IoT-Based Health Monitoring System with Real-Time Analytics

Salah-ddine Krit

Ibn Zohr University, Agadir, morocco

Email: salahddine.krit@gmail.com

Abstract

Thanks to advances in nanodevices and internet technology, it is now possible for devices from different manufacturers to be connected and communicate with one another. Among the fields that benefited from this technology integration were healthcare and general well-being. Healthcare had been established to lower healthcare expenses and offer enhanced and dependable services. Nevertheless, the primary difficulty in building such systems has continually been ensuring a high quality of service (QoS) in terms of quicker reaction and complicated analysis of data, given the sensitive and medical data. To solve these problems, this article suggests a heterogeneous Health Monitoring System built on mist, fog, and the cloud that can process and route data in both immediately and in form of a batch. In addition, the proposed system uses software-defined networking and load-stabilizing method to make sure that all available resources are being used effectively and efficiently. Experimental simulations validated that our system could achieve excellent QoS, with acceptable delay and packet delivery rate, which is crucial for the creation of sustainable healthcare solutions.

Keywords: Sustainability; Smart Healthcare; Internet of Things (IoT); Monitoring System, QoS

1. Introduction

A health monitoring system is a technology-based system that tracks and monitors an individual's health parameters over time. This system typically includes sensors or devices that collect data on vital signs, physical activity, and other health-related information, which is then analyzed and presented to the user in a meaningful way. Some common components of a health monitoring system may include wearable devices such as smartwatches, fitness trackers, or heart rate monitors, as well as mobile applications or web-based platforms that allow users to view their data and track their progress over time. Health monitoring systems can be used for a variety of purposes, including managing chronic health conditions, monitoring overall fitness and wellness, and providing early warning signs for potential health issues. These systems may also incorporate features such as goal setting, social support, and personalized recommendations to help users achieve their health goals.

The Internet of Things (IoT) is a network of physical objects or devices that are embedded with sensors, software, and other technologies to connect and exchange data with each other and with the internet. These devices can range from small sensors and wearables to large machines and appliances, and they can collect and transmit various types of data

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such as environmental conditions, energy usage, and user behavior. IoT technology has a wide range of applications, including healthcare, home automation, and industrial automation. By enabling devices to communicate and exchange data in real time, IoT technology can improve the efficiency, productivity, and safety of various industries, including healthcare.

IoT technology has immense potential in healthcare, where it can be used to improve patient outcomes and increase efficiency. One of the most significant ways in which IoT is being used in healthcare is through remote patient monitoring. IoT devices such as wearables, sensors, and medical equipment can collect real-time data on a patient's vital signs, activity levels, and other health-related information, allowing healthcare providers to monitor patients remotely and intervene as necessary. This technology can be especially useful for patients with chronic conditions who require regular monitoring but are unable to visit a healthcare facility frequently. Additionally, IoT-enabled medical equipment can automate tasks such as data collection and analysis, reducing the workload for healthcare providers and improving the accuracy and speed of diagnoses.

The computation and reaction times required by the healthcare ecosystem vary depending on the data source and the application. To do this, this research presents a Health Monitoring System that allows cloud-based connectivity via fog and mist computing, which composed of five main tiers namely perception, mist, fog, cloud, and application are that make up this heterogeneous healthcare platform. The novelty of our system lies in its capacity to regulate network load on request and distribute network resources appropriately and manage distinct data routing channels for different data kinds arriving from real-time and traditional data sources. Based on the findings, our system can be demonstrated as superior to the current e-healthcare systems in terms of QoS, energy usage, and delay.

2. Literature Review

With the increased interest in automated healthcare monitoring, several studies and research conducted in the area of intelligent IoT-based real-time health monitoring. For example, the paper [1] investigated the use of deep reinforcement learning (DRL) in detecting lung cancer using medical IoT devices. The system uses data from medical IoT devices, such as CT scans and X-rays, to make diagnoses. The system was designed to learn from experience and got improved its performance over time through trial and error. It was trained using a dataset of lung cancer images and corresponding diagnoses and is then able to make predictions on new images. The paper [2] provided a detailed overview of the state of the art in the medical IoT and its applications in medicine by defining IoMT as the integration of medical devices, applications, and services into a unified system that can collect and transmit data over the internet. They explained how IoMT can improve patient care, reduce costs, and increase efficiency in healthcare systems. The paper then reviewed recent contributions in the field of IoMT, focusing on cyber-physical systems (CPS) in medicine. The paper [3] studied the use of feature selection techniques to improve the classification accuracy of ovarian cancer data in the context of the healthcare system. It also explained that the healthcare system can enable the collection of large amounts of medical data, including data related to ovarian cancer. However, this data was demonstrated to be noisy and contain irrelevant features, which could decrease the accuracy of classification models. The paper [4] provided an overview of the current state of healthcare systems and their integration with wireless networks. It also highlighted several emerging trends in healthcare systems and wireless networks, including the usage of 5G networks for real-time data transmission and the development of edge computing for processing medical data closer to the source. The paper provided an overview of the state of research in these areas and pointed out several directions for future research, such as the development of new security protocols and the integration of ML techniques into health systems. The paper [5] proposes an IoT-based healthcare system for monitoring soldiers in the field, as they are at increased risk of injury and illness. It consisted of wearable devices that collect physiological data from soldiers, such as heart rate, body temperature, and blood pressure. This data was transmitted to a central server using an IoT network, where ML algorithms are used to analyze the data and identify patterns that could indicate a health problem. The authors demonstrated the effectiveness of their system using a dataset of physiological data collected from soldiers in

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the field. They show that their ML algorithms can accurately detect health problems, such as dehydration and heat exhaustion, and provide early warning to healthcare providers. The paper [6] investigated the implementation and analysis of an IoT-based healthcare monitoring system by explaining that the increasing availability of healthcare data generated by IoT devices presented a great opportunity to improve healthcare delivery and patient outcomes. This system was composed of IoT-enabled healthcare devices that collect physiological data from patients and transmit it to a central server. The data is then analyzed using big data analytics techniques, including ML algorithms, to identify patterns and trends that could inform clinical decision-making. The paper [7] studied that the kit includes various sensors and devices, such as a blood pressure monitor, heart rate monitor, and temperature sensor, which are connected to a central hub using IoT communication protocols. The central hub collected the data from the sensors and transmits it to a cloud-based server, where it is analyzed using ML algorithms to identify patterns and trends in the data. The authors demonstrated the effectiveness of their system by testing it on a group of patients with chronic diseases, showing that it can accurately monitor patients' health status and provide early warning of potential complications. The paper [8] studied the system that included various wearable and non-wearable sensors that could collect physiological data from patients, such as heart rate, blood pressure, and body temperature. The data was transmitted to a central server using IoT communication protocols, where it was analyzed using ML algorithms to detect abnormalities and trends in the data. The paper [10] studied the phases taken to create and develop a low-cost modular health monitoring system that used mobile phones to facilitate quicker and healthier medical interferences in emergency circumstances. The paper [11] determined that the usual remote health monitoring system's network needs, including the need for constant updates on events, a sizable amount of available bandwidth, and the ability to generate large amounts of data. It also analyzed the network communication protocols CoAP, MQTT, and HTTP to comprehend the data volume and transfer rate necessities of such a system. it developed IReHMo, an IoT health monitoring architecture that transmits healthcare data quickly and reliably to central servers.

3. Methodology of our intelligent healthcare system

Massive IoT implementation connects many objects. Most connected devices have limited computing power and storage. A cloud-based IoT architecture is efficient. A fog layer can reduce latency and power consumption in cloud-based operations. Fog-assisted IoT frameworks with smart gateways increase reliability, power efficiency, and performance. There is no need to process delay-sensitive and loss-sensitive data in each framework tier, yet transferring sensitive data raises QoS concerns. Making the framework process "on demand" input at different abstraction levels is an interesting solution. The five-level framework presented facilitates this. By adding a mist layer to the fog-based design, we can reduce the quantity of data IoT devices broadcast using rule-based preparation and compression. IoT devices generate fewer data, which lowers the framework's computational cost and latency. Thus, the proposed healthcare system could choose sufficient data-transferring policies that concentrate on the disconnected data sources to decrease interaction overhead; assure marginal network latency thru the proper load balancing; ensure the most beneficial data-sensitive service the provision for prioritized data transfer; and ensure optimal resource utilization by deferring and supplying procedures to layers with relatively fewer loads.

A. System Model

Interoperable devices, apps, and back-end systems are needed to build a healthcare architecture that allows for continuous information flow and quick decisions. Healthcare ecology projection. The healthcare ecosystem diagram indicates that the outer circle entities are linked to their inner circle counterparts to enable data sharing. The outer circle is most responsive and participatory but least analytical. As one enters the sphere, analytical tools, latency, and storage space improve. Perception Tier: The Perception Tier is a term used in the context of the Internet of Things (IoT) to refer to the layer of the IoT architecture that is responsible for collecting data from the physical world. This tier is the first point of contact between the physical world and the IoT system, and it consists of a network of sensors, cameras, microphones, and other devices that are used to gather information about the environment, objects, and people. The Perception Tier is also known as the edge layer or the sensor layer, and it is typically located at the

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outermost layer of the IoT system. The data collected by the sensors and devices in the Perception Tier is then transmitted to the next layer of the IoT architecture, which is the Network Tier. The Network Tier is responsible for transmitting the data to the Cloud Tier or the Application Tier, where it is processed and analyzed to extract meaningful insights. The Perception Tier plays a critical role in the success of an IoT system, as the quality and accuracy of the data collected by the sensors and devices in this layer have a significant impact on the accuracy and effectiveness of the entire system. Therefore, the selection of sensors and devices, as well as their placement and calibration, are important factors that need to be carefully considered during the design and implementation of an IoT system.

Cloud Tier: cloud, application, perception, and fog layers can communicate. The cloud layer stores medical data from the fog layer and performs big data and sophisticated analytics. This layer integrates data from nonsense sources such as electronic medical records (eMR), electronic health records (EHR), electronic prescription systems, etc. Cloud data analytics include deep learning, data analysis, regulation computation, and algorithmic logic. This advanced data analytics help make sense of diverse healthcare data. However, assigning important computing loads to the fog layer and using the cloud layer for intensive computational processing can increase system performance.

Fog tier: IoT technology has been driven by the need to analyze data "just in time" to detect anomalies, report in real time, and take autonomous action. This shows the need for a responsive, low-latency system. Centralized cloud-based solutions are too slow for this. In these cases, processing loads must be decentralized and distributed according to application needs. Decentralized fog layer architecture moves computational effort and enterprise applications to the network edge. Reduces reaction delay. The fog supports local storage, information extraction, quantization, pattern matching, and transitional data analytics. These components reduce cloud load, increase system performance and quality, and preserve core network bandwidth.

Mist Tier: The Mist Layer is a term used in the context of the IoT to refer to the layer of the IoT architecture that is responsible for local processing and analysis of data. This layer is located between the Perception Tier and the Cloud Tier. The Mist Layer is also known as the Fog Layer or Edge Computing Layer. It is designed to reduce latency and improve responsiveness by processing and analyzing data closer to the source of the data rather than sending all data to the cloud for processing. This layer can be made up of small computing devices such as gateways, routers, or edge servers that can perform some processing on the data, allowing it to be filtered, aggregated, and analyzed locally. By processing data locally, the Mist Layer can help to reduce the amount of data that needs to be sent to the Cloud Tier, which can help to reduce costs and improve performance. The Mist Layer is especially useful in scenarios where data needs to be processed in real-time, such as in industrial automation, healthcare, and transportation. For example, in a healthcare setting, the Mist Layer can be used to process data from wearable devices that monitor patients' vital signs, allowing healthcare providers to quickly identify potential health issues and take appropriate action.

Application Layer: The intelligent healthcare system ends with the application layer. It does this by establishing user lines between healthcare staff and customers and the system, so the framework can rapidly reflect the commercial and societal advantages. This layer also offers healthcare application developers and users immediate access to appropriate cloud or fog layer resources, depending on the accessbilities and licenses associated with those resources.

B. Intelligent system Functionality

The proposed system is a system that leverages the power of the IoT to track, collect, analyze, and communicate health-related data in real-time. The system involves a network of interconnected sensors, devices, and platforms that work together to monitor various aspects of a patient's health. In the following, we discuss some of the tasks of an IoT-based health monitoring system. First, data collection, the system collects data from various sensors and devices, including wearables such as smartwatches and fitness trackers, medical devices such as blood pressure monitors, and environmental sensors that measure temperature, humidity, and air quality. The collected data can be both structured

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and unstructured, and it is typically transmitted to a cloud-based platform for processing and analysis. second, data analytics, the system uses machine learning algorithms and data analytics tools to process and analyze the collected data. This allows for the detection of patterns and trends that can be used to identify potential health risks or to monitor the effectiveness of a treatment plan. Third, health monitoring task, in which the system continuously monitors a patient's health status, including vital signs such as heart rate, blood pressure, and oxygen levels. The system can also track other health-related metrics such as sleep patterns, activity levels, and medication adherence. Forth, notification task, where, once the system detects any potential health risks or abnormalities, it can generate alerts and notifications to the patient, caregiver, or healthcare provider. This can include reminders to take medication, notifications of abnormal readings, or alerts to seek medical attention if necessary. Personalization tasks, in which the system can be personalized to meet the unique needs of each patient. For example, the system can be customized to monitor specific health conditions, such as diabetes or hypertension, and can be tailored to provide personalized recommendations for lifestyle changes or treatment plans. Telemedicine tasks, in which the system can also facilitate telemedicine consultations between patients and healthcare providers. This can include video consultations, remote monitoring of patients, and the sharing of health-related data and information between the patient and healthcare provider. In order to eachieve any of the above tasks, we have to enhance the quality of our system by decreasing transmission delays and packet loss. By allocating their resources optimally, all of the healthcare nodes in the mist layer are able to meet the base requirements for both of these metrics. For ensuring the QoS obligation of $i - th$ IoMT device, the user constraint denoted as $< t_{D_i}, \mathrm{Pkt}_{\mathrm{drop}_i} >$ and the subsequent resource request denoted as $< B_i^d, L_i^d >$, in which $\boldsymbol{B_i^d}$ and $\boldsymbol{L_i^d}$ are the bandwidth need and memory length needed for the $i - th$ healthcare device. As the allotted resource to $i - th$ device is proportionate to the necessity of that client, the maximum resource (Γ_i) conferred to the i-th client by the SDN-based resource distributor is computed as follows:

$$\Gamma_i = \quad max\left[\frac{B_i}{C}, \frac{L_i}{L}\right] = max\left[\frac{B_i^d}{C}\frac{B_i}{B_i^d}, \frac{L_i^d}{L}\frac{L_i}{L_i^d}\right] = max[D_i^c U_i^c, D_i^l U_i^l] \tag{1}$$

where $D_i^c = \frac{B_i^d}{C}$ and $D_i^l = \frac{L_i^d}{L}$ denote the percentages of bandwidth need of the $i - th$ client, and the overall buffer size of AP, correspondingly. The $U_i^c = \frac{B_i}{B_i^d}$ and $U_i^l = \frac{L_i}{L_i^d}$ denote the prerequisite to require a proportion of bandwidth and buffer size, correspondingly.

The M/D/1 queue model is a mathematical model used to analyze waiting times in a system with one server, where arrivals are modeled as a Poisson process and service times are constant (i.e., deterministic). In this model, "M" refers to the arrival process being a Poisson process, "D" refers to the service time distribution being deterministic, and "1" refers to the fact that there is only one server. With M/D/1 queue model, our system can calculate various performance measures, such as the average waiting time, the average number of customers in the system, and the utilization of the server. the average waiting time involves the communication time $t_T x_i$, handling time t_P, and queuing time t_Q. This can be expressed as follows:

$$\boldsymbol{t_w} = t_T x_i + t_P + t_Q \tag{2}$$

$$\boldsymbol{t_w} = \sum_{cl} \sum_{\mathrm{fog}} \sum_{\mathrm{sen}} \left[\frac{N_{\mathrm{pkt}} \mathrm{Pkt}_{\mathrm{size}}}{C} + \left(\frac{\lambda}{2\mu(\mu - \lambda)} + \frac{1}{\mu}\right) + c\lambda\right] \tag{3}$$

In which λ and μ represent the coming and use ratio, N_{pkt} denote the number of packets, c is the endless interval needed to carry out work by a cpu, sen represents sensor, while cl denotes the server. The packet falling off happens

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as soon as the mean queue size $E[Q_i]$ is greater than the needed memory size $\frac{L_i^d}{\text{Pkt}_{\text{size}}}$. This way, the packet drop ratio can be designated as follow:

$$\text{Pkt}_{\text{drop}_i} = \frac{E[Q_i] - L_i^d/\text{Pkt}_{\text{size}}}{E[Q_i]}. \tag{4}$$

In conclusion, we define the optimization problem of resource distribution as:

$$max\ [(U_1^c, U_1^l), (U_2^c, U_2^l), \ldots, (U_N^c, U_N^l)]\ s.t. \sum_{n=1}^{N} B_n \leq C, \sum_{n=1}^{N} L_n \leq L \tag{5}$$

To lessen the impact of E2E latency in the Fog/access layer, it is possible to employ link dispersion and link fusion strategies. A link scheduler chooses several links, distributes traffic to minimize latency, and then combines data at the access layer's other end. They made great advances maximization issue can be summarized as follows if the link dispatcher chooses M links according to the needs of the healthcare consumers:

$$max\ f\left(T, \frac{1}{\text{Pkt}_{\text{drop}}}\right) \text{s.t.} \sum_{m=1}^{M} \gamma_m B^d \leq C, \sum_{m=1}^{M} \gamma_m L^d \leq L \tag{6}$$

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4. Results and Discussions

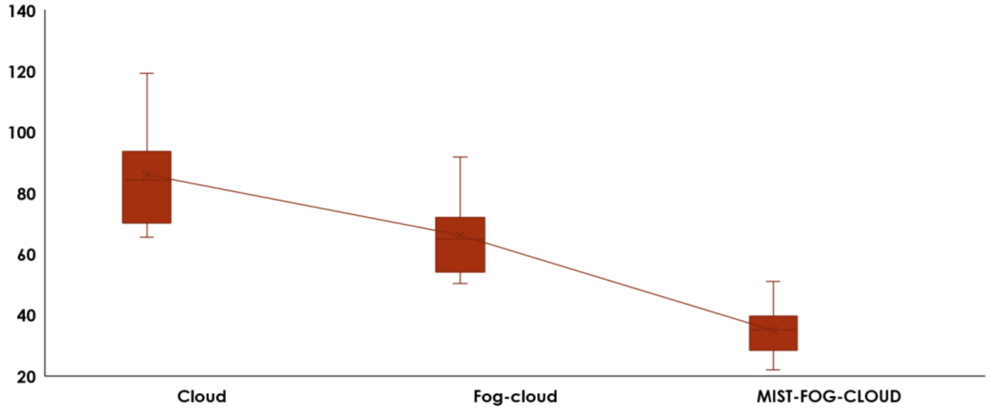

Figure 1. Experimental results obtained from our system under different structural designs.

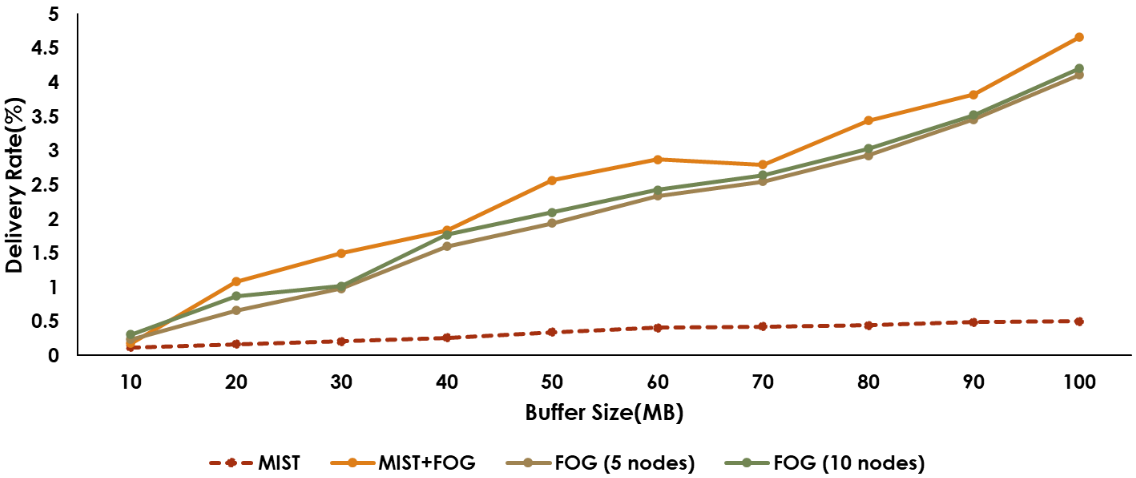

Figure 2: Experimental results for the relation between the memory size and packet supply ratio.

In this section, we look at a sample model to show how the suggested healthcare multilevel mist-fog-cloud design can work in practice. Suppose a hospital or private house has 150 healthcare nodes gathering time-critical, easily lost medical data. IEEE 802.11 is used for communication between the nodes of healthcare and the APs. With a data transfer rate of 54 Mb/s, one cloud server, and Five fog nodes, this setup is quite robust. When these healthcare nodes produce raw information, the assets at the mist layer may be utilized to analyze it. Processing offloading to fog nodes is used by mist once the procedure is elevated (i.e., strong computing delay). The accessibility of the procedure is determined at random. Furthermore, it is expected that the router's queue size and link bandwidth are both dispersed at the chance. Depending on the workload and the computation, the fog nodes could be chosen. The data collected in the mist or fog tier are then transmitted to a cloud. The data transfer rate from the cloud to the fog is 10 Gb/s. From mist to fog, the ratio is 1: 1000, and from fog to cloud, it's 1: 100 in terms of processing capabilities.

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Table 1: The parameters of the simulations designed for the proposed framework.

# Nodes	Link between AP and nods	Link rate (nodes, AP)	Link rate (AP, Fog)	Link rate (fog, cloud)	# Fog	#Cloud	Computation speed (AP, Fog)	Computation speed (fog, cloud)	# packets
150	IEEE 802.11	60Mbps	128Mbps	24Mbps	10	1	0.73611	0.11111	15,000

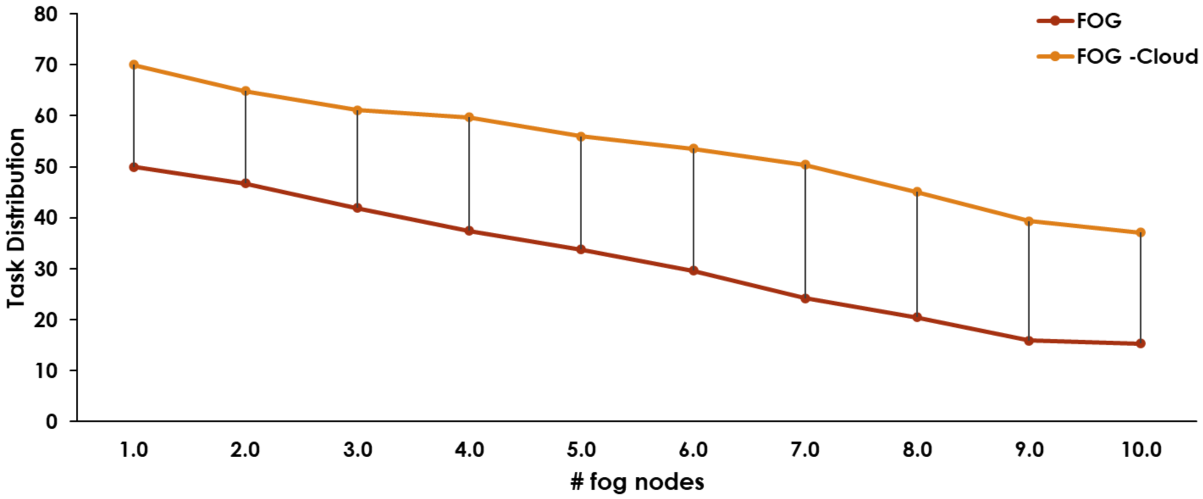

Figure 3: Simulation results for the impact of number of fog neighbors on the task allocation.

The time it takes for data to travel from one location to another, known as the E2E delay, is depicted in Figure. 1. When using mist-fog nodes in addition to cloud nodes, the E2E delay is shown to be reduced. However, the E2E latency can be decreased by enlisting more fog neighbors and mist resources, as doing so decreases the time spent waiting in queues and transmitting data. When more fog nodes are near one another, the computational latency reduces. Using the simulated parameters detailed in Table 1, Figure. 1 depicts the time it takes for clouds, fog clouds, and mist fog clouds to form. When all the cloud, fog, and mist tier are engaged in the data transfer and handling, the latency is negligible.

Figure 2 displays how changing the buffer size impacts the rate at which packets are delivered. It is notable that our system achieves less packet loss due to the big size of the buffer. Specifically, as the buffer size grows, the mist and mist-fog layers experience slower packet delivery rates. It's important to keep in mind, though, that as buffer sizes grow, so do queueing times and overall latency. Therefore, it is important to choose a buffer size that allows for both rapid delivery and minimal delays. Further, involving nearby fog neighbors influenced how the tasks were distributed across fog and cloud levels (See Figure 3). The simulation findings indicate that the cloud's load lowers as the computing efficiency of the fog nodes improves when the flow controller involves more fog neighbors in the task allocation process. When there is only one fog node, the cloud's burden is around 60%, but it lowers dramatically to 42% when there are four fog neighbors.

We evaluated our system’s transmission time to that of a leading fog computing-based system [10] to gauge its effectiveness. Table 2 illustrates that our health monitoring system needs a similar or lesser time to communicate the same quantity of treated samples as the fog-based framework described in [10]. As a result of the mist's contribution, transmission times for immediate data are shortened. The suggested mist-fog-cloud architecture requires 1.7, 2.31,

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and 3.18 ms to transmit 60 KB samples under various network circumstances, while the Fog-Cloud-based framework requires 2.03, 1.9, and 2.163 ms.

Table 2: simulation results for the impact of sample size on transmission time.

	Light load			**Middle load**			**Heavy load**		
	FOG-CLOUD	**MIST-FOG-CLOUD**	**Cloud**	**FOG-CLOUD**	**MIST-FOG-CLOUD**	**Cloud**	**FOG-CLOUD**	**MIST-FOG-CLOUD**	**Cloud**
40	3.020	3.735	3.844	1.507	-1.329	-1.265	9.155	6.878	11.510
80	4.989	4.855	4.773	2.375	2.190	-1.170	10.330	7.864	15.750
120	5.537	5.444	5.165	3.245	3.076	-1.018	12.696	9.262	17.148
160	6.323	5.763	6.359	3.683	4.568	1.922	13.578	11.512	17.679
200	6.909	6.888	7.599	6.494	8.048	5.869	15.342	13.909	19.255
240	7.900	7.902	8.623	9.813	9.404	10.303	15.421	15.341	21.119

5. Conclusion

This work introduces intelligent healthcare systems that integrate mist computing and fog computing into IoT architecture to help monitor health in real time. Each layer routes real-time or non-real-time data. E2E latency and packet drop rate must be reduced to improve heterogeneous communication system QoS. Our system enhanced QoS by better-allocating resources and regulating traffic flows. Our system has been shown to have a low E2E latency and packet delivery rate in simulations. Our health monitoring system can help to address some of the key challenges facing healthcare today, such as the rising cost of healthcare, the shortage of healthcare professionals, and the need for more personalized care. With continued advancements in IoT technology, we can expect to see further innovation and adoption of IoT-based health monitoring systems in the years to come.

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