Toward a Heterogeneous Mist, Fog, and Cloud-Based Framework for the Internet of Healthcare Things

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***Abstract*—Rapid developments in the fields of information and communication technology and microelectronics allowed seamless interconnection among various devices letting them to communicate with each other. This technological integration opened up new possibilities in many disciplines including healthcare and well-being. With the aim of reducing healthcare costs and providing improved and reliable services, several healthcare frameworks based on Internet of Healthcare Things (IoHT) have been developed. However, due to the critical and heterogeneous nature of healthcare data, maintaining high quality of service (QoS)—in terms of faster responsiveness and data-specific complex analytics—has always been the main challenge in designing such systems. Addressing these issues, this paper proposes a five-layered heterogeneous mist, fog, and cloud-based IoHT framework capable of efficiently handling and routing (near-)real-time as well as offline/batch mode data. Also, by employing software defined networking and link adaptation-based load balancing, the framework ensures optimal resource allocation and efficient resource utilization. The results, obtained by simulating the framework, indicate that the designed network via its various components can achieve high QoS, with reduced end-to-end latency and packet drop rate, which is essential for developing next generation *e*-healthcare systems.**

***Index Terms*—Data fusion, healthcare application, healthcare big data, load balancing, quality of service (QoS), real-time computing, resource allocation.**

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I. Introduction

WITH the sudden growth of electronic devices and improved connectivity of the Internet, nowadays more devices are connected to the Internet than people [1]. This has been facilitated by a concept, called "Internet of Things" or IoT, which was coined back in 1999 by Kevin Ashton and was meant to connect Radio-frequency identification (RFID) devices in the supply chain of a consumer goods manufacturer [2]. However, currently the term is used in almost every field to describe a network of communicable devices [3], [4].

In recent years, IoT enabled devices have emerged exponentially and the estimated number of connected devices are to exceed 28 billion by 2021 [see Fig. 1(a)]. As a technology, the IoT has been adopted at a varied pace among different industries and sectors with their respective applications. The healthcare sector, which is slow in adopting new technologies, however, shows an incredible estimated growth and is expected to have over 50 million connected devices worldwide by 2021 [see Fig. 1(b)] [5]. Also, different application domains in healthcare have shown varied opportunities in applying IoT and, as per the current trend, the smart healthcare products application domain [e.g., smart pills, smart dispensing devices and syringes, smart monitoring devices, smart RFID cabinets, electronic health record (eHR), etc.] is the hottest [see Fig. 1(c)] [6].

Considering the increase of life expectancy, the Population Reference Bureau projected that by 2050 the World's population will grow by 31% reaching 9.8 billion [7]. With this unprecedented growth rate, the older population (aged 65 and over) is expected to raise 16% more than the total population between 2025 and 2050 [8]. This will eventually result in increased vulnerability of the aging population toward chronic diseases which is expected to account for 73% of all deaths and 60% of the global burden diseases by 2020 [9]. On the other hand, as predicted by the World Health Organization, there will be a distressing

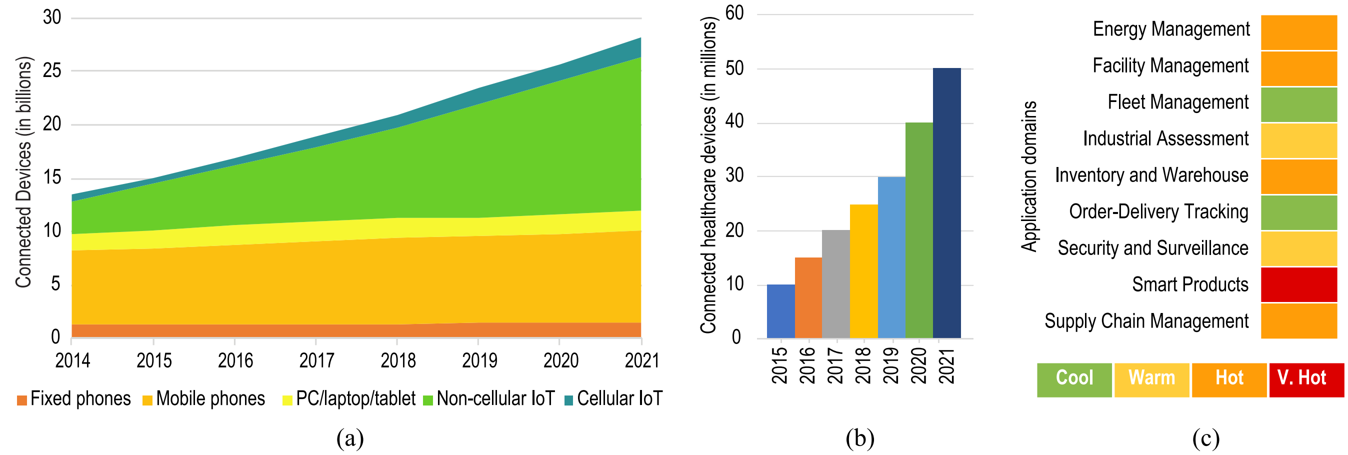

Fig. 1. Global connectivity through IoT devices. (a) Global estimation of connected IoT devices by the year 2021. (b) Global estimation of IoHT devices by the year 2021. (c) Heatmap of current IoHT application opportunities.

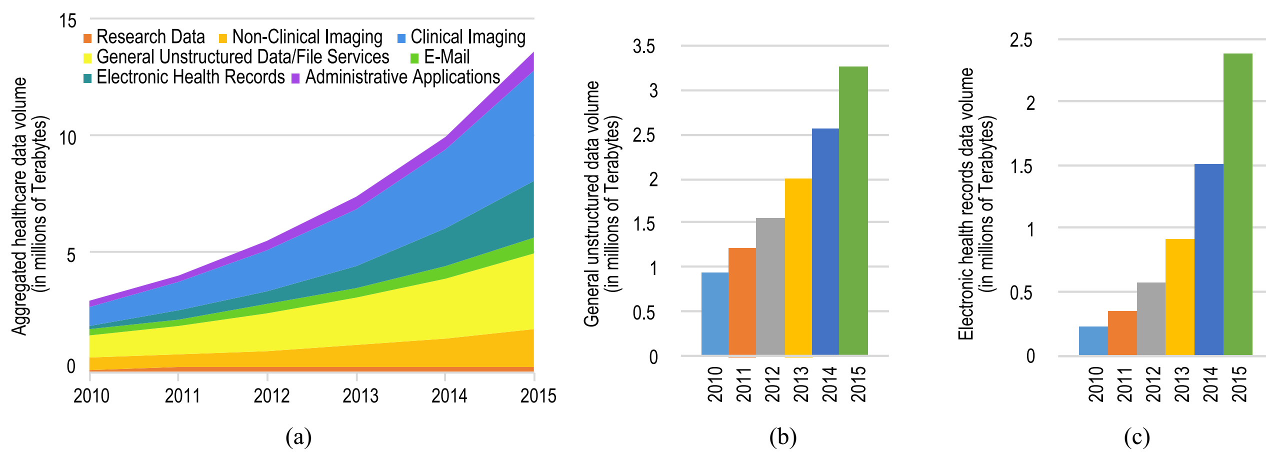

Fig. 2. Estimated data volume generated by different healthcare applications at North America between 2010 and 2015. (a) Aggregated volume of healthcare data, (b) volume of general unstructured data only, and (c) volume of electronic health records data only.

shortage of 12.9 million healthcare workforce worldwide by 2035 [10]. Hence, energy-efficient, low cost, and scalable healthcare solutions are needed to meet the shortage of healthcare workforce to support disease prevention, treatment, care, and cure.

Leveraging the fast advancements in information and communication technology, electronic healthcare (*e*-healthcare) emerged itself as a revolutionary new paradigm [11]. Following the technological improvements, *e*-healthcare is rapidly swapping the means of conventional healthcare [12], and fostering development of novel healthcare applications [13]. In this ever changing scenario of healthcare, IoT plays a key role [14] in redefining *e*-healthcare as the Internet of Healthcare Things (IoHT), where both people and devices interact, communicate, collect, and exchange data through integration of physical objects, hardware, softwares, and computing devices [15]. Connecting the digital world to the physical world [16], IoHT—with the help of pervasive and ubiquitous computing, and *e*-healthcare systems—allows healthcare devices (e.g., Fitbits, sensors, Bluetooth, mobile devices, etc.) to collect health related information (e.g., blood oxygen saturation, blood pressure, weight, glucose level, respiratory and heart rate, etc.) [17], [18] over an extended period of time and save as eHR.

However, the various players of the *e*-healthcare ecosystem generate a large amount of heterogeneous, multidimensional and multimodal data databasing which is a big challenge [19], [20]. In North America, during 2010 to 2015, the volume of healthcare data raised from 3 million Terabyte (TB) to 14 million TB [see Fig. 2(a)] [21] with general unstructured data and eHR had an incredible increment from 0.95 millon TB in 2010 to 3.26 million TB in 2015 [see Fig. 2(b)] and from 0.22 millon TB in 2010 to 2.36 million TB in 2015 [see Fig. 2(c)], respectively. In order to process this huge volume of healthcare data, systems with enormous storage and processing power are needed which can analyze the big data, thus, cloud computing was used [22], [23]. Therefore, to shape next generation of *e*-healthcare systems, IoHT, big data, and cloud computing needed to converge to create the IoHT ecosystem [24]. Cloud computing plays a prominent role in the IoHT ecosystem by providing ubiquitous and on-demand access to shared pool of reconfigurable resources. Nonetheless, the current number of growing IoHT devices cause increasing latency due to network overloading, thus, reducing the suitability of the system for real-time applications. To overcome this situation, the concept of fog computing was introduced, by Cisco Systems Inc., in 2012, which complemented the cloud by providing a substantial amount of storage, communication control, configuration, measurement and management at the edge devices [25], [26]. The concept of fog computing is to deploy cloud-like services closer to user end for local storage and preliminary data processing to reduce congestion and latency. The added flexibility of computation, geographical distribution and user mobility support make fog computing appealing for healthcare related applications which require secure data transfer with low latency [27]. However, fog computing architecture may susceptible to single point of failure as it mostly depends on gateway device [28]. To further increase the response time by reducing the data traffic on fog nodes in local networks, mist computing can be used to create an integrated network [29] which bridges the IoHT devices to the virtual computing world, thus, reducing the response latency and enhancing the performance and lifetime of IoHT devices.

Different data types and applications of the IoHT ecosystem require different processing and response times. To this aim, this paper proposes a novel heterogeneous cloud-based IoHT communication framework supported by fog and mist computing. This heterogeneous IoHT framework consists of five layers—perception, mist, fog, cloud, and application. The novelty of this architecture lies in its capability to handle separately data routing paths for different data types coming from real-time as well as conventional data sources, optimally balance the network load on demand, and optimally allocate network resources as needed. The obtained results show that the proposed IoHT framework provides better quality of service (QoS) with low power consumption and reduced latency, thus, improving the existing *e*-healthcare systems.

II. State-of-the-Art of IoHT Frameworks

Majority of the contributions concerning IoHT frameworks have been in integrating IoT technology to healthcare systems. Islam *et al.* [14] surveyed diverse aspects of IoT-based healthcare technologies with descriptions of various existing network architectures, platforms, industrial trends, and applications which facilitate healthcare solutions in the context of IoT. Additionally, the trends of IoT-based healthcare research activities were examined to showcase how IoT can address various healthcare issues like—pediatric and elderly care, private healthcare, chronic disease supervision and fitness management, and pointed out different research problems along with current security requirements and challenges. Through a brief discussion on an intelligent collaborative security model, the authors provided means for anomaly detection. The survey concluded with some *e*-health and IoT policies and regulations across the world to healthcare stakeholders better understand IoT-based healthcare technologies for sustainable development [14]. IoT enabled personalized healthcare systems (PHS) were systematically reviewed by Qi *et al.* [30], where the authors focused on identifying the breadth and diversity of existing IoT enabled PHS, the underlying key technologies along with their applications and case studies on healthcare, and listed future research trends and challenges. Farahani *et al.* [31] surveyed the existing literature on IoT related *e*-healthcare systems from a viewpoint of transitioning from the conventional clinic-centric treatment to patient-centric treatment. The authors discussed existing challenges of IoT-based *e*-healthcare systems and proposed a multilayer *e*-healthcare ecosystem with their respective applications, such as, assisted living, mobile health, warning systems, e-medicine, and population monitoring. Kraemer *et al.* [32] were among the first to survey the benefits and challenges of fog computing within pervasive healthcare applications. The authors provided a summary of deployment scenarios, requirement of future healthcare and variety of fog processing tasks. Mutlag *et al.* [33] performed a systematic literature review of the existing technologies focusing on fog computing's usage in the field of healthcare IoT systems. The study further identified the flaws of the current fog-based frameworks and provided some recommendations toward more secure and reliable IoT systems. Ahmad *et al.* [34] proposed HealthFog, a fog computing-based framework, capable of successfully removing additional E2E communication costs in comparison to their counterparts. Their framework also ensured enhanced privacy and security using cryptographic primitives. To enhance reliability of IoT architecture for healthcare, Rahmani *et al.* [35] combined fog computing with smart e-Health gateways and demonstrated that the proposed system is capable of coping with many challenges of pervasive healthcare systems. They also implemented it as an IoT-based early warning score health monitoring system.

In addition to the studies mentioned above, other reported works on IoT-based healthcare include: emergency medical service [36], smart rehabilitation system [37], do-it-yourself solution focusing on patient oriented infrastructure development [38], smart hospital system [39], anomaly detection [40], body sensor network-based healthcare system [41], cardiac arrhythmia management system [42], and self-aware early warning system [43]. Laplante and Laplante discussed about their view on negetive effects of IoT in healthcare and showcased an example of the dissociation between patient and caregiver resulting in loss of care [44].

With the growing amount of data, their processing and storage requirements also escalated. To tackle this need, the IoT-based healthcare systems were integrated into more extensive cloud computing architectures. This integration of "IoT" and "Cloud computing" has contributed toward the development of many innovative solutions [45]–[47] spanning in different fields including *e*-healthcare. With the aim of seamless integration of various remote health monitoring techniques (e.g., sensing analytics, visualization, etc.), Hassanalieragh *et al.* [48] discussed on the existing challenges related to such integration and their views on integrating those techniques in the clinical practice. Biswas *et al.* introduced *e*-health cloud, a three-layered cloud-based framework—capable of mining eHR data—where the network layer was designed using

Rich Internet Application[1]-based client, the server layer with SimpleDB,[2] and a logic layer [49]. Pathinarupothi *et al.* [50] presented a multilayered architecture consisting of IoT devices coupled with body sensors which was implemented to remotely monitor cardiac patients. The cloud HealthIIoT (Health-care Industrial IoT) framework proposed by Hossain and Muhammad [51] transmitted healthcare data securely to the cloud to be accessed by healhcare professionals, and was validated through an IoT driven ECG-based health monitoring application. Suciu *et al.* proposed an *e*-health architecture based on exalead cloudview[3] which securely integrates big data analytics with cloud-based Remote Telemetry Units[4] [52]. Ma *et al.* [53] proposed a four-layered big health application, system supported by IoHT and big data, for remote disease diagnosis, smart clothing-based healthcare, LTE assisted telemedicine, and robotic interactions. Similar frameworks include: monitoring systems for chronic diseases, such as cardiovascular and respiratory diseases through IoT sensors [54], mobile healthcare systems for patient monitoring using big data analytics applied on sensor data [55], [56], heterogeneous healthcare big data analytics system for decision making in risk management and patient care [57].

The cloud can also be deployed to process and manage the IoT data online [58], [59]. Dehury and Sahoo [60] implemented a cloud-based service management framework for analyzing real-time IoT data. Various cloud-IoT (cIoT) frameworks have been suggested for pervasive healthcare [61]–[63]. A case study of voice pathology monitoring was proposed using an cIoT model [64]. Bagula *et al.* [65] introduced cIoT model to prioritize situation aware patients. Hasan *et al.* [66] introduced a cIoT model, called Aura, which allowed mobile clients to create ad-hoc clouds using IoT devices in their adjacent environments and provided the clients full control of the range of analyses to be performed regardless of their physical locations.

Many studies have been reported which utilized the cIoT model to remotely monitor patients [67]–[69] using: ECG android application [70] along with other helathcare data [51], FIWARE[5] platform [71], and wearable sensors (IoT) and body area network [72]. Additionally, other cIoT frameworks include: personnel altering system regarding lifestyle diseases from physical activity data [73], [74], collecting real-time patient data from wireless body area network [75], accumulating physiological and healthcare data smart clothing with IoT sensors [76], [77], selecting personalized treatment plan [78], providing personalized medical diagnosis [79], supporting the physically challenged with assistive devices [80].

The transmission and processing latency is the major bottleneck for real-time handling of data in the cloud. Dastjerdi and Buyya [81] proposed fog computing along with edge and cloud computing to handle the big data generated by IoT sensors. Shi *et al.* [82] outlined the various characteristics of fog computing to manage real-time IoT healthcare

[1]https://en.wikipedia.org/wiki/Rich_Internet_application
[2]https://en.wikipedia.org/wiki/Amazon_SimpleDB
[3]https://en.wikipedia.org/wiki/Exalead#CloudView
[4]https://en.wikipedia.org/wiki/Remote_terminal_unit
[5]https://www.fiware.org/

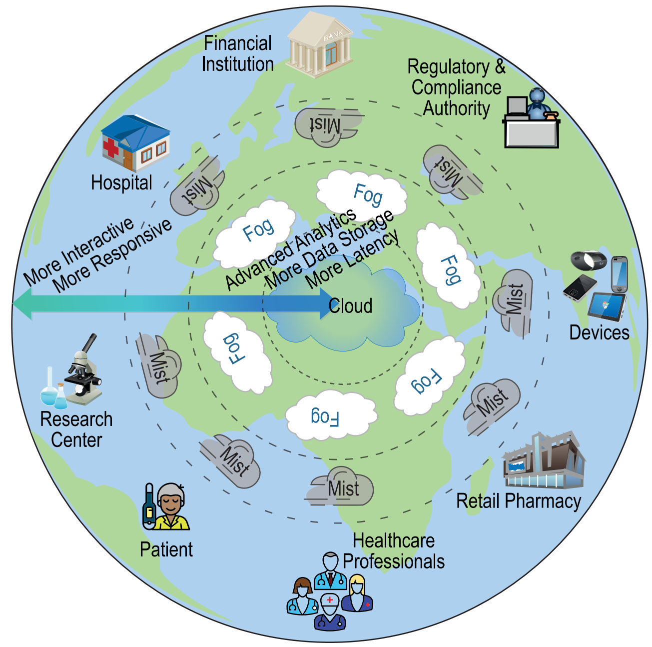

Fig. 3. Overview of an IoHT ecosystem with its various stakeholders which implements the proposed framework.

data. A low-cost fog-IoT healthcare system was presented which collected the ECG, respiration rate, and body temperature using energy-efficient sensor nodes and analyzed those data for automatic decision making which can be given to appropriate caregivers in real-time [83].

III. Proposed IoHT Framework

Large scale IoT implementation results in large number of connected devices. By default, most of these connected devices are with limited processing power and resources. But, the voluminous and heterogeneous data generated by these devices require efficient and data type specific processing. Centralized cloud-based IoT scheme brings out an effective solution in this regard. However, solo cloud dependent processing is constrained by latency and power consumption issues which can be solved—up to certain extent—by introducing a fog layer. The fog assisted IoT framework with smart gateways (as proposed in [35]) is an approach to enhance reliability, energy-efficiency and performance of IoT frameworks.

Nonetheless, there are still QoS issues with sensitive data transmission and there is no need to process various types of data (e.g., delay-sensitive and loss-sensitive) in each layer of a framework. An effective solution to this problem is to allow the framework to be able to handle different types of "on demand" data processing in different layers. This has been achieved in the proposed framework consisting of five layers (perception, mist, fog, cloud, and application). The introduction of an additional layer (i.e., the mist layer) to the existing fog-based architecture reduces data volume to be transmitted by the IoT devices through rule-based preprocessing of data. This reduction in data volume in turn reduces power consumption of the IoT devices, and latency (processing as

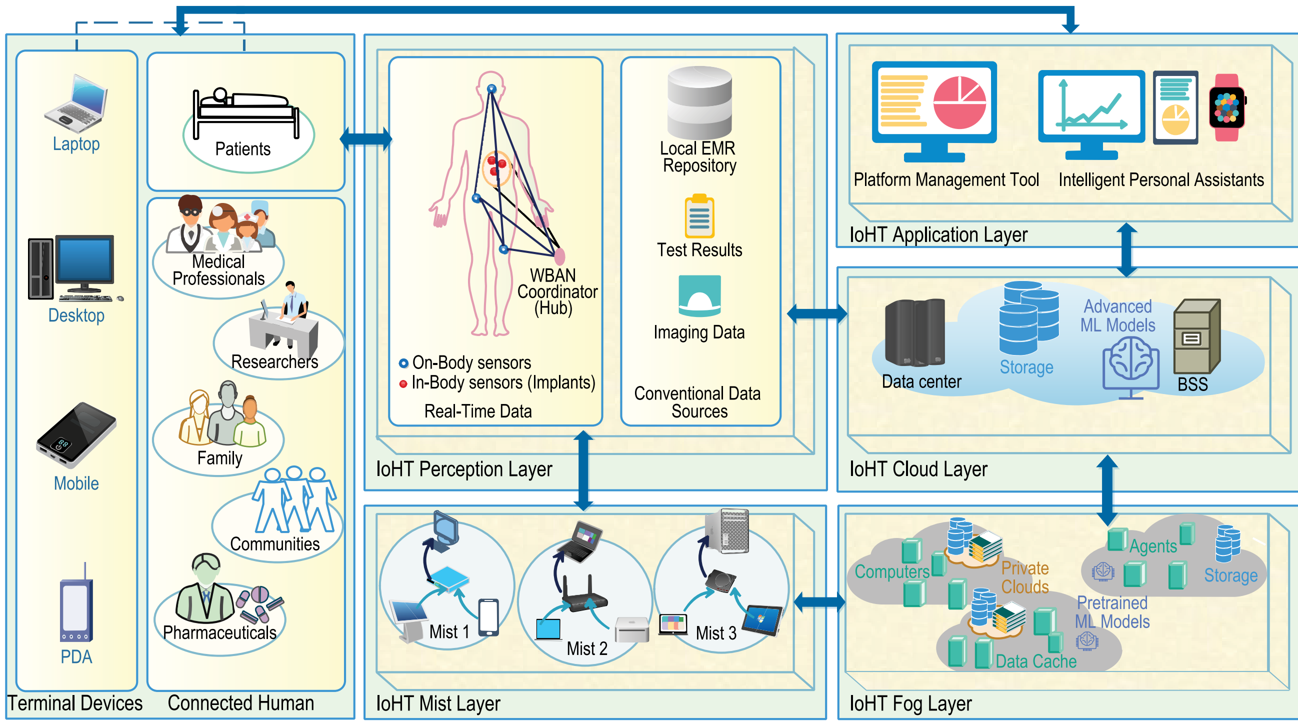

Fig. 4. Architecture of the proposed IoHT framework indicating different layers and possible connectivities among them. The arrow directions indicate the flow of data.

well as transmission) and computational complexity of the framework.

Therefore, the proposed IoHT framework is capable of selecting appropriate data transmission policies based on the disparate data sources to minimize latency; ensuring optimal resource utilization through delegating and delivering processes to layers with relatively less loads; guaranteeing minimal transmission delay through appropriate load balancing; and assuring most favorable data-sensitive resource allocation for prioritized data transmission. The following sections describes the various components of the framework.

A. *Ecosystem*

An interoperable ecosystem consisting of diverse devices, applications, and back-end systems is essential for successful architectural design of an IoHT framework which will ensure undisrupted information flow for accurate and timely decision making [84], [85]. A conceptual overview of the proposed IoHT ecosystem is shown in Fig. 3. As the ecosystem diagram indicates, various IoHT stakeholders who reside at the outer circle (e.g., healthcare organizations and professionals, patients, applications, and information systems) connect to their relevant counterparts to the inner circles aiming seamless information exchange. Outer circle is the most interactive and responsive one with very little analytical capabilities. Gradually moving toward the inner circles, the analytical capabilities along with latency and data storage increase. So, to ensure delay tolerant data transmission of real-time data as well as big data, the proposed architecture adopts appropriate layer-specific data transmission polices.

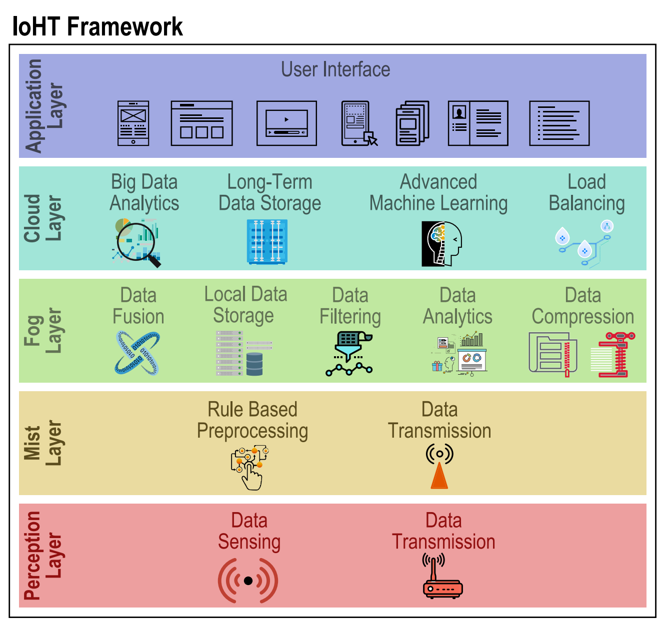

Fig. 5. Layer-wise functionality of the proposed IoHT framework.

B. *Network Architecture*

Fig. 4 shows the proposed IoHT framework's architecture. The five layers are: 1) perception layer; 2) mist layer; 3) fog layer; 4) cloud layer; and 5) application layer. Each of these layers has been designed with predefined functionalities relevant to the IoHT framework's data transmission and processing pipeline. Fig. 5 shows a block diagram with the functionality of individual layers.

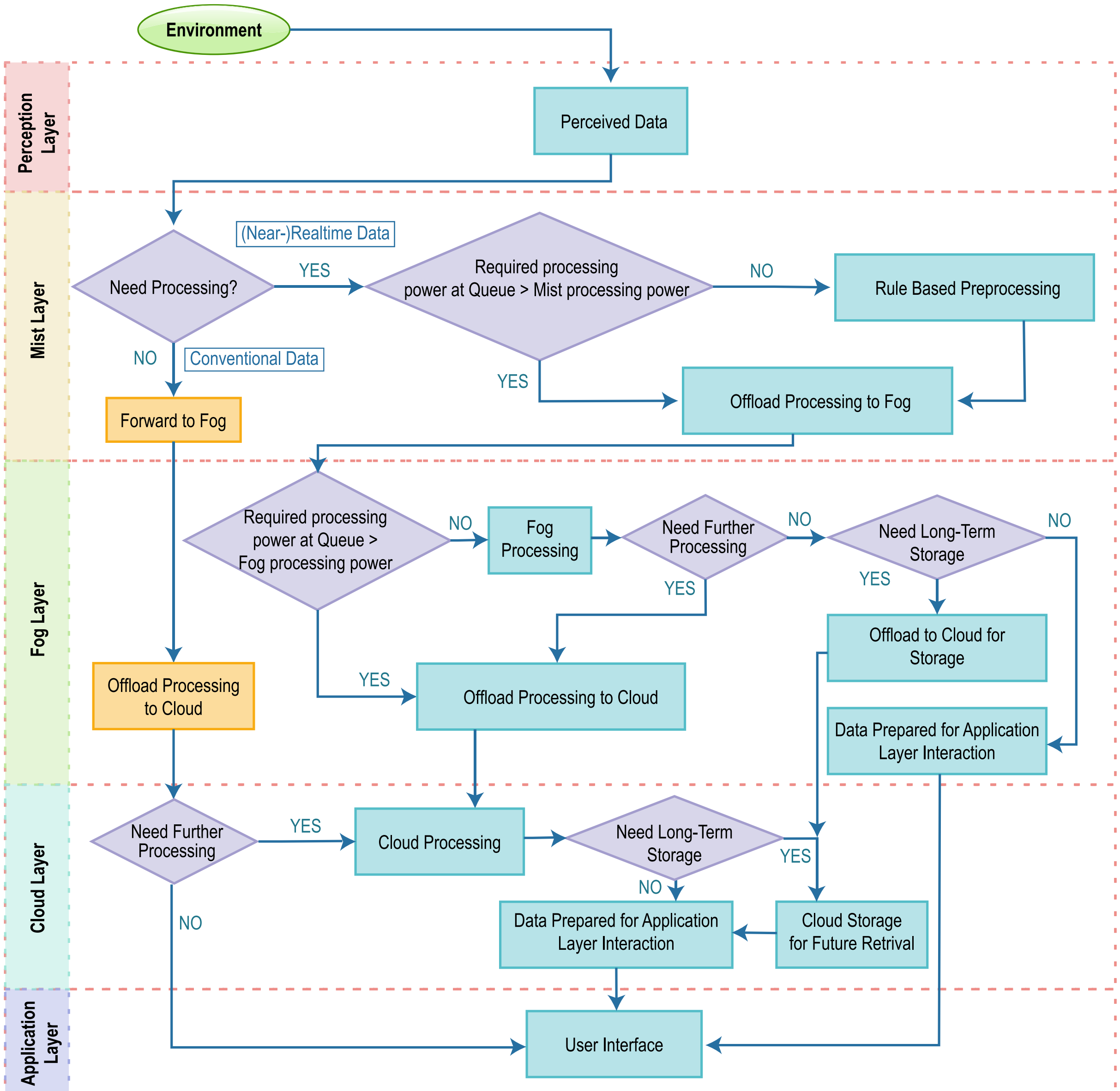

Fig. 6. Flowchart of data transmission and processing taking place at different layers of the IoHT framework.

1) Perception Layer: The perception layer is the lowest layer of the proposed IoHT framework. This layer is responsible for recognizing physical objects, and gathering contextual and healthcare data from devices generating (near) real-time as well as nonreal-time data. The data are mainly measured from individuals and their surroundings through small sensors, embedded systems, RFID tags, and readers, small to medium to large diagnostic and healthcare devices, medical and clinical imaging devices, and any data acquisition and transmission enabled devices. These hardware devices are, in general, connected to the data communication network.

Besides the real-time healthcare data, there are healthcare big data [e.g., structured eHR, electronic medical record (eMR), (non-)clinical/medical imaging data, unstructured clinical notes, etc.] which demand separate handling due to their requirement of advanced data analytics [86], [87]. In the proposed framework, both kinds of healthcare data are transmitted to specific overlaying layer (either mist or fog or cloud) based on the data type and their processing requirements.

2) Mist Layer: To facilitate time-critical data processing, the mist computing layer has been introduced in the model. Mist computing resides directly within the network fabric and operates on the extreme edge of it with the help of sensor and actuator controllers. This layer is responsible for performing basic rule-based preprocessing of the sensor data (e.g., data aggregation, fusion, and filtering). At the edge of the IoT network, a fair share of the “Things” are with limited resources (e.g., power, communication bandwidth, and memory). Mist computing contributes to optimal resource utilization of the Things. For example, since communication consumes ~5× the power of computing, ensuring required transmission instead of on demand transmission will facilitate in optimizing the power consumption [88].

3) Fog Layer: One of the main driving forces behind development of the IoT technology is the necessity to process data "on the fly" to detect anomalies, provide alerts at real-time, and activate necessary actions automatically. This clearly demands a system with high responsiveness and minimal latency. To this goal, using centralized cloud-based models are inappropriate due to their high latency. In such situations, decentralizing and delegating the processing loads on different layers based on the application's demand is needed. The fog layer forms a decentralized architectural pattern for bringing computing resources and application services closer to the edge, thus, reducing the response latency. As for the functional components, the fog layer supports—local data storage, data filtering, data compression, data fusion, and intermediate data analytics to reduce disposable load on the cloud, improve system performance and QoS, and save backbone bandwidth.

4) Cloud Layer: The cloud layer is capable of connecting to perception layer, fog layer, and application layer. Aggregated healthcare data from fog layer are sent to the cloud layer for long-term storage, and big data and advanced analytics. Also data from nonsensor sources, such as eMR, eHR, e-prescription platform, etc. get seamlessly integrated at this layer. In order to extract meaningful insights from the heterogeneous healthcare data, the cloud layer performs various advanced data analytics including, machine learning, data mining, rule-based processing, and automated reasoning-based algorithms. However, delegating appropriate computing loads to fog layer and using cloud layer for computationally expensive operations will improve system performance.

5) Application Layer: The application layer is the topmost layer of the proposed IoHT framework. It provides user interfaces between the IoHT stakeholders/consumers and the framework itself to directly reflect the generated economic and social benefits. Through these user interfaces various healthcare applications are delivered to the respective stakeholders. This layer also provides access—subject to access rights and privileges—to relevant resources from the cloud or fog layer directly to the healthcare application developers and consumers.

C. Data Transmission Policy

To facilitate seamless communication of heterogeneous data, a data-centric transmission scheme has been utilized in the proposed five-layered architecture of the IoHT framework. The perception layer generates three possible types of delay-sensitive data, i.e., real-time, near-real-time, and offline/batch mode data. In order to achieve better QoS, reduced latency, and optimized power consumption, separate transmission paths for real-time data and big data have been used. Fig. 6 represents the transmission and processing flow of data in the proposed model. Based on data traffic and resource availability, the computational loads (e.g., rule-based preprocessing, pretrained machine learning, advanced machine learning, big data analytics, etc.) are delegated to an appropriate layer (either mist or fog or cloud) in the layered architecture. This resulted in different scenarios with specific transmission paths as detailed in the following sections and shown in Fig. 7.

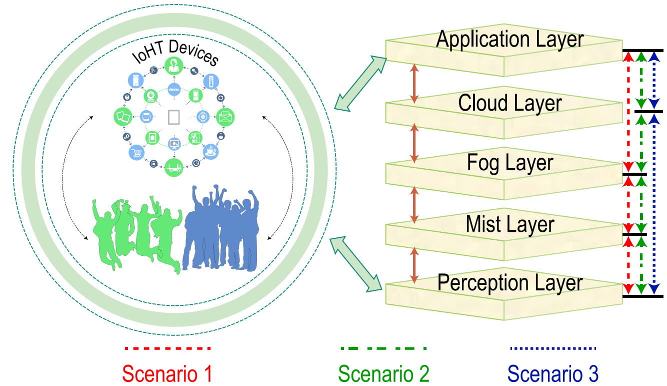

Fig. 7. Possible data transmission and processing paths in the IoHT framework's layer stack.

1) Real-Time Data Transmission:

a) Scenario 1: Many healthcare applications require data to be processed at real-time. In the proposed IoHT model, real-time data analytics are hosted at the closest possible location, where the data is generated. As indicated in Fig. 7 by the red-dashed lines with arrows, the generated time-sensitive sensor data are at first forwarded to the mist layer for preprocessing, followed by the fog layer for necessary intermediate analytics, and finally rendering decision to the application layer. For example, if a patient experiences high blood pressure fluctuations along with symptomatic discomforts, it is necessary to process the generated data and forward a decision to the caregiver as soon as possible to prevent a possible stroke. In this case, the preprocessed data from mist layer are further processed in fog layer and forwarded to the application layer for necessary actions by the stakeholders.

b) Scenario 2: The intermediate data analytics performed at the fog layer is not sufficient for some healthcare applications. Rendering a decision for these types of applications may require big data analytics and advanced machine learning or long-term data storage for longitudinal studies. In those cases, data are offloaded to the cloud layer for the required processing, analysis, and storage. This transmission path is shown in Fig. 7 using the green dotted-dashed line with arrows. The data and the analysis results are usually stored in the cloud for further reference. Adverse drug reaction (ADR) service can be an example of this scenario. Medication for a particular disease needs diagnosis as well as patients previous history as ADR is inherently generic. So, in this case, data sensed from patient's terminal are forwarded to mist layer for recognizing the drug. Later on, fog forwards the identified drug to the cloud, where after careful analysis of relevant eMR and allergy profiles the drug compatibility is decided and the decision is sent to the application layer to be accessed by the healthcare professionals.

2) Conventional Data Transmission:

a) Scenario 3: Massive data generated from advanced medical instruments, test results, eMR requires data mining, predictive analysis, and other advanced analytics. Only cloud computing is capable of performing these computationally demanding processing. So, in this scenario, data

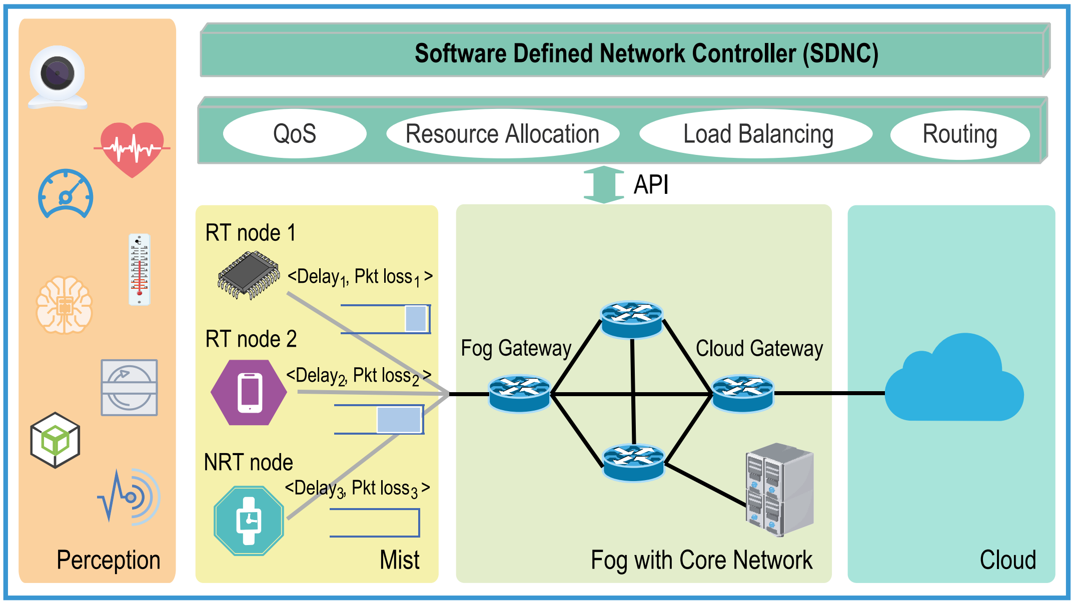

Fig. 8. Exemplary scenario of the IoHT framework with mist, fog, and cloud layers. The network is configured using SDN. The AP allocates resources based on the latency and packet drop rate demand of each IoHT nodes.

from conventional sources are directly offloaded to the cloud for processing. This transmission path is indicated by the arrowed blue dotted lines in Fig. 7. An example of such a scenario is that, MRI produces thousands of high resolution images per examination which require more computation power and storage, and can be efficiently served only by the cloud. In this scenario, data are directly forwarded to the cloud without any processing or holding in the mist or fog layers.

IV. Optimal Resource Allocation and Load Balancing

The IoHT nodes in the perception layer collect the (near) real-time as well as nonreal-time healthcare data to monitor patients. These collected data are forwarded to the IoT hub(s) (also called access point or AP). Based on the traffic class and processing requirements, these data can be processed in the mist, fog, and cloud layers as discussed in Sections III-B and III-C. In the process of effective handling of these data, the end-to-end (E2E) delay, throughput, packet loss, energy efficiency are crucial for maintaining the QoS of the proposed IoHT framework.

To handle these heterogeneous data efficiently while maintaining the high QoS, the network resources are to be dynamically allocated. To this goal, the proposed IoHT framework relies on software defined networking (SDN), which is a programmable network structure that can be deployed on the top of IoHT framework as a centralized/distributed control layer for resources (e.g., bandwidth and buffer size) allocation, scheduling, routing, and flow control through SDN controller (SDNC) [89]. As SDN fulfills the requirements of various applications and workloads through network virtualization by decoupling control plane from data plane [90], it has been considered with the IoHT framework to manage the resource demand of exponentially growing IoT devices.

TABLE I
Traffic Classification of IoHT Healthcare Data

P	Traffic Type	Description		Service Type	Example
		C	tQ		
1	$\mathcal{DS}$	H	L	Critical Traffic	RT Patient Monitoring
				Video Traffic	VidStream EM & MC
				Multiconf.	Teleconf.
2	$\mathcal{LS}$	L	H	Images/Video	Medical Imaging
				Test Results	EMR
3	$\mathcal{M}$	M	M	NCMeasure	Regular PhyMeas

Legend: H–High; L–Low; M–Medium; RT– Real-time; VidStream EM & MC– Video streaming of elderly monitoring & motion control; Multiconf– Multimedia conferencing; Teleconf– Teleconferencing; PhyMeas–Patient physiological measurements; NCMeasure– Noncritical healthcare parameter measurement.

A. *Traffic Classification*

The perception layer of the IoHT framework (as discussed in Section III-B1) generates heterogeneous data or network traffic. In order to achieve better QoS, these network traffic are classified as the delay-sensitive ($\mathcal{DS}$), loss-sensitive ($\mathcal{LS}$), and both delay- as well as loss-sensitive (termed as "Mixed") ($\mathcal{M}$) traffic. This classification is mainly based on transmission data rate (C) and queuing delay (tQ), and is used to prioritize the network traffic. Table I shows various traffic classes, their service types, transmission priority (P), and exemplary applications.

B. *Resource Allocation*

In order to achieve better QoS, the objective is to reduce the time delay (tD) and packet drop rate (Pkt_{drop}) during the transmission process. All the IoHT nodes in the mist layer achieve the minimum threshold requirement for both of these parameters through an optimal resource allocation. Fig. 8(a) illustrates an example scenario of the resource allocation problem.

TABLE II
QoS REQUIREMENT AND CORRESPONDING RESOURCE DEMAND TO ACHIEVE THE QoS REQUIREMENT OF THE iTH IoHT NODE

QoS requirement	Resource Demand
$< tD_i, Pkt_{drop_i} >$	$< B_i^d, L_i^d >$

Consider the output link capacity of an AP is C, there are N IoT devices in a mist (see Fig. 8), each IoHT device has packet size of Pkt_{size}. In order to ensure the QoS requirement of ith IoT device, the user requirement is $<tD_i, \text{Pkt}_{\text{drop}_i}>$ and the corresponding resource demand is $<B_i^d, L_i^d>$, where B_i^d and L_i^d are the bandwidth demand and buffer length demand of the ith IoHT user node (see Table II). As the allocated resource to ith IoHT device is proportional to the requirement of that user, the maximum resource (Γ_i) awarded to the ith IoHT node by the SDN-based resource allocator is

$$\begin{aligned}\Gamma_i &= \max\left[\frac{B_i}{C}, \frac{L_i}{L}\right]\\ &= \max\left[\frac{B_i^d}{C}\frac{B_i}{B_i^d}, \frac{L_i^d}{L}\frac{L_i}{L_i^d}\right] = \max\left[D_i^c U_i^c, D_i^l U_i^l\right] \quad (1)\end{aligned}$$

where $D_i^c = B_i^d/C$ and $D_i^l = L_i^d/L$ are the ratios of bandwidth demand of the ith node and the maximum capacity, and buffer length demand of the ith node and the total buffer length of AP, respectively. The $U_i^c = B_i/B_i^d$ and $U_i^l = L_i/L_i^d$ are the requirement to demand ratio of bandwidth and buffer length, respectively, for the ith node.

Using the M/D/1 queue model [91], the E2E delay tD includes the transmission delay tTx, processing delay tP, and queuing delay tQ which are calculated by

$$\begin{aligned}tD &= tTx_i + tP + tQ\\ &= \sum_{cl}\sum_{\text{fog}}\sum_{\text{sen}}\left[\frac{N_{\text{pkt}}\text{Pkt}_{\text{size}}}{C} + \left(\frac{\lambda}{2\mu(\mu-\lambda)} + \frac{1}{\mu}\right) + c\lambda\right] \quad (2)\end{aligned}$$

where λ and μ are the arrival and service rate, N_{pkt} is the number of packets, c is the constant duration required to complete a job by a processor, sen refers to sensor and cl refers to the cloud.

The packet drop occurs when the average queuing length $E[Q_i]$ is higher than demanded buffer length $L_i^d/\text{Pkt}_{\text{size}}$. Based on [91], the packet drop rate is expressed by

$$\text{Pkt}_{\text{drop}_i} = \frac{E[Q_i] - L_i^d/\text{Pkt}_{\text{size}}}{E[Q_i]}. \quad (3)$$

Finally, the resource allocation optimization problem is formulated as

$$\begin{aligned}\max\ & \left[\left(U_1^c, U_1^l\right), \left(U_2^c, U_2^l\right), \ldots, \left(U_N^c, U_N^l\right)\right]\\ \text{s.t}\ & \sum_{n=1}^{N} B_n \le C\\ & \sum_{n=1}^{N} L_n \le L. \quad (4)\end{aligned}$$

TABLE III
SIMULATION PARAMETERS FOR THE HETEROGENEOUS MIST-FOG-CLOUD-BASED IoHT FRAMEWORK SIMULATION

Parameter	Value
Number of IoHT nodes	100
Link between IoHT nodes and AP	IEEE 802.11 a/g
Link rate between IoHT nodes and AP	54 Mbps
Link rate between AP and Fog	100 Mbps
Link rate between Fog and Cloud	10Gbps
$tTx_{mist}, tTx_{fog}, tTx_{cloud} ms$	U[1,2], U[0.5,1.2], U[15,35]
N_{fog}	5
N_{cloud}	1
Processing speed (Mist:Fog)	(1:1000)
Processing speed (Fog:Cloud)	(1:100)
Pkt_{size}	100B and 80KB
$E[Q]$	random
Traffic Class	Delay priority, Loss priority
N_{pkt}	10,000

C. Load Distribution

In the Fog/access layer, the E2E latency can be reduced by link distribution and link fusion techniques. As illustrated in Fig. 8, a link scheduler selects multiple links, distributes the traffic to reduce the E2E delay and finally aggregates the traffic at the other end of the access layer.

If the link scheduler selects M links based on the demand of the IoHT users, the link adaptation optimization problem can be formulated as

$$\begin{aligned}\max\ & f(T, 1/\text{Pkt}_{\text{drop}})\\ \text{s.t.}\ & \sum_{m=1}^{M} \gamma_m B^d \le C\\ & \sum_{m=1}^{M} \gamma_m L^d \le L \quad (5)\end{aligned}$$

where T is throughput, B^d and L^d are the bandwidth demand and buffer length demand of an AP. γ_m is the fraction of bandwidth/buffer length allocated by the load balancer and is expressed by

$$\begin{aligned}\gamma_m &= \text{Fraction of allocation in the } m \text{ link}\\ &= \left(\frac{B_m}{\sum_m B_m}\right)\beta + \left(\frac{L_m}{\sum_m L_m}\right)(1-\beta) \quad (6)\end{aligned}$$

where

$$\beta = \begin{cases} 0, & \text{if Traffic type is } \mathcal{LS}\\ 1, & \text{if Traffic type is } \mathcal{DS}\\ 0.5, & \text{if Traffic type is } \mathcal{M}.\end{cases}$$

The proposed load balancing scheme is shown in Algorithm 1. The central SDN, as a logical controller, selects M multiple links according to traffic demand to coordinate load distribution. At the beginning of the process, network controller specifies traffic classes based on demand. For each outgoing link i the value of γ_i is calculated from (6). For delay-sensitive and loss-sensitive traffics, loads are distributed based on demanded bandwidth and demanded buffer length, respectively. For mixed type data traffic, load distribution is done based on comparatively greater requirement of demand.

Algorithm 1 Algorithm for Load Balancing

Require: *Output link capacity of AP* as C, *Queuing buffer length* as L, *Bandwidth length demand of AP* as B^d, *Buffer length demand of AP* as L^d

Ensure: Distributed Load

procedure BALANCELOADS(C, L, B^d, L^d)
  Initialize β, ν, η, Ω, ω;
  SDNC selects M links based on traffic demand;
  if *TrafficPriorityClass* $== 1$ **then**
    $\beta \longleftarrow 1$;
  else if *TrafficPriorityClass* $== 2$ **then**
    $\beta \longleftarrow 0$;
  else
    $\beta \longleftarrow 0.5$;
  end if
  for all *Selected Links* as i **do**
    Calculate γ_i using equation (6);
    $\Omega_i = \gamma_i B^d$; and $\omega_i = \gamma_i L^d$;
    if $\beta == 1$ **then**
      Distribute load to link i using Ω_i value;
    else if $\beta == 0$ **then**
      Distribute load to link i using ω_i value;
    else
      $\mathcal{B} = \frac{B^d}{\sum_i B_i}$; $\mathcal{L} = \frac{L^d}{\sum_i L_i}$; and $\eta = \max \mathrm{f}(\mathcal{B}, \mathcal{L})$;
      if $\eta == \mathcal{B}$ **then**
        Distribute load to link i using Ω_i value;
      else
        Distribute load to link i using ω_i value;
      end if
    end if
  end for
end procedure

D. Computational Complexity

Considering the decentralized data processing capability offered by the proposed framework enables it to perform processing at multiple levels reducing the amount of computations needed at subsequent levels. This is mainly because aggregating raw data from various IoT devices results in matrices with very large dimensions, leading to a resource demanding system with intolerable computation complexity. Therefore, the computational complexity of the proposed framework is lesser in comparison to other existing frameworks.

Additionally, the proposed load balancing algorithm's complexity has an upper bound of $O(n)$, where n is the number of active selected links of the network.

V. RESULTS

An example model is considered in this section to demonstrate the feasibility and advantages of the proposed multilayer mist-fog-cloud architecture for the IoHT framework. Considering, there are 100 IoHT nodes collecting delay-sensitive and loss-sensitive healthcare data from a hospital/home. The links between IoHT nodes (through microcontroller or microcomputer) and APs are IEEE 802.11. There are 5 fog nodes, 1 cloud server, and the link data rate

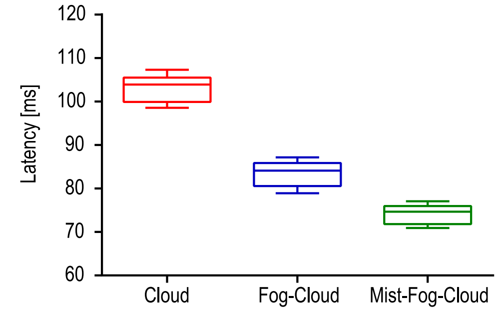

Fig. 9. E2E delay of cloud, fog-cloud, and mist-fog-cloud for the simulation setting listed in Table III. The latency is minimal when all the mist-fog-cloud layers are involved in the process of data transmission and processing.

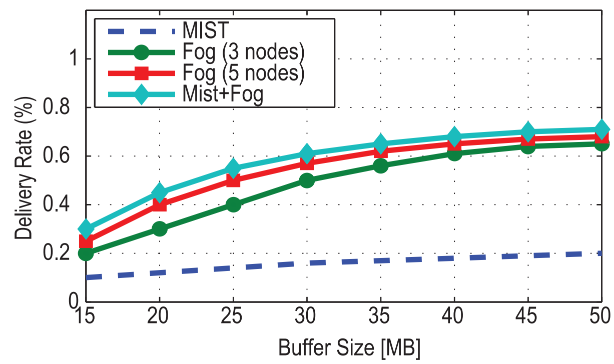

Fig. 10. Increase in buffer size reduces packet drop. When buffer size increases, packet delivery ratios improve for all the layers.

is 54 Mb/s. The raw data generated by these IoHT nodes can be processed using the resources available at the mist layer. When the process is high (i.e., high processing delay), the mist can offload the processing to the fog nodes (also called fog processors). The process availability are generated randomly. Also, the link bandwidth and the queue length in the router are assumed to be distributed randomly. The fog nodes can be selected based on the demand and the processing delay. Finally, the information extracted from the mist/fog layer are sent to the server in the cloud layer. The link speed between the fog and the cloud is 10 Gb/s. The processing speed ratio of the mist to fog and fog to cloud are 1 : 1000 and 1 : 100, respectively. The parameters used to simulate the heterogeneous mist-fog-cloud for the delay-sensitive and loss-sensitive IoHT healthcare data are listed in Table III.

Fig. 9 shows the E2E delay (or latency) for the simulation settings given in Table III. The results indicate that the E2E delay decreases when mist-fog nodes are involved in the computation along with the cloud. However, involvement of more fog neighbors and mist resources can reduce the E2E delay as this process reduces the queuing and transmission delays. The computational latency decreases when the number of neighboring fog nodes increase.

Fig. 10 shows the effect of buffer size on the packet delivery rate. The buffer size reduces the packet drop. When the buffer size increases the packet delivery rates in mist and mist-fog layers reduce. However, it should also be noted that the increase of buffer size also increases the queuing delay and total latency. Thus, the appropriate size of the buffer must be selected to ensure high delivery rate and low latency.

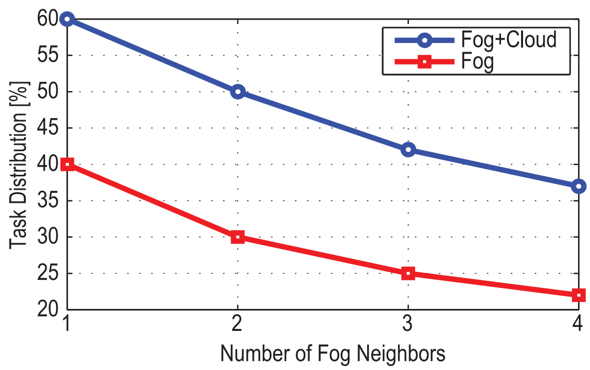

Fig. 11. Effect of number of fog neighbors on the task distribution of fog/fog-cloud layers. In both cases inclusion of more fog nodes decreases the work load on the layers.

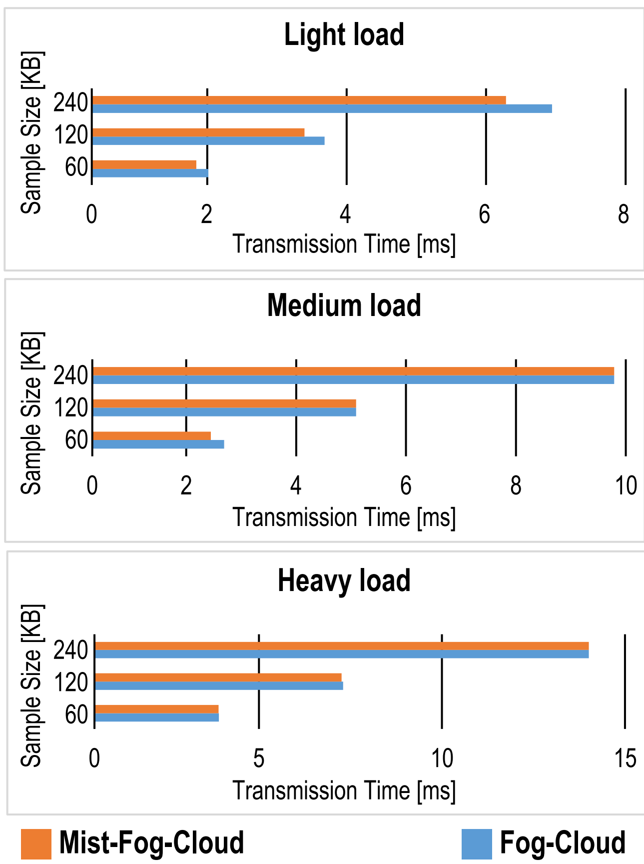

Fig. 12. Mist facilitates reduction in transmission time. At different network conditions the Mist-based proposed framework showed an improvement in the transmission time.

Fig. 11 illustrates the outcome of involving fog neighbors on the task distribution of fog and cloud layers. The simulation results suggest that when the flow controller includes more fog neighbors in the task distribution process, the load on the cloud decreases as the processing performance on the fog nodes increase. The load on the cloud is about 60% with one fog node, and the load drops exponentially to 37% when the number of fog neighbors are four.

While evaluating the efficacy of the proposed framework, we compared its transmission time with one of the state-of-the-art fog computing-based framework [35]. As shown in Fig. 12, the proposed heterogeneous framework (denoted by mist-fog-cloud) requires comparable or less time to transmit same amount of processed samples in comparison to fog-based framework (denoted by Fog-Cloud) proposed in [35]. The mist plays its role in reducing the transmission time while handling real-time data (i.e., smaller sample size). In transmitting 60 KB samples in different network conditions defined in [35] (e.g., light load, medium load, and heavy load), the proposed mist-fog-cloud framework would require 1.5, 2.16, and 3.39 ms in comparison to Fog-Cloud-based framework which would require 1.67, 2.4, and 3.395 ms.

The above specified lower transmission time is also facilitated by the fact that there are multiple levels of data filtering in our proposed model. This reduces the amount of real-time data to be transmitted along the network, thus, reducing computational complexity of the proposed framework [92]–[94]. Additionally, sophisticated data analytic schemes can also be employed to further reduce the computational complexity [95].

VI. Conclusion

This paper proposes a heterogeneous cloud-based IoHT communication framework with mist and fog computing. The framework consists of perception, mist, fog, cloud, and application layers which can handle separately data routing paths for real-time as well as conventional data sources. To ensure high QoS of such heterogeneous communication frameworks, reducing E2E latency and packet drop rate are two main challenges. Through optimizing resource allocation and flow control, the proposed framework delivers improved overall QoS. Simulation results show that the proposed framework can achieve low E2E latency and packet drop rate. The obtained results clearly indicate the suitability of the proposed IoHT framework in the healthcare domain. Nonetheless, this paper can be extended by incorporating advanced machine learning techniques (e.g., deep learning) in identifying the heterogeneous traffic, and employing bio-inspired models to ensure effective resource usage, schedule optimal flow to improve performance and increase data distribution to reduce overall computational complexity of next generation IoHT-based healthcare systems.

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