart home environment yields an impressive result of more than 99% accuracy in detecting a patient falling. This methodology is effective in non-edge architecture too [104]. To enhance the AAL scenario for fall detection, a combination of detection of falls along with the risk factors can be implemented. The work in [105] proposes an algorithm to estimate the risk factors and fall detection based on ML algorithms. However, this methodology uses gyroscope generated data as input. In the proposed scheme, four ML techniques are used with kNN yielding a peak accuracy of 82.2%, and with the inclusion of risk factors, the peak accuracy increases to 84.1%. The position of the gyro sensor affects the results with wrist-worn sensors yielding better results than the waist-worn sensor. AAL includes the monitoring of sleep patterns as one of the aspects of importance. The analysis of sleep patterns can help in developing healthy sleeping habits as there is a direct effect of sleep on human health. The sleep patterns can be detected by using multi-modal inputs such as ECG, EEG, and electrooculogram (EOG), which is the activity of the eye. In [106], a multimodal input is analyzed by using DL algorithms to classify the sleep patterns. A three-layer methodology is used, where the first step uses a DBN to classify the input signals that are captured from a smart mattress that detects the above-listed vitals. The classification is improved by the use of Long Short-Term Memory (LSTM) that helps in learning the long-range dependencies in temporal data. The processed data is then clustered for the different sleep patterns using a k-medoid algorithm into groups that label the sleep patterns into normal and abnormal classes. In addition, the eye movements are also taken into consideration for detecting the sleep phases such as the Rapid Eye Movements (REM). Posture recognition during sleep is essential for the analysis of sleep patterns. Usually, the posture during the sleep is detected by using a pressure sensing mattress that records the pressure on the different areas of the mattress. The SVM is an ML algorithm that is used for the classification of data into clusters. The sensor data is pre-processed using PCA for feature extraction. The features are then finally classified using SVM into three postures that can be used for the determination of healthy sleep [107]. One of the capabilities of the AAL systems is activity recognition in the smart environment. The capability to identify the activities of the user can help in improving the health services and personalizing the treatment. Implementing ML can exponentially enhance the performance of the activity recognition. The approach proposed in [108] is novel in the sense that it uses an indirect approach for sensing user activities. The proposed technique includes sensing the link quality between multiple nodes deployed around the user. The path loss between the nodes is computed to estimate the channel link quality, and this data is subjected to ML-based classifiers to identify the activities performed by the user. The transmitting and receiving nodes may be on the person or off person. The performance analysis for different scenarios concludes that SVM provides accurate results at the cost of latency. The Linear Discriminant (LD) analysis yields fast results, but the Random Forest (RF) classifier offers the best accuracy. The classification algorithms tested offer impressive results in identifying the activities performed by the user, but the optimality of usage depends on the QoS requirements, such as computational simplicity and latency.

The breakthroughs in prosthetics technologies are a direct impact of advances made in the Brain-Computer Interfacing (BCI) systems. The BCI systems are gradually improving the Quality of Life (QoL) for the people inflicted by disabilities and debilitating disorders by realizing what is known as Assistive Systems. A system of learning the EEG patterns to enable the quadriplegic patients to lead a normal life by assisting them in generating speech from brain waves using the text-to-speech functionalities [109]. The Intel cloud-based analytics systems enable the interpretation of emotions from the EEG signals. The sensors also record the vital body signals of the patients to monitor their health. Authors in [110] have proposed a system to identify the blinking movements of the eyes as the input to control the devices to enable disabled patients to lead an independent life. The proposed system in [111] extends the use of BCI for the development of typing systems from the EEG patterns. The other application tested is the control of robots for domestic assistive purposes. This approach helps to provide support to the speech impaired or disabled people. The use of RL is central to the study and classification of EEG patterns that are used as the input. This work uses a combination of Selective Attention Mechanism (SAM) and LSTM to develop a self-learning system that adapts to the user and becomes personalized to the user. The use of deep learning algorithms can establish the baseline features of the human EEG for that particular user. The ramifications of this feature are immense in the detection of the disorders of the Central Nervous System (CNS). A DL approach for the prediction and localization of the epileptic seizures is proposed [76]. The authors have proposed a prediction system and a seizure localization system as two sequential steps with a combination of ML and DL systems for feature extraction from the EEG and Electrocorticogram signal (ECoG) input. The SVM classifies the features as normal and abnormal. The results are optimized by including an optimization algorithm based on a hybrid approach. The future work outlined includes the design of a system for the delivery of inhibitory signals for seizure suppression. The proposed systems should fulfill the QoS parameters for their application area. However, all these systems are IoT based, so it becomes imperative that the proposed systems are suited to resource-constrained environments. The work in [112] is aimed at compressing the data by 50% by exploiting the sparse representation methods. The accuracy reconstruction of the compressed data is nearly 90%. The proposed system is implemented on a Field-Programmable Gate Array (FPGA) hardware equipped with an Advanced RISC Machine (ARM) processor. The algorithm used is based on Multi-Layer Perceptron (MLP) that consists of multiple cascaded layers for compression and reconstruction of the input signals. The added benefit of the compression is the energy efficiency of the system, which accompanies the reduced transmission and stored data. Multiple works have been identified in [113] that outline the use of BCI and ML mechanisms for application in the BCI field for operating prosthetics.

The development of real-time disease detection systems is an area of interest for many researchers. In this direction, many researchers have proposed frameworks for an online system for the detection of common disorders using System-on-Chip (SoC) based IoT systems. A use case for the detection of breast cancer using a programmable device for microfluidic analysis is proposed in [114]. The analysis of body fluids can be performed on at the Point-of-Care (PoC) using an implant or a wearable. The results can be analyzed using ML-based data analytic tools. This paper lays out the requirements and presents the argument for such online systems. The work in [115] presents a system for managing healthcare data using ML in an IoT environment for patients suffering from diabetes. The integration of big data, IoT, ML, and cloud technologies in the proposed system helps to assist the caregivers in providing personalized treatment to diabetic patients based on the health data collected over a period of time. To combat the diseases proactively, authors in [116] present a framework to classify the recorded health parameters from an IoT environment using ML-based classifiers to estimate the prevalence of a medical condition. The classifiers analyze the patient records and compare the historical records to check for breach in the threshold limits of the vital parameters. In case of a breach, an alert or feedback is generated. The performance of this system is, however, based on the ability of the classifiers to group the data accurately, which in turn depends on the quality of the labeled data fed during the training of the classifier. A Generative Adversarial Network (GAN) is an unsupervised learning algorithm that is used for improving the quality of the labeled data for improving the classification process [117]. The GAN is, in essence, an unsupervised learning algorithm that is implemented to generate artificial data to balance out the datasets with each type of data in a well-distributed manner. This data is used to train classic classifiers such as SVM and KNN, for improving their performance. Therefore, the entire process can be termed as a semi-supervised. The results tested against the datasets for cerebral stroke reaffirm the positive impact of this approach in assisting the doctors in making informed decisions for the treatment of the patients. The use of ML can then also be extended in the decision-making process for the caregivers in the real-time. Based on data mining tools along with the ML tools, robust feedback systems can be implemented in the AAL and self-care environments [118].

Several sensors are embedded in many common devices that we use in our daily life. ML can open a number of avenues for application in several fields, especially H-IoT [119]. The integration of the AI at the device level can help in expanding the adaptability by making these systems smarter, personalized, and accurate [120]. To validate the importance of the on-node processing capabilities, authors in [121] have implemented a DL based proposal that adapts to the low resources by reducing the number of hidden layers in the neural network. The obtained results demonstrate the feasibility of implementing this algorithm at the mobile device level. However, the real challenge lies in adapting to the low power sensors that are the most constrained.

One of the primary concerns associated with the implementation of H-IoT systems is security and privacy. This issue is serious when the patient-generated data is sent to the cloud for processing. It becomes imperative that the data should be protected from all breaches. The manipulation of data can have severe implications for the users and may prove fatal in some cases. Any manipulation in labeled data can create biases while training an algorithm. Therefore, there is a requirement of efforts to secure the system at all levels. ML is a powerful tool being used for improving the security of the H-IoT system. Authors in [122] have proposed a system for preserving the privacy of the users in an AAL environment by using DL. The proposed method uses LSTM for encoding and decoding the data. The encoding and decoding are done based on the data access permission. The appropriate permission holder can access the data by having the adequately matched decoder based on the permission. The LSTM can identify the different data types and is, therefore, able to assign access based on the permission levels of the users. The manipulation of data by a malicious entity or by the operation of the sensors in non-optimum conditions can skew the performance of the H-IoT system. The proposed method [123] uses statistical methods along with the Otsu's thresholding method to define the boundaries of the feasible values that a sensor can detect. A liner kernel SVM, a supervised ML algorithm, is used to classify the data into true and modified classes. The algorithm has displayed impressive accuracy for classification when implemented on a blood glucose sensor in an H-IoT environment. The use of nature-inspired algorithms for the *Intrusion Detection System* (IDS) in IoT is well documented. The bio-algorithms have the potential for implementing autonomous control in H-IoT. Additionally, to secure the sensitive health data, Swarm Intelligence-based IDS [124]

We have discussed human activity recognition in previous paragraphs. However, the same methodologies can be applied for the localization of a user in a smart environment using ML. The proposed approach [125] can identify the location of the user by using the data from multiple sensors, MEMS-based gyroscope, magnetometer, and accelerometer. Multiple nodes of the combination of these sensors are deployed to gather data on the activities. The data gathered is subjected to ML classifiers such as Naïve Bayes, kNN, SVM, and ANN that estimate the position based on the activities of the user. Different classifiers had varying performance based on the activity. The use of cellular data for activity recognition is proposed in [126]. In the proposed system, the cellular signal quality (CSQ) is exploited to determine the location in the surroundings and, in essence, determine the actions performed by the user from the change in CSQ. The supervised learning-based classifiers can identify the actions performed by discriminating between the body movements and the environment. The decision tree (DT) classifier and LSTM demonstrate a similar performance with an accuracy of 90%.

ML algorithms help in enhancing the overall performance of the H-IoT systems. A standout parameter that can be enhanced is the battery life of the wearable sensors in an H-IoT system using ML [127]. Usually, the sensors send all the raw data to the processing unit, thereby utilizing energy resources. The proposed work implements the SVM optimized embedded ML to preprocess the data and classify the data onboard. The results show an astounding increase in the battery lifetime from 13 days to 997 days.

IEEE 802.15.6 is standard developed by IEEE for real-time monitoring of health parameters for WBANs. The selection of frequency channels in WBANs is a critical operation as the QoS for such applications includes low latency and high fault tolerance [128], [129]. The work proposed in [130] proposes a channel selection algorithm based on RL to meet the QoS requirement of the H-IoT. The proposed method called an RL Channel Assignment Algorithm (RL-CAA). It utilizes the channel loads to learn traffic patterns on different channels. The proposed scheme outperforms the static methods of channel allocation.

The routing algorithms proposed for the healthcare-focused IoT systems should optimize not only the routing decisions but also improve the energy efficiency and network lifetime. Most of the energy efficiency-based routing protocols are successful in the elongation of network lifetime [131]. But, the fulfillment of the other QoS parameters is equally essential. The proposed work introduces the use of RL for the routing decisions in the WBANs [132]. The use of clustering helps in the reduction of the power utilization of the power-constrained network. Q-Learning is an RL learning technique that is utilized for finding the optimal routes between the source and the sinks and improving the power consumption at the same time. Clustering mechanisms help in improving the energy efficiency by reducing the load from all the nodes and selecting a cluster head that bears the most load. This principle can be applied by taking into consideration that sensors in an area may collect redundant data. Therefore, data aggregation methods based on ML can be used to aggregate the data that is useful and has a higher priority. In [133], the authors propose an SVM based classifying mechanism to aggregate the data based on the priority and the data type. This method improves load –balancing and hence, energy efficiency. This can assist the routing algorithms in making more informed routing decisions in a critical IoT system.

*Summary of the Section:* From the above discussion, we can conclude that the impact of ML on H-IoT is immensely profound. The ML algorithms in H-IoT not only optimize the performance parameters by enhancing the network metrics but also enhance the overall QoS of the deployed system. Data analytics is an important area where ML is used in H-IoT. The classification of input health vitals and generation of feedback based on the classification is the primary use of ML at this level. Activity recognition for tracking the fitness and detection of falls and injuries is another promising application. The alert generating systems in AAL environments using vital data monitoring and activity recognition are some of the most important applications of ML in H-IoT based systems. BCI systems exploit the advantages of AI for high-performance prosthetics. The modalities like routing, energy management constitute the QoS enhancement using ML. ML is actively used in data management, network security, and data preservation.

We can depict the summary of this section using Fig. 12. Similarly, Table V presents the findings from the surveyed literature in a tabular representation. While this section provides an insight into the applicability of AI in H-IoT. There is a primary challenge that is required to be addressed in terms of processing capabilities. Most of the algorithms that the authors have proposed using neural networks that are usually more resource-intensive. The RL algorithms, at the same time, require much lower computational resources. Additionally, there is a large volume of data that is collected per unit time. However, the current algorithms fail to exploit all the useful information from the collected data. Thus, resulting in a significant performance loss as the processing power is dedicated

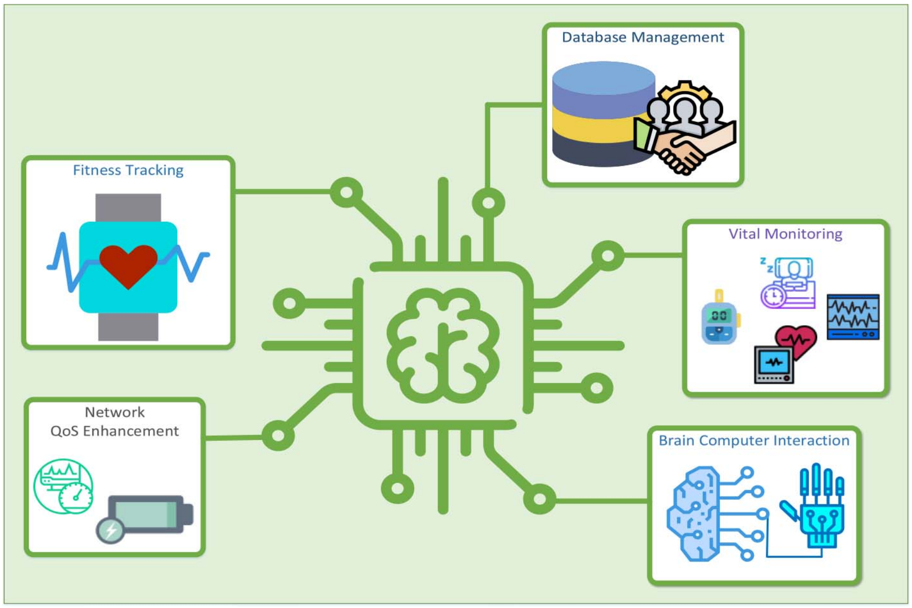


Fig. 12. Role of ML in H-IoT Systems.

to computing the limited amount of information from a large dataset resulting in information deficit.

One of the future goals of H-IoT systems is autonomous operation and maintenance. Therefore, the use of the ML and specifically RL for the autonomous operation is yet to be realized. This is reflected in the legend in Table V.

## VI. Edge Computing in H-IoT

The increasing amount of data being generated by devices and then transmitted over the network is increasing at unprecedented rates. This has resulted in a need for bringing computational capability near the edge of the network to eliminate the need for transmitting the data to the cloud for processing [134]. Apart from this, the QoS requirements of the H-IoT system requires a guaranteed data rate and latency. The time-critical application systems, such as stroke alert systems based on ECG monitoring, require a maximum delay of 500ms for each electrode with a data rate of 4 kbps [135]. Similarly, real-time input-driven feedback systems also require low latency and strict data integrity. To alleviate the critical issues pertaining to latency, energy consumption, bandwidth utilization, and scalability, a new paradigm known as edge computing is being widely adopted. The inclusion of cloud computing has already contributed in mitigating the problems associated with the scalability of IoT systems. As a large volume of data is generated every second by massively deployed IoT systems, it becomes likely that the network resources are burdened beyond capacity. Therefore, to address these challenges, edge computing enables a faster response rate along with efficient usage bandwidth and power source [136]. Apart from ensuring the functions mentioned above, edge computing enables optimizing the network performance along with ensuring network security [137].

In 2012, Cisco introduced fog computing to bring the capabilities of the cloud systems to the network itself. Additionally, fog computing has been integrated with IoT to enhance scalability, security, ease of deployment, and autonomously manage the optimal functioning of the IoT network [138]. Fog computing enables the network to deliver the cloud services at the network level with the computational capabilities distributed locally at the network level, unlike the cloud systems, which are strictly centralized. The fog network is composed of cloudlets that can be considered as an extension of cloud servers. The fog nodes can be deployed on mobile nodes such as smartphones, high capability sensors, and gateways. These are usually at a single hop distance from the sensor nodes [139]. Fog nodes can also implement virtualization functions, which are supported by SDN and Network Function Virtualization (NFV). Fog computing can also be implemented at the base stations of mobile networks, therefore extending the scope of applications for its implementation [140]. The terms "edge" and "fog" are widely interchanged, but they are slightly different. Fog computing or fogging is more of an architecture that implements cloudlets as a part of architecture for performing a myriad of functions. In edge computing, the edge of the network, like a gateway or an access point, is made intelligent to perform a specific network optimizing tasks [141]. Edge computing is a hardware concept as opposed to fog computing. Fig. 13 illustrates the implementation of this paradigm to highlight the differences between the edge and fog computing in H-IoT.

H-IoT capitalizes on the advantages provided by these technologies. For H-IoT, the applications of edge and fog computing can be grouped into the following categories.

1. To reduce latency and improve response time
2. To reduce the energy consumption
3. To optimize network traffic and bandwidth utilization

TABLE V
SUMMARY OF THE ML APPLIED IN H-IOT

| Reference | Proposed Work and Use Case | Outcome |
|---|---|---|
| Walinjker *et al*. [101] | Calculation of HRV value from ECG data | 97% classification accuracy using kNN Classifier |
| Satija *et al*. [102] | Signal quality aware ECG classification system in IoT | Overall accuracy of 97% achieved |
| Yang *et al*. [103] | A stroke rehabilitation system utilizing EMG data for gesture recognition on prosthetic devices | Classification accuracy 99.87 % with PCA observed |
| Hsu *et al*. [104] | A fall detection system using sensors in smart home | Prediction accuracy of 99% achieved |
| Anupama *et al*. [105] | Fall detection using wearable motion sensors with risk factors taken into account | kNN classifier has an accuracy of 84.1% |
| Hong *et al*. [106] | Sleep pattern classification in an AAL environment | 91% classification accuracy using DBN-LSTM |
| Matar *et al*. [107] | Posture recognition for sleep pattern analysis | High accuracy observed with Cohen's Kappa =0.866 |
| Negra *et al*. [108] | Activity recognition using machine learning on path loss data in WBANs using two methodologies (M1 & M2) | The mean accuracy for Random Forest in M1 is recorded at 98.77 and for M2 is 49.6% |
| Kanagasabai *et al*. [109] | EEG data classification for BCI focussed on quadriplegics | Model for creating an independent life for disabled |
| Jagdish *et al*. [110] | BCI based system to control the smart home using ML | An average accuracy of recognition is 95.2% |
| Zhang *et al*. [111] | System for generating speech and automation from EEG signal analysis | The proposed technique has an accuracy of 93.63% |
| Shrivastava *et al*. [112] | A compression scheme based on ML for data compression in IoT | A compression ratio of 50% and reconstruction accuracy of 89.85% is realized with a MLP |
| Firouzi *et al*. [114] | Development of a model of an IoT based diagnosis system | A model for breast cancer testing on a micro-fluid testing IoT node is presented |
| Ara *et al*. [115] | Diabetes management system using ML | An ML and cloud-based system is tested for patients suffering from diabetes |
| Asthana *et al*. [116] | Classifying the input data and mapping the disorder with the wearable using ML algorithms | Generation of an alert based on the data |
| Yang *et al*. [117] | Decision support system using ML and data labelling using GAN | Semi-supervised learning for labelling the training data and a high accuracy stroke decision system |
| Nguyen *et al*. [118] | Review of the technologies for supporting H-IoT | ML base techniques for generating feedback in real-time |
| Shanthamallu *et al*. [119] | The scope of ML in the IoT applications is reviewed | The tools for implementing ML sensor level are reviewed |
| Knickerbocker *et al*. [120] | Heterogeneous integration of IoT technologies with AI | Lay the base for design of the PoC diagnostic sensors for disease detection |
| Ravi *et al*. [121] | Deep learning-based activity recognition using wearable sensors | Human activity recognition system with accuracy ranging from 95%-99% in different scenarios |
| Psychoula *et al*. [122] | Privacy improvement using LSTM Encoder Decoder | Permission based data access in AAL environment |
| Verner *et al*. [123] | ML based data classification system to detect data manipulations in WBANs | SVM based classification for with 100% precision and 99.22% recall |
| deArruda *et al*. [125] | Localization of the user using MEMS based sensors and ML | An accuracy of 97% recorded using kNN |
| Savazzi *et al*. [126] | ML based analysis of cellular signal quality for activity recognition | A 90% accuracy of detection of body movements using decision tree and LSTM |
| Fafoutis *et al*. [127] | Enhancing the battery life of the sensors using ML | SVM data classifier discriminates between essential and redundant transmission data extending the life of the sensor from 13 days 997 days |
| Ahmad *et al*. [130] | RL based channel selection technique in WBANs | RL-CAA is proposed based on the channel loads |
| Kiani [132] | Clustering approach for routing the data in WBAN | Q-Learning based QL-CLUSTER resulted in low latency scheme |
| Ghate *et al*. [133] | Data aggregation technique in the IoT environment | Achieving energy efficiency by aggregating the similar data in labelled classes |

Legend

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ECG Data | Activity Recognition | EEG Data | Diagnosis System | Sensor Level | Data Privacy | Cellular Level Application | H-IoT QoS | Channel Selection | Data Management |

4. To enhance the security of the transmitted data
5. To enhance the overall QoS of the H-IoT system

Several approaches have been adopted by many authors to implement the fog/edge paradigm in the H-IoT field. The latest developments in this domain have been discussed in this section.

The authors in [142] propose a multimodal hybrid system for monitoring the health vitals as well as the environment of the industrial workers to ensure their safety in the industrial

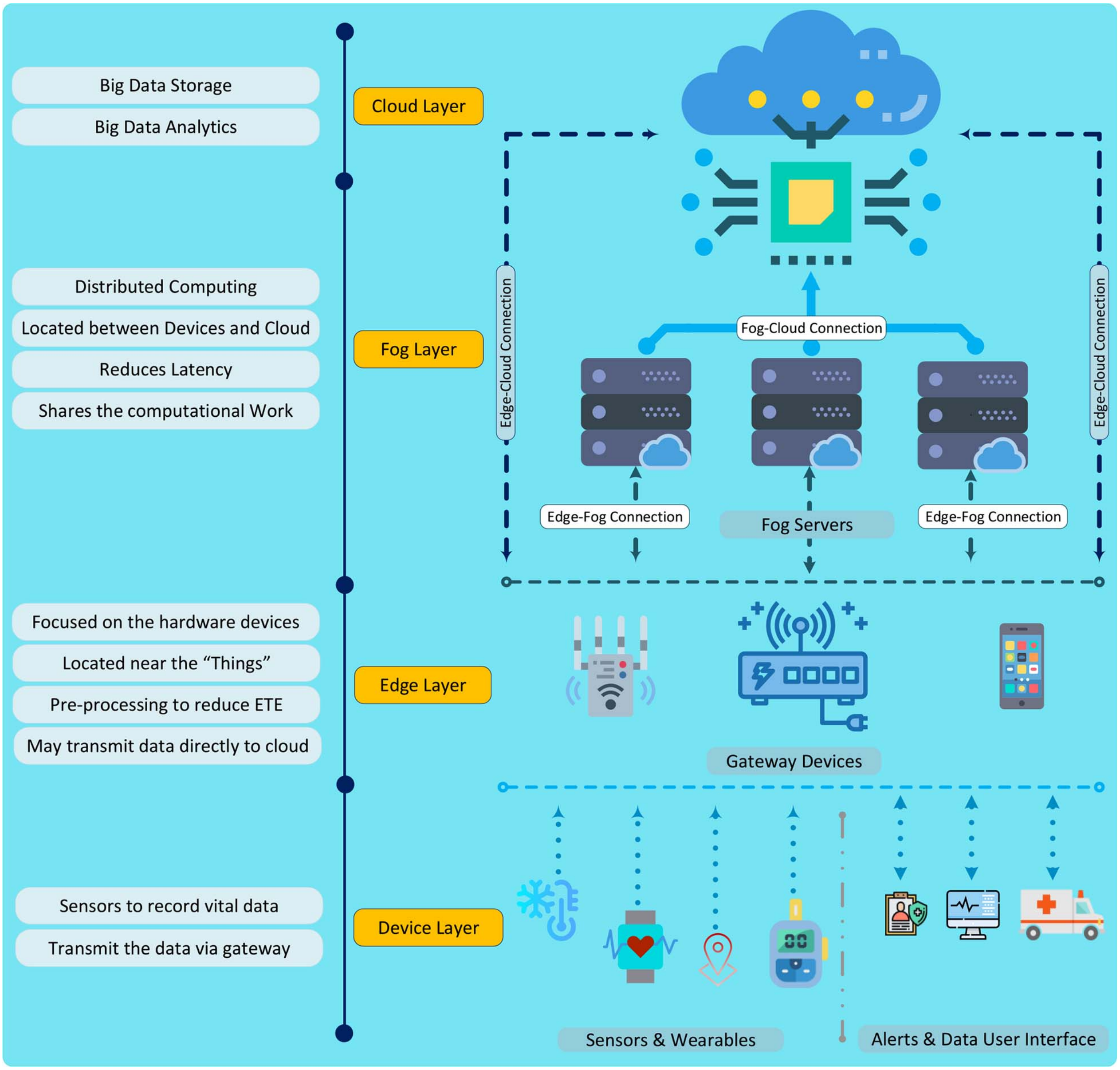


Fig. 13. The Difference between Edge and Fog in Implementation.

environment. The system tests the coexistence of Bluetooth Low Energy (BLE) and LoRa. The edge nodes perform the functions of alert generation from the sensor data as the data is preprocessed at the edge nodes, which are implemented at the IoT gateway. The edge node also provides a user interface for viewing the information as well as transmitting the data to the cloud server. The processing at the IoT gateway reduces the response time significantly. In [143], the authors implement an Internet Protocol version 6 (IPv6) based IoT system that employs fog nodes for locally processing the vital data for risk assessment in patients. The implementation of the fog node serves to reduce the latency as well as improving the accuracy of risk assessment. The disease detection system uses cascaded DL to assess chronic diseases with high accuracy levels for each category like chronic heart disease, hypertension, and diabetes. The fog assistance enables the implementation of the classification. Additionally, the results for latency are well within the standard values. The fog nodes also help in reducing energy usage by limiting long-distance transmissions using a time threshold algorithm for selecting the neighbors. The fog nodes can optimize the network traffic by pre-processing the raw data and only transmitting the non-redundant data to the cloud servers. The response time has been greatly reduced in fitness monitoring systems by implementing edge computing. These claims are verified from the results obtained from two case studies presented by authors in [144] who propose a novel architecture called BodyEdge. The proposed system has two main constituents, a software client and a hardware gateway. The client component enables an interface for multi-radio technologies to provide reliable connectivity while the gateway ensures smooth connectivity with the cloud servers. The experimental studies conclude that the response time meets the standards for H-IoT applications. The results are obtained in an industrial environment and for athletes. The results show that the response time of the edge-based architecture is half of the cloud-based system. Authors in [145] present a comprehensive early warning system based on fog computing. The introduction of a fog gateway called UT-GATE. The fog-based gateway is responsible for multiple functions from data processing, mobility, and alert generation. The results demonstrate the feasibility of fog computing in all the associated areas of H-IoT systems. The connectivity between the nodes and gateway is ensured by support for multiple communication technologies like Bluetooth, Wi-Fi, and IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN). Additionally, the data is encrypted before storing it in the cloud to ensure data security. The compression of the sensed data helps in efficiently using network bandwidth and low energy consumption. The results show that the latency is reduced by 48.5% when implemented with a fog-based approach. The early warning system (EWS) provides warnings to the patients and the families based on the processed data. The EWS score is a metric that indicates the health status of the patients, and based on the EWS score, the sampling rate of the data collection is modulated to track minute changes in the patient's health status. In the AAL environment, the number of users is high. Therefore, fog computing helps in alleviating challenges due to the high concentration of users. Additionally, the users in the AAL environment require extra monitoring for changes in their health status. For monitoring patients suffering from neurological disorders, a fog based AAL system is proposed in [146]. The authors propose to collect the data at a cluster head from sensors and transmit it to the cloud through a fog node. The fog node or a cloudlet perform multiple regression analysis on the sensor data. The redundant data is discarded, and only a subset of data is forwarded, thereby saving precious bandwidth and energy. Based on the severity of the results of the processing, the alerts are appropriately generated. The experimental results demonstrate a reduction in latency, energy consumption, and network traffic. In [147], the requirements of the patients is assessed based on the condition. The authors identify the security challenges of the H-IoT systems and propose a fog-based architecture to mitigate the latency and security challenges. The fog node is implemented on a smartphone that can accept multiple sensor data. The system works by assigning the category to the patient based on the collected data and therefore makes appropriate responses within acceptable time periods.

The energy efficiency is among the primal requirements in H-IoT. To efficiently use the resources and provide optimum security, Hayajneh *et al.* [148] have proposed a protocol for fog assisted WBANs. The authors postulate a channel assignment algorithm that mitigates security threats by reducing the effects of jamming and interference. To complement the dynamic route selection using the Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) protocols, and energy-aware routing metric called DEAR is proposed, which enhances the energy efficiency and security of the transmitted data. A Secure Association and Routing Protocol for Fog Assisted WBAN (SARFW) is presented. A positive impact on mobility, packet delivery ratio (PDR), the delay is observed from the results, which demonstrate a reduced end to end (ETE) delay with increasing distance and high PDR in various mobility scenarios. A fog server can provide the patient information to the authorized users over an IPv6 network in a secure and energy-efficient fog-based system, as proposed in [149]. A four-tier architecture consisting of a fog server gathers data from various coordinators. The case presented by the authors collects multimodal data before the fog node processes and classifies the data according to the patient. The processed and readable data is forwarded to the administrators and cloud, leaving out the redundant information, therefore, achieving energy and memory efficiency in the process. Another technique to save energy and bandwidth is through compression of sensed data. The use of compressed sensing can convert extensive data into sparse datasets that are more efficient to handle. The authors in [150] propose a multi-tiered architecture for real-time monitoring of patients based on fog computing. It enhances the capabilities of deployed sensors and associated infrastructure by providing compatibility across multiple platforms. For ECG data, the authors demonstrate that the use of hybrid compression can result in saving 200 nW of energy. In [151], the authors employ compressive sensing (CS) to compress the sensed data. The proposed system enhances energy efficiency by approximating the redundant data, which forms the majority of biomedical data. CS is implemented at the edge node of the proposed system. The results demonstrate that 59% of energy savings are achieved with a 40% approximation. As more data is approximated, the energy efficiency is decreased due to computational costs.

Multiple approaches are employed for achieving the QoS necessary for H-IoT applications. A context-aware approach is used to enhance the performance of data processing algorithms. Ramalho *et al.* [152] propose a MeCA framework or Multi eHealth Cloud Service framework to demonstrate the applicability of fog approach in enhancing the overall QoS of H-IoT. The authors use a contextual approach to create correlations between the sensed data and various scenarios. This enhances the accuracy of the processing algorithms. The real testbed implementation by the authors demonstrates the reduction in network traffic generation, battery, and computational usage. This work is based on an earlier proposed framework by the same authors, but in this work, the capabilities of the cloud are extrapolated to the network resulting in better QoS results. The coordinated use of the cloud and fog nodes can result in improved performance, as demonstrated by the authors in [153]. The authors implement a four-step process that includes the collection and preprocessing of data. The analysis of the data includes the use of deep neural networks (DNN) in the cloud. The classification algorithm is implemented at the edge of the network, which is complemented by the DNN. The final step is the actuation of the output based on the result of the classification. The distributed efforts show a reduction of response time with the response time for ECG based applications within the 10 ms standard. The accuracy achieved for the classification is 96%. The authors present a scheme to reduce the data that is transmitted over the network by adaptively aggregating the redundant data in real-time from multiple sources in close proximity [154]. A collector node such as a smartphone collects data from multiple sensors around it and transmits only a single stream of data until the data crosses a threshold value. The data is segregated for each user at the cloud repository. An adaptive chunking algorithm is implemented and tested that performs significantly well while maintaining security and reducing the response time.

The authors in [155], attempt to improve the signal quality of the collected ECG data from a novel smart fabric. The motion artifacts degrade the quality of the signals significantly. The collected data is processed at the fog node to gather the necessary data from the ECG waveforms. The current implementation does not include a diagnosis platform, but the extraction of useful data is demonstrated. The results obtained are for four electrodes, which show a high signal to noise ratio (SNR) value. The authors in [156] propose a multi-step process to enhance the QoS of the H-IoT system by exploiting the benefits of LoRa and fog computing. The authors present a step model where the data is sent and received between the nodes and the gateways. The second step involves the classification of the data at the fog server. The third step assigns priority to the user based on the outcomes of the data processing. If the user data is classified as critical, an alert is generated for the ambulance or the caregivers. If a non-critical data is found, then the data is stored at the cloud server. The priority-based data transmission helps in achieving an 88% PDR. The results also demonstrate a better-received signal strength (RSS) at long distances. These results also validate the applicability of LoRa for critical IoT applications like H-IoT. Muhammed *et al.* [157] propose a framework called UbeHealth for ubiquitous health monitoring based on the cloud and edge paradigm. The comprehensive framework converges IoT, DL, big data, and high-power computing for healthcare applications. The edge nodes are responsible for optimizing network performance. The introduction of fog infrastructure optimizes the data rate and routing. The system is implemented in multiple cities in Saudi Arabia, with results showing a significant reduction in latency and energy requirements.

In [158], the authors present a review of cloud technology in H-IoT. Even though the cloud dramatically improves the performance of the H-IoT systems, the QoS requirements of H-IoT are very high. The surveyed literature directs the argument towards the use of intelligent gateways where the responsibilities of the cloud are shared. Though the cloud can reduce the storage and computational burden, the fog can enhance network performance. In [159], the authors demonstrate a decrease in the CPU load, the power consumption, and the response time when the processing is done at the fog layer. The results are compared for the same data at the cloud using the Edison IoT analytics service while the fog is implemented using a Raspberry Pi for quantifying the temporal data of hand movements collected from a glove on the Unified Parkinson's Disease Rating Scale (UPDRS) scale. The authors also estimate the heart rate using a pair of wearable glasses that sense the pulse around the nasal bridge.

*Summary of the Section:* The discussion in this section provides an insight into the advantages of adopting a distributed intelligence system in H-IoT. The fog and edge computing both bring the computational capabilities in the network. However, fog and edge differ from each other in terms of the location of implementation. While edge computing is more hardware-oriented, the fog is a computational resource implemented as a cloudlet.

The use of fog and edge approach enhances the efficiency of resource utilization of the network. The proposed methods demonstrate significant enhancement in energy and resource management. At the same time, the overall QoS of the system is improved. And importantly, the delay of the system, end to end and processing, is reduced. The summary of this section is tabulated in Table VI.

Despite the various advantages, there are challenges in implementing a distributed intelligence system. The sensors, in essence, are resource-constrained devices that do not have memory and energy resources to support the edge capabilities for long-term operation. Thus, presenting a significant hurdle in the massive deployment of H-IoT systems. The performance of edge and fog computing is significantly affected by the ML algorithms implemented on the fog and edge. But the limited resources demand the use of light-weight ML algorithms.

## VII. Big Data in H-IoT

The volume of data generated daily is astronomically high. Consequently, there is a requirement for processing the large data sets either in real-time as well as for the future. Several real-time data analytics schemes have been proposed for IoT systems [160], [161], but the QoS requirement for H-IoT differs from other IoT scenarios. The use of ML algorithms complements the ability to process such large quantities of data. DL is a star among ML algorithms that is implemented for data analytics [162]. In healthcare, DL has found its application in medical image recognition, pathology, and temporal signal processing. The sources of data in the field of healthcare are the monitoring devices such as the wearables and body sensors, the electronic health records (EHR) collected by the health providers, and mobile phone applications [163]. The defining characteristics of big data are three V's, viz. Volume, velocity, and variety. The volume refers to the vastness of the data, velocity to the rate and manner of data arrival, while variety represents the diversity of the data sources and types. Therefore, the data can be structured and unstructured or maybe semi-structured. The structure is based on the manner of data collection and source [164]. To reap the full benefits of the collected data, analytics are applied to extract trends from the datasets, which in turn help in faster and more accurate outcomes. However, for enhancing the performance, it is necessary to share the data freely but ensuring the privacy of the users at the same time [165]. There are undoubtedly considerable challenges in handling vast quantities of data, but H-IoT can surely benefit through the implementation of big data analytics on the biomedical data collected via different sources [166]. To strengthen the understanding of the application of big data in H- IoT, various authors have identified challenges faced in bringing H-IoT and big data together. To mitigate the challenges, an architecture for big data assisted

TABLE VI
SUMMARY OF EDGE/ FOG PARADIGM IN H-IOT

| Reference | Proposed Work and Use Case | Outcome | Target |
|---|---|---|---|
| Wu *et al.* [142] | Multimodal hybrid system for health and environmental monitoring | Reduced latency and interface for monitoring data | Reducing latency<br>Multi-radio coexistence |
| Hu *et al.* [143] | An IPv6 based fog assisted H-IoT framework | High classification accuracy and reduction in delay | Reducing latency |
| Pace *et al.* [144] | H-IoT framework called BodyEdge to reduce network traffic and response time | Observed reduced response time and transmitted data for two scenarios | Decrease processing time |
| Rahmani *et al.* [145] | A fog-based H-IoT framework for an early warning system | Reducing the latency by 48.5% | Reduction in latency, energy and bandwidth usage |
| Vora *et al.* [146] | A fog-based platform for AAL | Improved response time, energy usage and reduced network traffic | Reduction in latency, energy and bandwidth usage |
| Ullah *et al.* [154] | De-duplicated data dissemination in H-IoT | Reduction of network traffic and response time. Enhanced security of data | Data security<br>Reduction in latency, energy and bandwidth usage |
| | | | |
| Rias *et al.* [149] | Fog and Cloud assisted IPv6 based framework | Reduced network traffic and enhanced bandwidth usage | QoS improvement<br>Improved energy efficiency |
| Jangra *et al.* [150] | Multi-layered framework for H-IoT | Energy conservation of 200 nW using a hybrid compression scheme | Improved energy efficiency |
| Siddique *et al.* [151] | CS based data compression algorithm | 59% savings in energy for 40% approximation | Improved energy efficiency |
| Ramalho *et al.* [152] | MeCA framework using a contextual approach | Reduction in network traffic generation, battery and CPU usage | Improved resource efficiency |
| | | | |
| George *et al.* [147] | Data classification at fog node | Improved bandwidth utilization | Overall QoS improvement |
| Hayajneh *et al.* [148] | Fog based data delivery system for Channel assignment, routing and channel assignment | Improved PDR and ETE delay | Latency reduction<br>Enhanced QoS |
| Azimi *et al.* [153] | Hybrid hierarchical model for H-IoT | Improved accuracy using CNN at cloud and classifier at edge | QoS improvement |
| Wu *et al.* [155] | Optimization of signal quality in H-IoT | Improved SNR at the fog node | Improved QoS |
| Kharel *et al.* [156] | Fog based monitoring system using LoRa | 88% PDR and high RSS | Improved Accuracy and QoS |
| Muhammed *et al.* [157] | UbeHealth: A H-IoT framework | Reduced latency and energy use | Overall QoS |
| Farahani *et al.* [159] | Quantification of temporal data on UPDRS using fog assistance | Reduced CPU, energy and response time | Improved resource consumption |

H- IoT is also presented. The big data in H-IoT is discussed under three broad intertwined categories. The architecture for big data and H-IoT forms the base category. The application-specific cases build upon a general architecture, while privacy preservation forms a very critical area of study. The structure of this discussion is illustrated in Fig. 14.

Authors in [167], [168] and [169] have identified the challenges of implementing big data analytics in H-IoT and IoT in general. The authors outline the preservation of privacy, seamless integration of data from various data sources, data mining techniques, and appropriate data visualization methods as the major challenges. Preservation of privacy is a unanimously accepted challenge faced during the implementation of the H-IoT system with critical data from multiple nodes being shared over the network. The issues of interoperability are present when data from different sources is shared in different formats for processing. This also increases the need for a unified and diverse algorithm for processing the data with high accuracy and less processing time. The processed data is required to be presented in the readable form via a user interface designed according to the users' authority. The novel solutions to these challenges have been presented in Table VII.


Fig. 14. Applications of Big Data in H-IoT.

TABLE VII
SUMMARY OF BIG DATA IN H-IOT

| Reference | Proposed Work and Use Case | Outcome |
|---|---|---|
| Y. Ma et al. [170] | Three-tier cloud enabled architecture for Big Health | Model to mitigate challenges of scalability and interoperability |
| G. Manogaran et al. [9] | Fog supported architecture for big data | Reduced response time and error in heart disease detection. 72.82% accuracy observed |
| A. P. Plageras et al. [171] | A research proposal for big data in medical IoT | A model for extracting useful medical information using data mining |
| Dineshkumar et al. [172] | A smart phone-based heart monitoring system using Intel Galileo and MapReduce | Observed response time for arrhythmia detection is under 40 secs |
| Ukil et al. [173] | Anomaly detection in cardiac activity using heart rate and fingertip moisture | A model algorithm for detection of cardiac anomalies by applying a threshold on FNR and a case for use of ML for predicting future medical issues in the patient |
| Alamri [174] | A generic model for anomaly detection for chronic illnesses | An argument for the use of ML in the signal processing and predictive analysis |
| Vuppalapati et al. [175] | Rule based real-time pressure monitoring framework using big data analytics | Creation of digitized Sanjeevni EHR which following standardized metrics |
| Malek et al. [10] | Big data-based system for health monitoring and prediction | Correlation between the environment and the patient health established in real-time using data analytics tools |
| Hossain et al. [176] | Voice pathology assessment using ML based classification algorithms | An accuracy of 95.6% in detection of features in about a second |
| Yacchirema et al. [177] | Sleep assessment system using big data-based H-IoT | Detection of obstructive sleep apnea syndrome with a latency in range of milliseconds |
| Yassine et al. [178] | Activity recognition using K-means clustering and Bayesian networks | Prediction of activity from energy usage big data with accuracies in the range of 70-90% for different deployments |
| Sahoo et al. [179] | Health prediction model using a probabilistic data acquisition model and a stochastic model for prediction of future medical problems | A 98% accuracy in detecting the future medical conditions |
| Chen et al. [180] | A 5G Diabetes diagnosis system using ML on big data | A personalized diabetes diagnosis system that analyses the personalized data and shared health records to diagnose as well as provide treatment suggestions |
| Sharma et al. [181] | Study of the privacy preservation in kHealth, an H-IoT system | Identification of security risks and analysis of privacy requirements |
| Yang et al. [182] | Privacy preservation mechanism for health big data | Stratified access control for emergency and normal situations with a deduplication mechanism |
| Luo et al. [183] | PrivacyProtector scheme for data protection using Slepian-Wolf coding | A distributed mechanism for protecting the data even if some of the participating servers are attacked |
| Elhosney et al. [184] | Data preservation using a hybrid AES-RSA encryption method and DWT based stenography | A low mean square error and peak signal to noise ratio during embedding data to an image |

| Legend | Application Cases | Privacy Issues |
|---|---|---|

The architecture for the big data supported H-IoT systems is proposed in [9] and [170]. In [9], a three-tier architecture demonstrates an end to cloud fusion. The cloud layer is responsible for data processing and providing an interface for user interaction. The cloud layer is responsible for processing the collected data, which is also stored on the cloud. The H-IoT data has some unique features that are taken into consideration in the big health data, such as the heterogeneity, which is caused by multiple data sources. For mitigating this challenge, a structured data format is adopted. Additionally, there is a high correlation between the different data generated by the sensors deployed on the body. Therefore, detecting the relation of changes in one feature with numerous probable outcomes is essential. The data requires real-time processing as the primary aim of majority H-IoT systems is alert generation from the sensor data. There are multiple sources of noise in the sensor data; therefore, the extraction of useful information requires specialized analytic tools that are aware of time and space. Similarly, in [171], the authors propose a fog assisted architecture that has two sub-architectures to mitigate the challenges of scalability, real-time processing, and security. The architecture is evaluated for the detection of heart disease. The Meta Fog and Redirection (MF-R) subsection is responsible for data collection, storage, and processing while the Grouping and Choosing (G and C) subsection is responsible for the security of data. The evaluation of the system yields improved response time and error reduction.

The work [171] is a research proposal for implementing big medical data analytics in H-IoT. The abstract model identifies the requirement of the data mining tools for the extraction of useful information from the vast collection of sensors gathered data. The understanding of such a model is reinforced by the results obtained for multiple network metrics on the Cooja emulator.

There are various real-time alert generation applications that exploit the advantages of big data in H-IoT. The authors in [172] and [173] have presented a big data-based anomaly detection system for cardiac monitoring. Additionally, [174] presents a scheme for monitoring chronic diseases using the big data assisted framework. Authors in [172] validate their proposed framework using an Arduino based cardiac and finger moisture sensor setup, which gathers the data and uses an IoT proxy called the Intel Galileo Gen2. It provides an interface for the data that is recorded by the sensors and the cloud where the data is processed using Map Reduce. The data is handled by the Hadoop Distributed File System (HDFS). The results obtained from the experimental evaluation demonstrate a response time, i.e., the instant when the data is transmitted, and an alert about arrhythmia is obtained well under 40 seconds. In [173], the authors argue that the accuracy of the anomaly detection system depends on the number of false-negative rates (FNR). The work proposes the use of a threshold FNR value. Alongside this, the work also identifies the impact of big data on electronic health records (EHR), data mining, and predictive analysis. The work highlights the importance of ML algorithms in the analytics as well as predictive analysis. Authors in [174] present a case for the implementation of ML in the analysis of the aggregated data in a generic scenario for chronic illnesses. A three-tier architecture presented supports an alert generation mechanism that triggers an alarm as soon as a health issue is identified from the wearable collected data. The authors in [175] propose a model to populate the EHR supported by wearable sensors in the H-IoT environment. The big data-driven architecture exploits various open source technologies to implement the *Sanjeevani* HER that records the patients' medical history, prescriptions, and personal details. The architecture is supported by BLE and edge computing, where the data is validated. ML is implemented for rule processing in blood pressure monitoring on real-time data streams. Authors of [10] have presented a preliminary trial to validate the usefulness of IoT and big data in the healthcare environment. The authors use an open-source platform KAA for data acquisition and Apache Storm for processing the data. The stored data is visualized using MongoDB, a data storage, and a Web application tool. The proposed system is validated from the experimental results that are obtained by implementing the proposed system to confirm the relation between the increased $CO_2$ and $O_2$ levels in the blood.

Big data is also helping the assistive and rehabilitative H-IoT systems. Multimedia data, such as the voice signals are analyzed to assess the problems in human voice [176] using the big data framework. The proposed system in [176] system utilizes the speech signals in the MPEG-7 format along with the interlaced derivative patterns (IDP) to identify the speech features and asses the quality of speech. ML-based classification algorithms impart a high accuracy while taking a little bit over a second during the real-time implementation. The authors argue that the system can be extended to the other applications as well, which can be observed in work proposed in [177]. Authors in [177] present a system for sleep monitoring for the elderly supported by fog and cloud. Several wearables monitor the overall health, and a snoring intensity sensor is used to detect the sleeping patterns in turn to detect Obstructive Sleep Apnea Syndrome (OSA). The system utilizes the Apache Spark and Hadoop for big data analysis and storage. The system also considers the air quality of the city to guide the proper rehabilitation of the patients. The overall results show a latency in the range of milliseconds, which is suitable for H-IoT applications. An indirect approach to assess the health of patients or users is to monitor their daily activities. It can be done by monitoring the energy consumption of the living spaces. Authors in [178] proposed a big data-based system to monitor the usage of the various appliances in the living space of the patient to make an assessment of the health and predict any future health-related issues based on the lifestyle of the user. The big data is analyzed using the K-means clustering algorithm while the Bayesian networks map the usage of the energy to the activities. This work can be extended to detect real-time energy usage and also track the activity. However, a stochastic model is presented in [179] for predicting future health conditions. The data sets are analyzed in a big data formulation using MapReduce, while the predictions about the future conditions are made from the use of Hidden Markov Models (HMM). The paper also uses a probabilistic model for the data acquisition that is suited for cloud-based H-IoT systems. In [180], Chen *et al.*[] test the feasibility of 5G communication technology to endorse the applicability in H-IoT by implementing a diabetes diagnosis system. Utilizing the electronic medical records and compare the personalized medical data using an assortment of ML and neural networks to diagnose the disorder as well as provide inputs on the course of treatment.

One of the key requirements of H-IoT systems is maintaining the security of the data and upholding the privacy of the users. The data shared on the cloud in the big data environment faces multiple threats during storage as well as transmission. Several authors have proposed solutions for different challenges faced in H-IoT systems. The authors in [181] assess the requisites and methodologies for privacy preservation in cloud-based H-IoT systems. The authors attempt to identify the balance between fulfilling privacy requirements while maintaining a high QoS. The kHealth platform is a digital health monitoring system that provides the basis of their arguments. In the case of big data, the risk is faced by the user-generated data, the processing models, and the outcomes of the processing. For different processing models, the tradeoff between processing and privacy is implemented. The access lists can be implemented based on the authority level of the users. It can ensure that only limited information is released to a user ensuring the safety is maintained. In [182], a system is proposed for providing limited access to emergency personnel, while greater access is provided for other healthcare facilities. The access is provided to the emergency personnel using a break-glass mechanism, which is essentially a key generated for emergencies. Additionally, a deduplication mechanism generates a new ciphertext from the existing ciphertext that contains the same plain text data. Access to the new ciphertext is provided to all the authorized users. In [183], the authors present a model for secretly sharing the data using the Slepian-Wolf coding (SWC). The secret share method is sharing the data among distributed storage locations to protect data privacy. The proposed technique also implements a patient data access scheme based on ID-based signcryption, i.e., signature-based encryption. It ensures the safety of data even if some of the participating servers get compromised.

The transfer of data between the nodes and the server can be compromised, which raises the demand for a secure data transmission mechanism. The use of stenography has extended into the H-IoT by the implementation of encryption of healthy data into images. Stenography essentially means hiding some useful data into some other data. The work of Elhoseny *et al.* [184] proposes a discrete wavelet transformation method to hide the medical data into biomedical images. The system tries to exploit the AES and RSA cryptographic algorithms to encrypt the data. The encrypted data is hidden in a cover image that makes it highly improbable for the attackers to compromise the sensitive medical data.

*Summary of the Section:* The data collected by the wearable sensors and the other monitoring devices is exponentially increasing. To solve the various issues in big data for H-IoT, various authors have presented novel solutions. The literature indicates multiple applications that exploit big data analytic tools for the detection of anomalies as well as monitoring the health parameters. Additionally, for the big data, there are colossal concerns about privacy and data security. The vast repositories of data contain Personal Identifiable Information (PII), and multiple policies are to be followed for handling the data based on the source [185]. To streamline the process, there is a critical need for intelligent and secure algorithms to handle the flow and storage of health data.

One of the primary limitations of the current methodologies is the limited capability of the data processing algorithms to extract complete information from the available dataset. The algorithms in vogue are not capable enough to process the complete data due to its sheer volume and data generation rate. There is a redundancy in the datasets, and the computational resources are redundantly utilized, which results in the wastage of the resources. Additionally, the time constraint should be respected for the same as the H-IoT applications are time-critical in principle.

## VIII. Blockchain in H-IoT

Blockchain is listed among the top technological trends for the future. Traditionally, blockchain is associated mostly with cryptocurrency, but blockchains have found their applications in multiple fields. A blockchain is a distributed and completely decentralized peer-to-peer data storage system that is designed to store the information in the form of a chain of immutable blocks of data, hence the name *blockchain* [186]. In 2008, when a white paper was published by a still unknown group or a person, named Satoshi Nakamoto, blockchain was described as a peer-to-peer cash transferring system, and it became as what we know as Bitcoin in 2009 [187]. Each block in the blockchain is essentially a set of data which is signed cryptographically using the private key as well as using the data as an input for generating a unique hash. This hash is unique to the data block and changes if the data in the block is changed. This hash is used to maintain the chain or provenance of the block. The block is distributed across the network to all the users. The validity of the block is established by completing a proof-of-work which is actually a complex mathematical problem. A set of users on the blockchain, called as miners try to obtain the proof-of-work to validate the block in the chain in return for a reward. This approach makes the blockchain transparent, secure, and immune to unauthorized changes [188]. The working of blockchain is illustrated in Fig. 15.

The requirements of the H-IoT systems include security, integrity, and privacy, while the blockchain is based on offering features like decentralization, integrity, and anonymity [189], [190]. The use cases and performance of IoT systems is enhanced by implementing the blockchains alongside with the IoT systems. The use of blockchains is helping in the deployment of services in healthcare, smart grids, and smart cities; however, the issues of storage, security, scalability, and consensus are still a big challenge [191]–[193]. The primary application of blockchain in healthcare lies in the storage and access control of the collected medical data [192]. However, the potential of blockchain is yet to be realized in the H-IoT paradigm.

The work in [194] is an architecture for continuously monitoring the health of the patients. The architecture is supported by using a blockchain for privacy preservation. The remote monitoring system implements a customized blockchain that is managed by a proposed Patient-Centric Agent (PCA). The PCA is responsible for the classification of stored data based on their criticality, selecting the miners, and in some cases fulfill the role of a miner if none is available. The PCA is also responsible for the security by managing the authentication keys in the RPM blockchain.

However, the focus of the most blockchain applications in healthcare is data management and security. Authors in [195] outline the application of big data along with blockchain in the medical data management in the H-IoT scenario. The authors conclude that the utilization of blockchain imparts resilience and security to the data collected by the sensor nodes.

The proposed work in [196] presents a protocol to distribute the collected data among the pervasive social network (PSN) nodes or health data collecting sensor nodes following the IEEE 802.15.6 standard. The proposed blockchain-enabled key verification permits the users to seek medical assistance remotely without compromising privacy.

The work of authors in [197] involves the formulation of a four-layer structure known as MedShare that uses the smart contracts for managing the access to the data in the blockchain. The proposed method is tested experimentally to establish the validity of the proposed method.

*Summary of the Section:* Blockchain is a trust-less distributed ledger that provides a transparent data storage system. Initially designed for secure bookkeeping of online transactions. Additionally, smart contracts enhance the usability of blockchains to applications in healthcare, smart cities, e-governance. The use of blockchain lies mostly in storing critical patient data and data security. The sharing of the data with the authorized personnel and sharing the security keys is greatly supported by blockchain. The tabular summary of the applications of blockchain in H-IoT is presented in Table VIII.

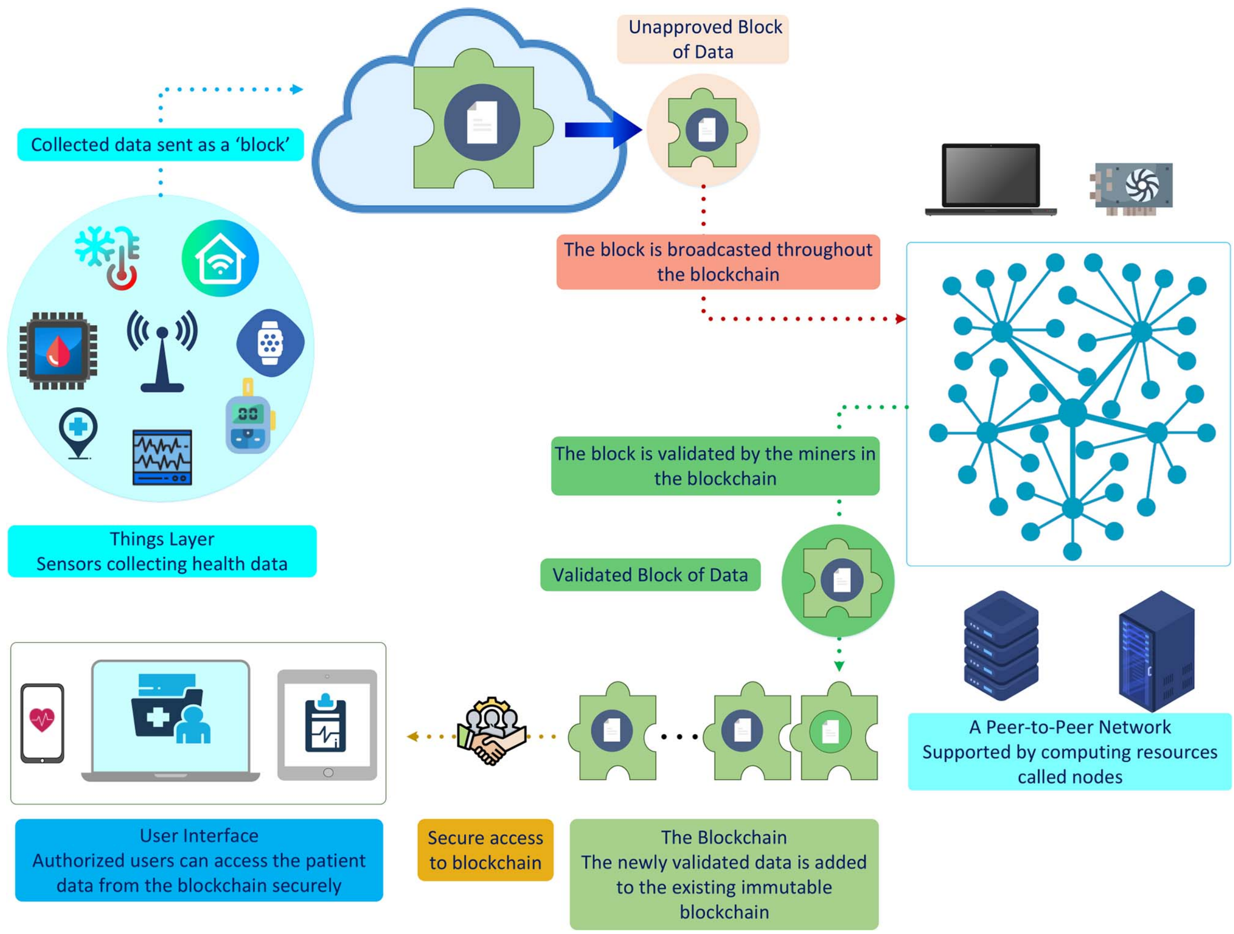


Fig. 15. Working of a Blockchain for H-IoT Data Sharing.

TABLE VIII
BLOCKCHAIN SUPPORTED H-IOT SYSTEMS

| Reference | Proposed Work and Use Case | Outcome |
|---|---|---|
| Uddin et al. [194] | Continuous monitoring architecture supported by blockchain | A privacy preserving PCA agent that selects miners based on criticality of the data |
| Simic et al. [195] | Medical data management collected in H-IoT scenario using blockchain | Enhanced resilience and security offered by including the blockchain in H-IoT |
| Zhang et al. [196] | Security protocol for IEEE 802.15.6 Healthcare WSN | Key based data security system to provide remote data access |
| Xia et al. [197] | A four-layer MedShare architecture using smart contracts | Validating the use of smart contracts for providing data access |

One of the major bottlenecks in the use of H-IoT is the use of the consensus algorithm. The current consensus algorithms do not allow their widespread utilization in the H-IoT framework. The time duration for the approval of blocks is not compliant with H-IoT QoS. Additionally, many consensus algorithms require high computational resources, which are not available in H-IoT. There are critical challenges in terms of cryptographic key sharing in a distributed WBAN that need to be mitigated. These solutions can also be instrumental in solving the identity-based network layer security threats.

## IX. SOFTWARE-DEFINED NETWORKS IN H-IOT

Traditionally in an IoT network, various devices are responsible for managing the network, i.e., routers, switches, and intermediary devices. These devices are equipped with integrated circuits that are pre-programmed to perform predetermined operations, which cannot multitask in real-time applications to manage the network. The size of the worldwide network with connected heterogeneous devices will stretch towards billions of things [198]. The tremendous increase of network size and diversity creates heterogeneity in the network and generates massive data that requires analysis, feature extraction, and processing. The current IoT architecture is incapable of offering flexibility, reconfiguration, and interoperability. To address these limitations of IoT network, SDN offers network management [199], network virtualization [200], network accessibility [201], resource utilization [202], energy management [203], and, security and privacy [204], [205], [206] by separating network control from hardware devices [13]. The main functionality of the SDN is to isolate the control plane from the data plane of the network to streamline the network performance. This network device acts as a forwarding device only, which forwards a sequence of packets from source to destination by regulating the flows under various policies [207]. The control plane in SDN is a centralized unit, while the data plane works in a distributed manner. The telecommunication management network (TMN) architecture comprises of three planes: management plane, data plane, and control plane. Management plane forms the maintenance and operations unit of the network, i.e., human operators and software that monitors the network status, and configures the network and updates the network. The data plane performs data transmission by following a flow table. Routers, switches, firewalls, and circuits are equipped with a flow table to transmit the data. The control plane is located in the centralized controller to configure the network according to the application requirements, e.g., network path, routing protocols, network policies [208]. These requirements are specified by the application plane. The SDN has two types of vertical application programming interfaces (APIs): northbound API and southbound API. Northbound API is responsible for providing communication between application plane and controller, whereas southbound API supports communication between the controller and network devices. Two more APIs are also provided by SDNs that are eastbound and westbound, which provides interfacing between multi SDN controllers. These functionalities further extend network capacities and coverage. SDN offers hardware reusability by reconfigurable characteristics, policy updation to update the software of various modules and fix bugs, quality-aware architectures for IoT by implementing network logic, and cost-effectiveness for the researcher to achieve more realistic results. In this section, utilization of the SDN framework to enhance the reliability, efficiency, interoperability of real-time online H-IoT and offline H-IoT networks is presented. To the best of our knowledge, an unsubstantial amount of work on SDN for optimizing the network performance specific to the H-IoT systems is available until now. The majority of the research articles related to the SDNs focus on the optimization of network performance in the generic IoT networks. Therefore, this section explores the applicability of the SDN system for enhancing the QoS in IoT networks. This analysis can be used as a basis for optimizing the network performance in H-IoT as well. The QoS requirements for H-IoT are stringent; therefore, the advantages of SDN can be exploited for improving the performance of the H-IoT networks.

WBANs involve various sensors or actuators, which are wearables, body implants, and environmental sensors. These sensors generate a massive volume of data. SDN offers better data management for WBAN by implementing a personal digital assistant (PDA) on the SDN controller. Sallabi *et al.* in [209] propose an SDN data plane-based PDA for WBAN to manage and classify data traffic from heterogeneous sensors. The SDN controller is implemented as a PDA to collect and classify data from various sensors and route the data to the desired destination. The data traffic is classified as periodic physiological traffic related to an individual's health, and in case of emergency, it is categorized as emergency data. The sensors' management data comprises of the sensor's health while the environmental data includes patients' environmental parameters. The proposed architecture aims to increase the efficiency of the system by reducing overheads and enhancing reliability. Implementing efficient machine learning and optimization approaches can increase the efficiency of the system.

El Amraoui and Sethom [210] present a four-layered cloudlet based SDN integrated WBAN architecture for the patient monitoring system. Cloudlet is a small-scale mobile cloud data center that is located at the network's edge, which is in close proximity of the patient for efficient processing, resource allocation, and reducing the delay and jitter of the network. Authors propose that all the network controllers reside in the cloudlet to observe the complete view of the network and serve network traffic to optimize the QoS. SDN based network operating system (NOS) layer lies between cloudlet and WBAN sensors, provides data plane, open interfaces for various sensors, service requirements, and network management. The proposed work lacks security mechanisms against challenges to secure a patient's data.

Hasan *et al.* [211] outline a three-layered SDN based WBAN framework named as SDWBAN. Data plane, control plane, and application plan comprehend SDWBAN. Multiple SDN switches associated with various body sensors and implants cover the data plane, which links with the local controller available at the control layer. The interconnection of all local controllers provides redundancy to the system in case of failure. A centralized controller manages the entire local controller and connects them with the cloud unit. Traffic prioritization is performed by exploiting SDN switches. Higher priority packets, which indicate an emergency, are analyzed and the process by the network on priority by efficient resource allocation, i.e., bandwidth, path allocation, and cloud computing. With a tremendous increase in remote medical sensors to monitor patient health in hospitals, a significant amount of network resources and network management system is required to provide QoS.

Authors in [212] present an SDN based service function chain (SFC) to formulate a heuristic model for packet path allocation. SFC utilizes SDN to create service chains of all the connected network device services. Such a scheme is capable of managing when multiple services share a single connection or network. The transmission delay is optimized by formulating the heuristic assignment model to minimize the time cost function of each service, which includes transmission time and cost of service. The selection of the shortest path and load balancing for each service of the network to optimize the transmission time is required.

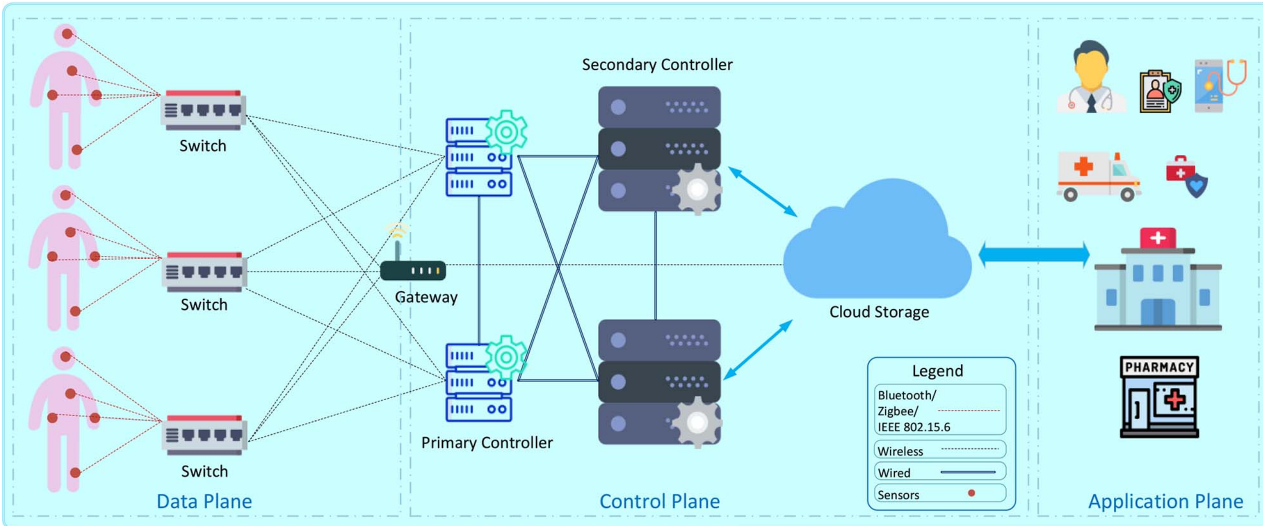


Fig. 16. A Framework of Software Defined Network based H-IoT System.

Du *et al.* [213] presented the concept and implementation of context-aware mobile virtual network operators (MVNOs) framework based on SDN for high-cost effectiveness. MVNO are operators that obtain network services from mobile operators and provide services to the customers on their own service costs. The introduction of MVNO increases the security and privacy of the network by sharing only limited information to the Internet, e.g., location information is not necessary for a heart monitoring application. Trailer slicing is proposed for meta-info to equip the network with context-awareness. The meta-info tags provide contextual information, which is then efficiently handled by MVNO switches.

Sinh *et al.* [214] proposed a full software-defined mobile network (SDMN) framework to deal with the IoT network requirements to support interoperability, high throughput, delay sensitivity, and high performance in a heterogeneous network (HetNet). Secure and timely data delivery are two crucial factors, which directly affect the patient's life. SDN provides a platform to reduce the complexity of the network and maintain QoS.

Framework for secure software-defined virtual hospitals is presented in [215]. Authors exploit 'Kerberos,' a secure networking protocol for authentication and efficient data delivery system for secure virtual hospitals. SDN controllers are employed to classify the traffic, which will be authenticated using Kerberos protocol, and sufficient bandwidth is allocated to meet the QoS requirements by timely data delivery. The sensitive data is encrypted using Kerberos and stored in a private cloud, whereas periodic health data is stored in a public cloud using a firewall with an access list. For downlink transmission, user access to medical data from the hospital or examiner uses encapsulated packets are to authenticate and establish a secure connection. Biometric authentication and optimization techniques for path selection and bandwidth allocation can further enhance the performance of the proposed system. The structure of an SDN based H-IoT system is illustrated in Fig. 16 [211]. While Meng *et al.* [216] present a Bayesian inference for IDS in the healthcare SDN architecture.

*Summary of the Section:* This section presents the motivation behind employing SDNs to cope with the issues and challenges of interoperability and QoS with IoT HetNet. The basic concept and advantages of SDN for IoT are highlighted in this section, but the literature in terms of H-IoT implementation is limited. Various proposed work related to SDN for the enhancement of IoT performance has been presented. The existing SDN research work is focused on network management for real-time applications; however, machine learning and optimization techniques in SDNs have not been investigated. Table IX summarizes the literature available for the application of SDN in the WBAN based H-IoT system. The available literature for H-IoT indicates that the scope of SDN is currently limited to optimizing the data priority determination process and securing the data for global access. However, H-IoT QoS can be further enhanced by adopting autonomous network management systems. The virtualization of network hardware on shared computational resources in a distributed H-IoT paradigm would allow the autonomous path selection and minimization of ETE delay. SDN offers flexibility in terms of adopting network architecture, therefore, offering opportunities for a wide array of applications.

## X. Internet of Nano-Things: An Introduction

The advances in the MEMS is leading to an exponential increase in the range of sensor nodes available for monitoring the vital parameters of the human body. The "nano-things" have displayed an explosive growth in the market and are therefore leaving a huge impact on H-IoT systems [217]. There are a number of nano-sensors that are developed for specialized applications based on MEMS [218]. So, it becomes necessary to provide support for the nano-things in the H-IoT system for a wide range of applications.

The basic understanding of the IoNT from the perspective of H-IoT can be understood from Fig. 17. The nano things, enabled by the MEMS and precision fabrication techniques, are the sensing and the actuation devices. These are deployed

TABLE IX
SOFTWARE DEFINED NETWORKS BASED FRAMEWORKS IN H-IOT

| Reference | Proposed Work and Use Case | Outcome |
|---|---|---|
| Sallabi et al. [209] | SDN Based Personal Digital Assistant For WBAN Data Management | Heterogeneous data from various wearable devices is gathered and forwarded to SDN based PDA. It segregates and classifies the data, minimizing systems overhead |
| Aymen et al. [210] | Cloudlet Based SDN Integrated WBAN Architecture | Cloudlet computation and WBAN integration for efficient computation and to access globally. |
| Khalid et al. [211] | SDN Based WBAN Framework 'SDWBAN' | SDN Based Switches, Gateways and Controllers for packet prioritization, network management and authentication. |
| Li et al. [212] | E-Health Systems based on SDN Based Service Function Chain (SFC) | SDN-SFC adopts heuristic assignments model to improve reliability by optimizing path allocation and transmission delay |
| Du et al. [213] | Context-Aware Mobile Virtual Network Operator (MVNO) Framework Based On SDN | Trailer slicing for context awareness and induction of MVNO to increase the security for personal information |
| Sinh et al. [214] | Software-Defined Mobile Network (SDMN) For HetNet | End-To-End Multi Network Slicing to maintain QoS for IoT services from different providers |
| Shayokh et al. [215] | Software Defined Secure Virtual Hospitals | SDN controller implements 'Kerberos' a secure networking protocol for authentication and sufficient bandwidth allocation to maintain QoS |
| Meng et al. [216] | IDS detection in Healthcare SDN Architecture | Implementation od a security policy for a scalable network for a big data scenario |

in the organs or bloodstream. They communicate via one of the multiple communication technologies enabling nano communication to convey the sensed information and the controlled feedback. The applications for the IoNT are immense, ranging from precision drug delivery, precision sensing, and micro procedures in the inaccessible organs of the body. Their applications are also found in many other fields such as petroleum exploration, monitoring and discovery of groundwater, damage assessment in structures and concrete, agriculture, smart cities, industrial processes monitoring, wildlife monitoring, and high-speed communication [217]. The authors in [219] have presented an extensive study of the communication in the purview of Molecular Communication (MC). The authors identify the applicability in applications like drug delivery based on the *leader-follower mobility model*. The different mobility models that are followed by the nodes in the MC affect the analytical frameworks for developing an information model [220].

The communication between the nodes in an IoNT paradigm is different from the conventional WBANs and other IoT networks. Therefore, there are no unified works that have presented a unified view of the protocol stack models. There are two network models identified by [221], layer-less, and layered models. The layer-less model is supported by a signal flooding scheme where the nodes are deployed densely, and disseminate the data unilaterally reducing the importance of addressing, node identification, routing, and forwarding. All the functions are assumed by the physical layer, and it is based on the assumption that the communication model is extremely simple, with the nodes forwarding the data to their neighbors without any regard to their location and identity. On the other end, there is a simplified TCP/IP model for the IoNT that is resource-constrained and cannot use the conventional TCP/IP model. The various layers perform their designated tasks adapted to the available resources. Thus, there is no standardized model to govern the communication between the IoNT.

The design of the transmission and reception modules is governed by the number of factors, chief among them are the size, mobility, and location. The transmission of the data is also affected by the encoding techniques, which depend on the medium of transmission [222]. The other constraints include the biocompatibility and the chemical composition of the transmission medium. These issues have been extensively identified and influence the fabrication and deployment of the IoNT systems [223], [224].

Nano things communicate with each other using MC, nanomechanicals or acoustics, ultrasonic communications, and high-frequency electromagnetics. There are design problems that have to be addressed with respect to antenna design, routing, MAC protocols, and analysis of big data generated from nano-sensors. Terahertz (THz) frequencies are not susceptible to scattering, and the biological tissues remain nonionized at THz that make electromagnetics at THz feasible for IoNT communication [225]. Minute variation in tissues can be detected by molecular resonance at these frequencies that makes THz frequencies more feasible to IoNT. However, the applicability of THz for IoNT and MAC designs is yet to be investigated in detail [226]. The terahertz based communication range in the IoNT network is expected to be between 1 cm and 1m, and MC supports 1 nm to 1 cm that makes routing and multi-hop communication critical aspects for exploration. Moreover, the mobility of nano-sensors is dependent on its drift velocity inside the human body, which makes the communication route non-deterministic [221].

MC provides an important pathway for communication in the IoNT application. Therefore, the molecular pathways present in the body act as communication channels. The

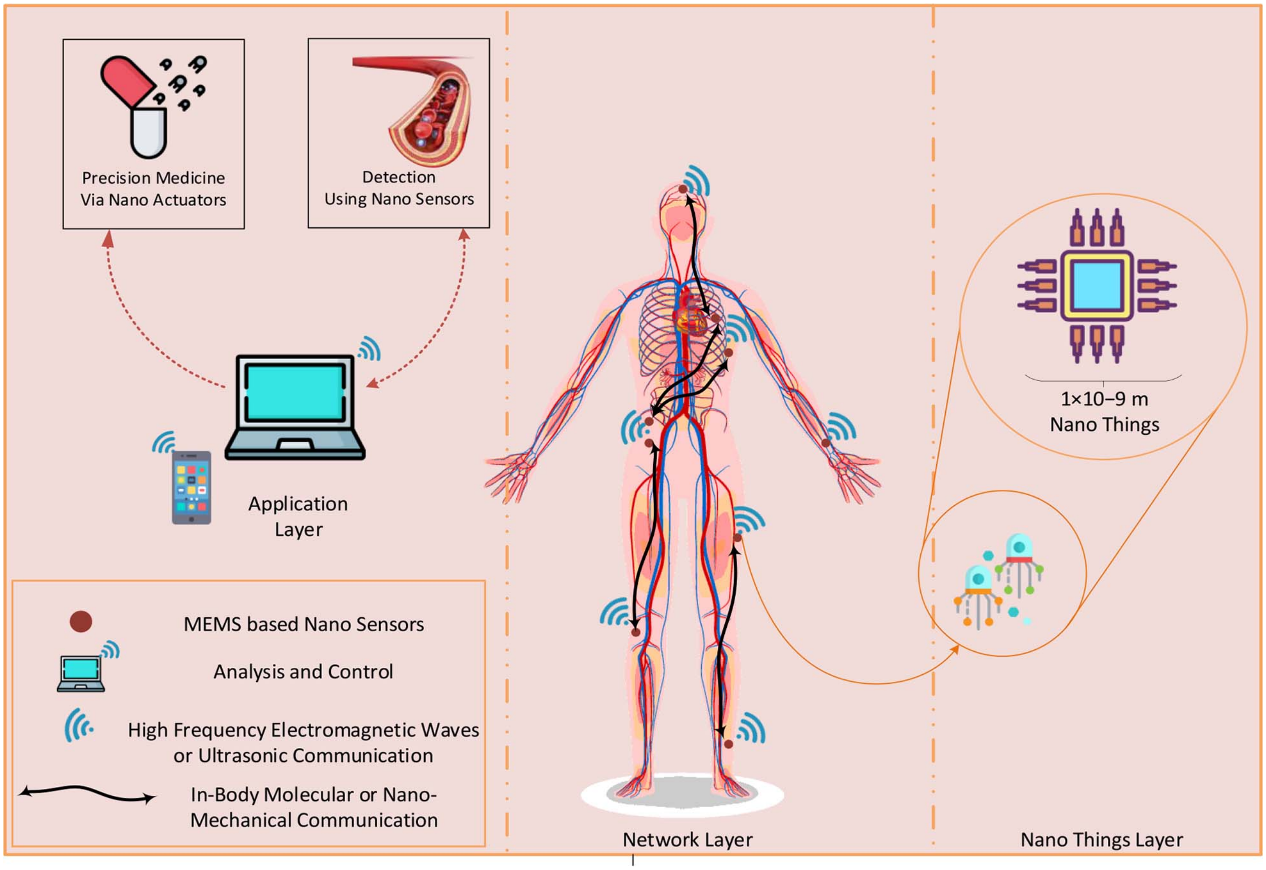


Fig. 17. A Generic IoNT Network.

Internet of Bio Nanao Things (IoBNT) is fundamentally based on the principle of sensing the biological data at an intercellular level [227]. Thus, the modeling of these channels to study their applicability for communication is ultimately necessary. The work [228] presents a mathematical model for the communication pathway between two cells participating in the Insulin-Glucose cycle. This system involves the release of insulin, a hormone that regulates the amount of glucose uptake by the cells. The release of insulin and glucose can be compared to a two-way communication process occurring through a communication medium, the blood in capillaries. The conclusion from the study found a correlation between increased insulin resistance and decreased data rate and channel capacity. The applications for the same are outlined in the design of insulin pumps, implanted insulin regulators, and energy harvesting solutions for implants.

The MC encodes the information as the molecules that are circulated around the body. These data units are modulated by a number of modulation protocols such as *molecule shift keying* (MSK), which is similar to the conventional *frequency shifting keying* (FSK). The *concentration shift keying* (CSK) uses the concentration of the information for encoding the information [229]. The detection of symbols in the MC is affected by a number of factors, usually due to the straying of molecules that constitute a transmitted data unit. This straying results in *inter-symbol-interference* (ISI). To reduce ISI, hybrid approaches are proposed. The work [229] proposes a thresholdless symbol detection technique called *Coded Modulation Scheme* (CMS) that can be used for 2-ary and 4-ary CSK schemes. However, The miniature nature of nano-machines makes IoNT sensors strictly scarce in terms of storage, memory, and processing that indicates the routing protocol at a node has no prior knowledge of network topology. Opportunistic and geographic routing can be suitable solutions for the IoNT-H network [230], [231]. The design and deployment constraints in the IoNT require the routing protocols that increase the lifetime of the network by decreasing the energy consumption during routing. *Al-Turjman* [232] presents a cognitive routing protocol that uses reasoning and learning for making the routing decisions, prioritizing the data generated by the *nano-nodes,* and following a non-position based strategy where the hop count is adaptive according to the feedback during the learning process. The traditional MAC protocols for WSN are not capable of supporting characteristics of THz communication; therefore, they cannot be implemented in IoNT. The probability of collision and interference is significantly less because of the short transmission time and enormous bandwidth provided by THz communication. Transparent MAC is a simple protocol that provides a solution for IoNT. However, error control MAC protocols require addressing the THz channel access mechanism [233]. There are time scheduled schemes that can ensure the timely delivery of the data without any significant loss of information, which is a critical concern as the nanodevices are bufferless

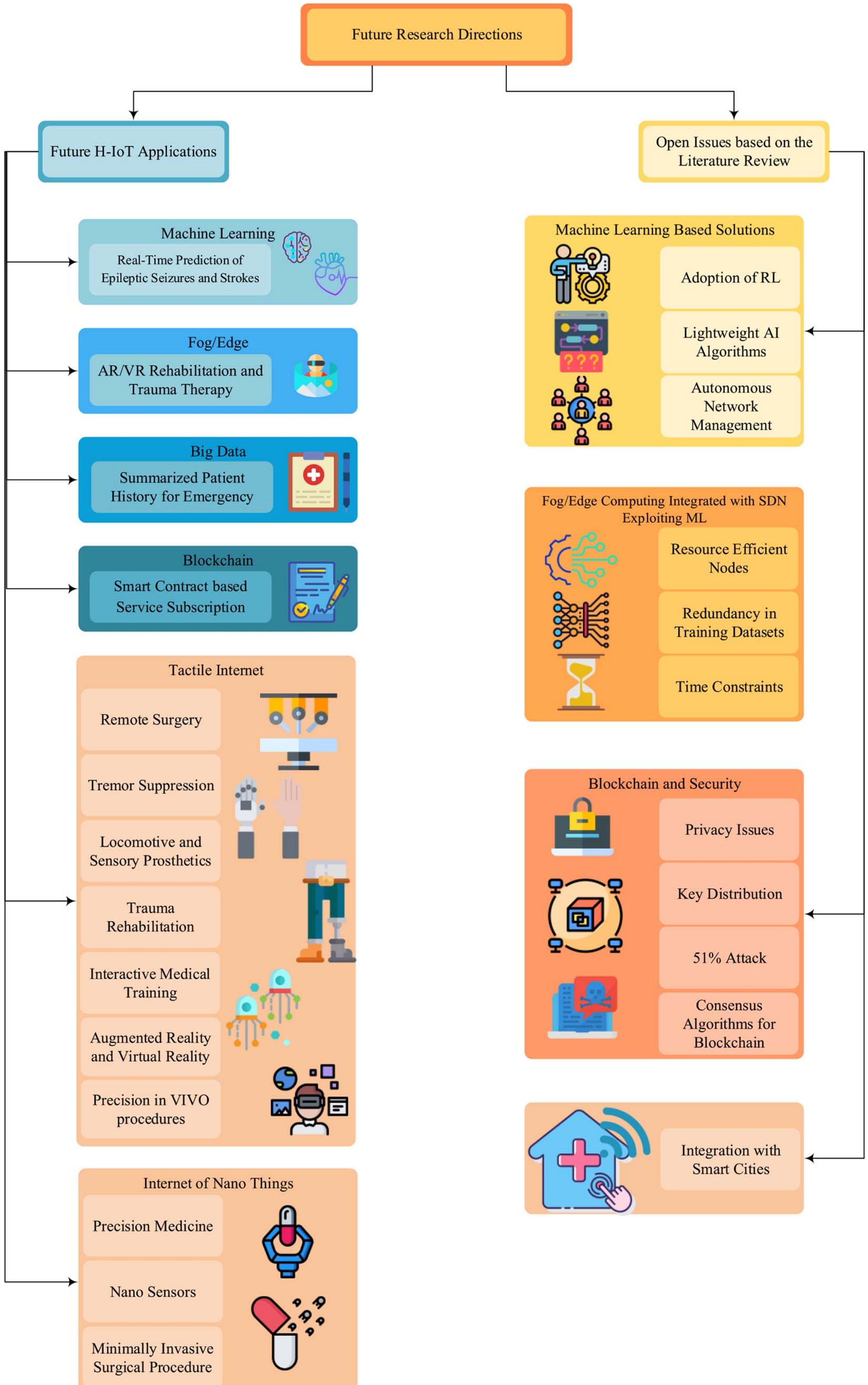


Fig. 18. The Future Research Directions in H-IoT.

due to their structure. A priority-based algorithm is proposed in [234] that harvests energy from the biological processes and takes into consideration the incoming traffic rate, channel condition, and virtual debts. Similar to [234], a receiver-initiated MAC protocol is proposed in [235] called RIH-MAC that is founded on distributed and probabilistic schemes to

TABLE X
DESCRIPTION OF IONT AND ENABLING TECHNOLOGIES

| Stack Layer | Functionality | Cited Work |
|---|---|---|
| Communication Layer | Molecular Communication | [219] Information System Modelling of MC<br>[220] An Information Model MC- Leader-Follower Mobility Model<br>[222] Review of communication models in MC<br>[223] Tx and Rx Design considerations in MC<br>[228] An Glucose Cycle based system modelling for MC in IoNT |
| | Terahertz Communication | [225] Design Constraints for THz communication<br>[226] THz communication for IoNT (In-Vivo) |
| | Routing | [230] Identification of Routing Challenges and Information Processing in IoNT<br>[231] A geographic routing protocol called CORONA<br>[232] A cognitive routing protocol for IoNT that uses reasoning and learning to reduce the hop-count and optimizing energy usage |
| MAC Layer | Channel Access | [233] MAC protocol called Transparent MAC for efficient channel access<br>[234] Scheduling algorithm for channel access based on traffic patterns and energy harvesting<br>[235] A collision-free MAC protocol called RIH-MAC for IoNT |
| PHY Layer | Modulation | [229] Review of encoding techniques and CMS scheme for data encoding based on molecular concentration |
| | Energy Harvesting | [236] Event detection method and transmission module using passive sensors based on energy harvesting |

generate a scalable solution, that minimizes collisions and maximizes the utilization of harvested energy.

Powering the IoNT nodes is a critical challenge; therefore, energy harvesting is a favored technique to fulfill the energy needs of the IoNT nodes. The authors in [236] present an energy harvesting solution that uses passive nodes to power the transmission modules and detects the events from the amount of energy generated by the event. The proposed work evaluates the performance by comparing the detection accuracy using a *single pulse transmission* and a *dual pulse transmission* approach. The latter approach is able to detect the events as well as localize them.

The analytical capability to analyze the big data generated by IoNT is one of the critical aspects of the healthcare systems. The analysis of IoNT data exploiting the learning methodologies detailed in the previous section, integrated with a conventional health and medical data, will lead towards proactive healthcare instead of reactive healthcare that can not only detect infections, injuries, or diseases as soon as they happen but, even before they start [237].

*Summary of Section:* The IoNT is ushering in the age of specialized healthcare monitoring systems. These do not involve the use of uncomfortable sensing devices; instead, minute sensors and actuators powered by nanotechnology are deployed. And they remain minimally disruptive. The standardization for communication in IoNT is still underway. Therefore, there is a vast scope for the development of hardware, communication, and processing faculties for this new paradigm. Table X summarizes this discussion.

## XI. FUTURE RESEARCH DIRECTIONS

The commercial launch of 5G technology is a driving force for developing a fully connected society in which the machine to machine and machine to human interaction is envisioned to be seamless. The development of micro-electro-mechanical systems (MEMS) based sensors, intelligent materials, smart fabrics, and novel bio-materials along with remote monitoring and disease diagnosis is a gravitating research area. There is a need for low power, reliable, and secure network capabilities to support these sensor devices. The data collected via the sensors require real-time and accurate processing algorithms that can handle big data. The overall performance of the system can be judged based on the QoS of the system. The scope for improvements in the QoS provides an insight into the future research directions for H-IoT. There are immense opportunities for enhancement and innovation in the current technological environment. The research community has contributed to the development of several key technologies that are paving the way for futuristic healthcare services delivered via the H-IoT system. In this section, these key innovative technologies are discussed in the perspective of enabling the future of H-IoT. Fig. 18 illustrates the major areas which demand innovation and contribution from different research and regulatory communities for the improvement of the overall H-IoT performance. The different areas which present opportunities for further research can be classified and discussed under the following headings.

A. Future H-IoT Applications
B. Open Issues based on the Literature Review.

### A. Future H-IoT Applications

The applications of H-IoT are increasingly being adopted in the commercial space. A large number of commercial solutions are available for tracking the health status of a person. But, there is still immense potential for converting the H-IoT systems as a primary healthcare facility and elevating the hospitals into secondary care units. Therefore, it is highly significant to identify potential technologies for addressing the challenges in achieving the said goal.

*1) Machine Learning:* A collaboration of intelligent systems can exploit the potential advantages of future applications supported by TI and IoNT. The use of AI for the real-time detection of anomalies and the generation of realtime feedback is a widely accepted problem statement. However, the potential for improvement lies in the prediction of anomalies before the occurrence of the real event.

- *Prediction of Epileptic Seizures and Stroke in Real-Time:* Stroke is the second leading cause of death throughout the world [248]. While the number of people who have Epilepsy stands at 50 million worldwide [249]. Therefore, the focus on predicting an epileptic seizure or a stroke is significant, which is gauged by the interest of the research work in this field. Ample literature is available in the detection of these episodes; however, there is a significant need for the development of algorithms that can predict these episodes before they occur so that proper precautions are taken, and countermeasures are deployed. RL algorithms are capable of learning the behavior of the agent in real-time. Hence, the use of RL can significantly increase the accuracy of an integrated real-time H-IoT system to predict the occurrence of a seizure or a stroke with the capability for using countermeasures.

*2) Edge and Fog Computing:* The primary advantage of the Fog/Edge-based architecture is the ability to reduce latency and allowing higher computational complexity within limited resources [250]. Therefore, the applications which require high computational power and low delay can be supported.

- *AR/VR Based Applications:* The experience of rehabilitative therapies based on AR/VR can have a comparatively significant impact over traditional treatment [251]. The use of fog/edge computing allows fast graphical processing, which is resource-intensive. Additionally, the IoT systems are devoid of such processing power; therefore, the fog/edge systems are essential requirements for such applications. With the use of TI, this application can be realized in a consumer space.

*3) Big Data:* The H-IoT systems combine the advantages of multiple technologies that work seamlessly at various levels of H-IoT architecture. This interaction of the different technologies provides a seamless experience. The massive amount of data that is collected is useful for developing models that are used for the detection of anomalies. Therefore, the availability of the collected EHR is critical for such systems. The availability of prescription drug databases can also help in tracking and managing the intake of drugs. Based on the model presented in [252], a drug management system can be designed.

- *Summarized Mobile Electronic Health Records:* The prompt availability of health records can play a critical role in emergency cases. The information such as blood type and allergies. Additionally, the patient data which is readily available can be life-saving in critical situations. Therefore, this data must be available in a summarized form for emergency caregivers.

*4) Blockchain:* Blockchains are increasingly gaining significance in IoT applications. The challenges with regards to the consensus are a major obstacle in the IoT implementation. The applications supported by blockchain include secure data storage, device authentication, and intelligent subscription management.

- *Smart Contract Based Service Subscription:* The H-IoT services can be accessed using a subscription service managed by *smart contracts* supported by blockchain [253]. The users can access services such as health monitoring and treatment management using a smart contract-based linked service agreement. This can provide secure and accurate health services in the consumer market.

*5) Tactile Internet:* IEEE made an initiative in 2015 to standardize the communication among devices for reproducing the senses and stimuli for enabling perception in the digital world [238]. This vision of sensory connectivity via the Internet is termed as Tactile Internet (TI). *G. P. Fetweis* initially coined the term Tactile Internet in 2014. With the advent of 5G communication technology, the applications based on TI are being explored, especially in the areas of robotics, healthcare, and entertainment. TI is revolutionizing the human-machine interaction by fulfilling the requirements of ultra-low latency and ultra-high reliability in communication [239]. The International Telecommunications Union (ITU) published a paper in 2014, outlining the scope and applicability of TI in various industries. It defined the architecture for the same by incorporating technologies like Mobile Edge Computing (MEC), fog computing, and NFV [240]. IEEE has already constituted a working group (WG) to standardize the communication in TI [241]. The IEEE 1918.1 is a standard that defines the communication in the TI paradigm. While the IEEE the standard 1918.1.1 defines the "Haptic Codecs for TI." The TI is envisioned to power the Internet of Skills or Human 4.0 [242]. This implies that TI is based on remote physical interaction, which is, in turn, based on two components, command and feedback. The command and feedback constitute the haptics. The term haptics refers to (1) Kinesthetic Perception and (2) Tactile Perception. The Kinesthetic Perception refers to the data representing motion defined by torque, velocity, position.

Whereas the Tactile Perception is the information defining the perception of touch, such as the texture of the surface, friction, and likewise [243]. This interplay of command and feedback can only be effective if the communication between the nodes is ultra-fast and highly reliable. The Kinesthetic Perception follows a closed-loop communication; therefore, it requires a zero-delay communication. On the other hand, the Tactile Perception is an open-loop system; therefore, the time constraints are not as stringent. The TI is enabled by haptic communication, which allows transmitting the perception of touch and actuation in real-time. Therefore, there is a set of stringent limitations of latency in TI communication. A maximum round trip delay of 1ms has to be achieved for the TI standard [244]. However, there are two cases defined in limiting the maximum round trip time (RTT) in TI. The maximum RTT tolerable for a human to client communication is 1ms while for machine-to-client is 5ms.

The primary driver for TI is going to be 5G Ultra-Reliable Low Latency Communication (URLLC) New Radio (NR), and URLLC evolved long-term evolution (LTE) [245]. The SDN is set to play a vital role in the architecture enabling the deployment of the TI using 5G [246]. The applications that the TI has found itself are quite diverse and have strict QoS parameters. The TI is revolutionizing the autonomous vehicular networks, Industrial Automation Systems, Tele-Medicine, Virtual and Augmented Reality, and Defense [247]. The role of TI in healthcare is particularly important. Some of the potential applications of TI in H-IoT are identified as future research opportunities.

- *Remote Surgery:* TI provides a feasible and reliable avenue for performing surgical procedures remotely by specialists via the Internet. The ultra-fast and ultra-reliable communication offer complete control during the procedure. Therefore, realizing the hardware and communication protocols for conveying the accurate haptic feedback is required.
- *Tremor Suppression in Parkinson's Disease:* The online system for suppressing the tremors based on the motion of the hands has already been designed. However, the current algorithms are not able to modulate the counter-measures according to the intensity of the tremors. It has side-effects in the long run. Therefore, a system for delivering adaptive feedback to suppress the tremors is required.
- *Locomotive and Sensory Prosthetics:* The prosthetics based on the TI communication standard are one of the primary applications in healthcare. There is a requirement for the development of highly responsive sensors that sense the environment and can filter out the noise from the useful information. Additionally, the sensory prosthetics like olfactory and visual sensors is an important area for research and development. Therefore, there is an excellent opportunity for the development of algorithms for extracting useful information from the sensed input data. The AI-based algorithms can be explored for imparting the human-like capabilities for such applications. Additionally, there is a requirement in terms of actuators that can mimic human locomotion. The output should be modeled based on the feedback generated by the sensors. Therefore, there is a requirement for the algorithms to model the human process as accurately as possible.
- *Trauma Rehabilitation:* The patients who undergo treatment for the trauma require rehabilitative therapy. TI is a promising solution that can contribute positively to the development of the rehabilitative aids that are intelligent and tailor-made to the requirements of the user. The algorithms that can learn the features of the user can allow a more personalized regimen. Which, in turn, result in early recovery. Additionally, specialized sensor and actuator modules are required for such applications, therefore presenting a new research challenge.
- *Interactive Medical Training:* The interactive systems that respond to a stimulus in real-time open a great opportunity for hands-on training for medical applications. Since the life-like haptic feedback can be generated based on the input; better pedagogical tools can be employed for healthcare training. Therefore, opportunities for the development of signal processing algorithms for generating feedback based on the input are required.
- *Augmented Reality (AR) and Virtual Reality (VR) Based Training and Rehabilitation:* The AR/VR based system combines the advantages of a visual perception along with the haptic feedback for several applications, including medical training, emergency first aid training, and sports training. Such systems have also found their application in rehabilitation processes such as breathing exercises, sports exercises, and cognitive exercises.
- *Precision in-Vivo Procedures:* The use of nanorobots for performing complex in-vivo procedures can be accomplished by using the TI. This application is a sub-area of remote surgery; however, additional functions such as precision drug delivery, minimally invasive procedures can also be achieved by using TI.

*6) Internet of Nano Things:* There are myriad challenges that are impeding the development of IoNT and hence, the Internet of Nano-Things for Healthcare (IoNT-H). Firstly, there are immense energy constraints. Energy harvesting can provide a promising solution for a power-constrained IoNT network. There are design problems that have to be addressed with respect to antenna design. Additionally, there are challenges for interoperable protocols for communication and data sharing. There are concerns with regards to security and maintenance of privacy, as well as operational deployment. The challenges offered due to signal interference within the body are also to be tackled.

Some of the applications that can be realized in the future by IoNT are listed.

- *Precision Medicine:* The nanorobots can be deployed to deliver drugs to specific organs with pinpoint accuracy, thereby resulting in more effective treatment and reducing the side-effects. Therefore, a clear vision for the development of nano-robots synthesized from specialized materials is presented. Additionally, there is a need for the development of communication standards for reliable control and co-ordination. The localization of the nano-robots inside the human body requires state-of-the-art solutions. Therefore, a number of avenues can be identified for future research and development.
- *Nano Sensors:* The performance of IoNT-H is significantly affected by the quality of the input that is sensed by the specialized sensors. However, in IoNT-H, the sensors shrink down to the nano level. Therefore, the design of the nanosensors requires an exploration of a vast area in terms of materials, fabrication, antenna design, and processing power. There is a cross-domain research

challenge while designing a nanosensor that offers an unlimited opportunity for research and development.

- *Minimally Invasive Surgical Procedures:* A swarm of nanorobots can be coordinated to perform procedures in the most inaccessible parts of the human body. Therefore, a vision is presented in terms of the development of algorithms for the co-ordination of the numerous sensors deployed for a task. Additionally, the communication protocols with high reliability and low latency are required for the same. The issues of signal obstruction inside the body cavity are to be tackled head-on.

### B. Open Issues Based on the Literature Review

Based on the analysis of the literature in the preceding sections, the following challenges are identified that present an obstacle in the large-scale deployment of H-IoT systems.

*1) Machine Learning in H-IoT:*

I. *Adoption of Reinforcement Learning Algorithms:* The defining characteristic of an H-IoT system is resource-starved. Therefore, default supervised and unsupervised ML algorithms are not suited for the H-IoT operation due to their resource-intensive operation. Therefore, the focus should be turned to the RL algorithms that require lesser computational complexity and memory resources. The RL algorithms learn from their previous experiences and do not require any training with the datasets. Thereby saving time as well as computational resources. The RL based systems can not only be applied for the detection of abnormal behavior and generation of alerts but also for the autonomous network management.

II. *Lightweight AI Algorithms:* It is evident from the discussion in the preceding sections that high accuracy is achieved in processing vital data for the detection of diseases and the generation of emergency alerts using DL algorithms in a fog/edge-based framework. Some of the works using the simple SVM algorithm also achieve high accuracy but at the expense of high computational cost. The efficient resource utilization calls for the development of light-weight AI algorithms supporting the analysis of large volumes of data streams generated each second in a monitoring system.

III. *Autonomous Network Management and Security:* One of the goals of the AI in H-IoT is to achieve complete autonomy for network management. The routing protocols based on RL algorithms can provide robust and intelligent traffic management systems. The use of light-weight RL algorithms can also support channel selection in a distributed random-access environment [254]. An intelligent IDS system enabled by ML can help in preventing the security breaches and also learn the network behavior for independently mitigating any future threats.

The role of SDN is very critical in implementing autonomous network management. The virtualization of network devices and functions can be controlled using learning algorithms to create a self-regulated H-IoT system.

*2) Fog/ Edge Computing Integrated With SDN Exploiting ML and Big Data:*

I. *Resource-Efficient Nodes:* The advances in memory design and fabrication can be exploited to design resource-efficient WBAN nodes that can contribute to building a distributed intelligence system using edge computing. As more and more devices get added to the network, collaborative computational resources can be implemented, thereby improving the QoS of the system.

II. *Redundancy in Training Datasets:* The training datasets used in the DL algorithms, such as ANN and CNNs, are composed of a large sample space. Each sample contains several features that are used in either the prediction or detection of some anomaly. However, there is considerable redundancy in terms of samples conveying similar information. The computational resources are utilized multiple times to compute the same information, which could be avoided by designing algorithms for resource-efficient and non-redundant training. Pre-processing the datasets to remove the redundancy and assigning the weights to the individual features in the feature vectors are a few approaches to mitigate this issue.

III. *Time Constraints:* The data analytics for H-IoT systems show remarkable performance in terms of accuracy. However, accuracy is achieved at the cost of time, which is of critical importance. Therefore, the requirement of time-sensitive algorithms is very acute. The time efficiency can be improved by either using intelligent feature selection algorithms or by reducing the training period for the supervised learning or DL algorithms.

In some of the applications like the path selection, the time limitation for the generation of an optimal path may be smaller than the transmission time, thereby rendering the approach futile. Therefore, it must be ensured that the algorithms adopted to fulfill the functional requirements within the prescribed time constraint.

*3) Blockchain Supported by SDN:*

I. *Privacy Issues:* The protection of privacy and securing the data remains one of the primary challenges in the H-IoT [258]. The transmission of data to the data processing unit for big data analysis is vulnerable to eavesdropping as well as data manipulation. Therefore, it is highly essential to identify the ways to secure the transmission between the nodes and the processing unit [259], [260]. Additionally, the identity of the user should be protected during the data processing by ensuring the processing algorithms do not map the data to the user explicitly. Instead, cryptographic methods can be adopted.

In the purview of the SDNs, the privacy protection remains a critical concern as the node information is readily available with the control plane. The malicious intents can be fulfilled if the identity of the nodes is not masked.

II. *Key Distribution:* A cryptographic key protects the identity of a node in a blockchain. The distribution of the public keys should be secured from threats like the selective forwarding and grey hole attacks. It should be ensured that no malicious node can overhear the control traffic. There is a potential for a Sybil attack as well, which allows the malicious nodes to take up a false identity. Therefore, a secure identification mechanism can ensure that the identity of a node is preserved. The solutions that can ensure the secure key distribution without additional cost are required for optimum performance. Additionally, the time constraints should be respected as the current works demonstrate the end-to-end delay for key distribution systems is greater than the acceptable QoS values [256].

III. *51% Attack:* A critical loophole in small and private blockchains is the 51% attack. In this scenario, if a malicious entity controls 51% of miners, the security of the blockchain is compromised. Therefore, it is necessary to identify solutions to avoid this severe scenario. The strict hashing is usually adopted in Bitcoin to avoid this situation, but the H-IoT systems do not have computational capabilities for strict hashing. One of the suggested approaches is to change the rights of the miners in the blockchain randomly. It ensures no miner is able to approve the blocks continuously.

IV. *Consensus Algorithms for Blockchain:* The biggest challenge in using the blockchain for network management in H-IoT is the consensus between the nodes. The computational resources in the H-IoT devices are very scarce and cannot be used for implementing the consensus algorithms that are used for the traditional blockchain applications. Therefore, an alternative solution must be developed that can fulfill the QoS requirement at the same time while tackling resource limitations.

V. *Integration With Smart Cities:* The H-IoT systems are expected to be integrated with the living environment of the users. The smart cities are the future of infrastructural developments. Therefore, integrating the H-IoT system with the services in the smart city architecture is an efficient approach for massive adoption of H-IoT. Smart contracts in the blockchain technology can be used for distributing services in the smart city environment. Therefore, ensuring the security and privacy of the data and the user, respectively. Additionally, blockchain can be utilized for the development of secure smart city databases and thus allowing the provision for better services. Localization technologies can also offer better emergency services in a connected environment.

## XII. Conclusion

H-IoT is a system of sensors collecting the vital health data ubiquitously and sharing it over a secure network. The collected data is processed to look for any inconsistencies, and hence, an alert is generated if any are found. This forms the basis of Medicine 4.0, the new automated platform for patient monitoring and diagnosis powered by IoT. This work reviews some of the new technologies that power the H-IoT systems. A number of architectures using different computing paradigms are implemented in H-IoT. These architectures are driven by ML, edge computing, and new technologies like SDN blockchains. The capabilities of ML are exploited in multiple use cases of H-IoT and even maintaining the network and helping in achieving optimal network and service performance. Edge computing has a significant role in reducing the latency of the system and enhancing the reliability of the system by bringing the computing power to the edge of the network. It eliminates the need to send the traffic over to the cloud via an unsecured network, therefore contributing to the security of the data as well. Fog computing provides computational capabilities for a host of functions, ranging from storage to security, and processing to alert generation. The potential of big data analytics is realized in H-IoT for processing large data sets that are recorded continuously. Big data analytics provide a framework for real-time discovery of abnormal behavior as well as making future predictions about the patient's condition. The blockchain is enhancing the data storage capabilities by introducing a transparent and secure method of information and delivery. SDNs are allowing for more flexibility in maintaining the network and enhancing the capabilities by introducing the separation in the data and network management planes. The IoNT is driving the network revolution at the nanoscale with applications in precision medicine and sensing. Overall, these novel technologies are providing a driving force for large scale adoption of H-IoT, which would be further accelerated by the introduction of 5G and efficient wearables and other implantable sensors. Many serious challenges have been identified, which are impeding the widespread adoption of the H-IoT systems, but there are several novel solutions to mitigate these challenges. These challenges have been identified in this work, and on their basis, the future research directions are identified. Tactile Internet is a leading paradigm shift in H-IoT communication, and it is opening new avenues in healthcare. By close analysis of the literature and the market trends, it is clear that large-scale adoption of H-IoT is inevitable.

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