CoronaCare: Real-Time Multi-Access Edge Computing-Based Healthcare Infrastructure for Monitoring COVID-19 in 5G Networks

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***Abstract*— Since the outbreak of the novel coronavirus (COVID-19) disease pandemic in 2019, social distancing and quarantining have become normal practices all over the world. Frequent hospital contact visits are discouraged due to the full adoption of the above control practices. Contact-based hospital visits are now considered non-obligatory due to rapid technological advances in the areas of Internet of Things (IoT) technology, healthcare systems, and smart home automation. To this end, a real-time healthcare infrastructure called (CoronaCare) is proposed in this paper for monitoring patients' health status and receiving doctors' prescriptions while staying at home. The doctors can diagnose illnesses using the physiological health parameters collected remotely from patients through a live video conferencing-based interactive system that enables healthcare professionals to discuss with patients and help them. It would collect real-time symptom data from smartphone videos. The system is based on Multi-access Edge Computing (MEC) as an IoT infrastructure and Cloud Radio Access Network (C-RAN) in 5G cellular networks structure which enables high bandwidth and ultra-low latency for efficient patients-doctors dual real-time communication. The system is simulated and the results demonstrate high throughput and low latency as the evaluation of service time is approximately 2 seconds and the average utilization of Virtual Machines (VMs) is approximately 98% for different edge computing architectures which effectively improve the system performance.**

Keywords*— COVID-19 pandemic, Multi-access Edge Computing (MEC), 5G mobile network, Real-time healthcare platform, Internet of Things (IoT)

I. Introduction

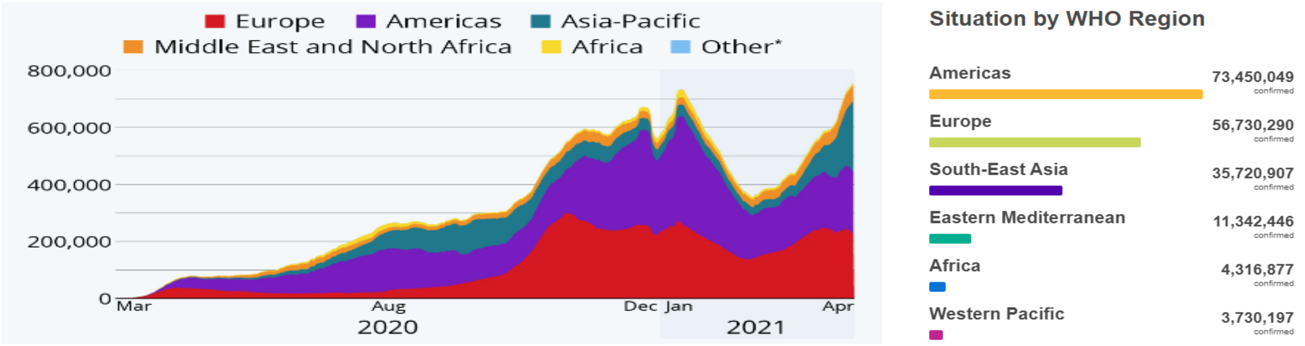
Over 185 million positive cases of COVID-19 had been reported by the World Health Organization (WHO) by the end of June 2021, resulting in over 4 million deaths, as illustrated in Figure 1. As a result of the COVID-19 pandemic, countries have faced several issues of healthcare, financial, and societal. Overburdened healthcare facilities are encountering disruptions in the delivery of routine health services as a result of the rapid development of new COVID-19 patients. Furthermore, healthcare workers are growing prone to COVID-19, putting even more strain on hospital resources. The current healthcare systems are under tremendous strain as a result of the rising number of COVID-19 patients and the resulting longer hospitalizations. COVID-19 symptoms include moderate manifestation in the majority of patients, protracted hospitalization in a small percentage of severe cases, and rapid spread [1]. As a result, the most effective technique for reducing the spread of the disease has been recommended as self-isolation and social distancing. Because of the particular circumstances of this disease, it is critical to keep track of patients to prevent rapid deterioration. This surveillance can also be extended to people who have been exposed to COVID-19 and the general population.

The effectiveness of a consolidated monitoring technique would be determined by its widespread availability and low cost of implementation. Consequently, the Internet of Medical Things (IoMT), as a powerful solution, is an IoT framework for a medical and healthcare-related specific purpose, for collection and analysis of data, and monitoring [2]. The IoMT has been referenced as smart healthcare as the technology to build a digitized healthcare system, linking accessible medical resources and healthcare services [3- 4].

The majorities of IoT healthcare systems have proprietary software interfaces defined by their makers and communicate using a variety of proprietary protocols [5-6]. This adds complexity not only for developers who construct new sensor-based apps, but also for providers of gateways, portals, and services that may access this data. As a result, monitoring a massive population, such as the COVID-19 pandemic, presents significant interoperability issues. It's critical to address the problems of heterogeneity and access networks [7-9].

In this regard, the emergence of edge computing is very important. Edge computing, which performs computing at the edge of the network, has created a great revolution in both academia and the industry [10-11]. Edge computing pushes the computing from the centralized cloud to decentralized edges, close to the data source such as mobile devices by the huge deployment of massive edge nodes, such as base stations. Edge computing builds hierarchical computing layers as mobile devices, edge nodes, and the cloud, forming edge-centric computing [12-14].

Consequently, the remarkable characteristic of edge computing is that it provides ultra-low latency, high bandwidth, reduces the influx of data to the backbone, and applications can access heterogeneous networks in real-time [15-16].



(a) (b)

Fig. 1: COVID-19 pandemic, (a) new cases surge to pandemic high, (b) statistics situation reported by World Health Organization (WHO) at June 2021.

Recently, MEC provides the capabilities of cloud computing within the C-RAN at the edge of the network, and it is considered as the key enabler in 5G networks [17].

Compared to 4G, 5G communications represents a new paradigm from existing mobile networks, providing universal high-rate connectivity and a seamless user experience [18]. 5G networks target delivering 100x higher number of connected devices, 1000x higher mobile data volume per area, 10x longer battery life for low power massive machine communications, 100x higher user data rate, and 5x reduced End-to-End (E2E) latency. Key technologies including small cell networks, beamforming, and mmWave, massive Multiple Input Multiple Output (MIMO) will help achieve these goals. 5G will primarily enable three service classes using these technologies: Ultra-Reliable and Low Latency Communication (URLLC), enhanced Mobile Broadband (eMBB), and massive Machine Type Communication (mMTC). Fundamental technologies such as Network Function Virtualization (NFV), Software-Defined Networking (SDN), Multi-access Edge Computing (MEC), and Network Slicing (NS) will be used to build the new 5G networks. NFV and SDN make 5G networks programmable, allowing for flexible management and rapid deployment of 5G services. MEC brings intelligence to the radio network's edge, as well as increased processing and storage capacity. With 5G networks, NS develops logical networks on a shared infrastructure to enable various sorts of services [19].

The mmWave spectrum is used in 5G networks, allowing for the development of ultra-dense small cell networks. Massive MIMO integrated with beamforming technologies will help provide extraordinarily high data rates for a large number of users. These technologies work together to deliver superior indoor localization. They develop the eMBB service class, which enables the transmission of 4K/8K videos between a healthcare expert and a patient regardless of access location [20].

Meanwhile, on the flip side, Software-Defined Networking (SDN) facilitates network virtualization such that multiple virtual networks can run on given physical network infrastructure. 5G networks enable the development of new network services as software Network Functions (NFs), in contrast to current 4G networks. Because the network is programmable, increasing the capacity of the 5G network is considerably easier. SDN provides important functions as control schemes and data schemes isolated from each other [21]. Network Function Virtualization (NFV) can isolate network functionality from hardware infrastructure; network functions can be managed as software modules and deployed on edge computing infrastructures according to any standard [22]. To maximize resource utilization, NFV enables a single infrastructure to provide computing services for multiple mobile devices by creating multiple VMs to perform different tasks simultaneously or to run different network functions.

On the other hand, as indicated in Figure 2, telehealth is the delivery of healthcare services through the internet using telecommunication technologies. Telenursing, Telemedicine, Telesurgery, and Telepharmacy are examples of these services. Due to various factors, including a lack of resources (i.e., human resources, hospital capacity, and protective equipment), social distancing, the need to maintain regular healthcare services while adhering to the new guidelines, and the need to reduce the risk of healthcare professionals contracting COVID-19, all of these healthcare-related teleservices are strongly encouraged in the post-COVID-19 period.

Although several patient monitoring systems' researches provide cooperative monitoring healthcare systems, most of these researches lack offering of the end-to-end management of the disease, delivering a high number of connected devices, introducing a high data volume per area, or reducing the (E2E) latency. These issues are considered as the main shortages in these monitoring systems. Our proposal can overcome these shortages by bridging the gap between current technologies and patient monitoring systems. In our framework, the MEC capabilities of cloud computing within the C-RAN at the edge of the network in 5G networks, the IoT technology, and the clinical decision support system are integrated to provide a comprehensive and complete model for disease detection and monitoring a person with COVID-19 in real-time with high throughput and low latency.

This paper proposes a monitoring real-time healthcare infrastructure called (CoronaCare). CoronaCare is designed to facilitate remote ePrescribe medicines and treatments and detect fluctuations in patients' medical conditions through remote consultations based on a live video conferencing-based interactive system that enables healthcare professionals to discuss with patients and help them. In CoronaCare; signs and symptoms data of (COVID-19) generated by smartphone videos are processed in real-time. In our proposal, patients and self-isolation people at home will be monitored.

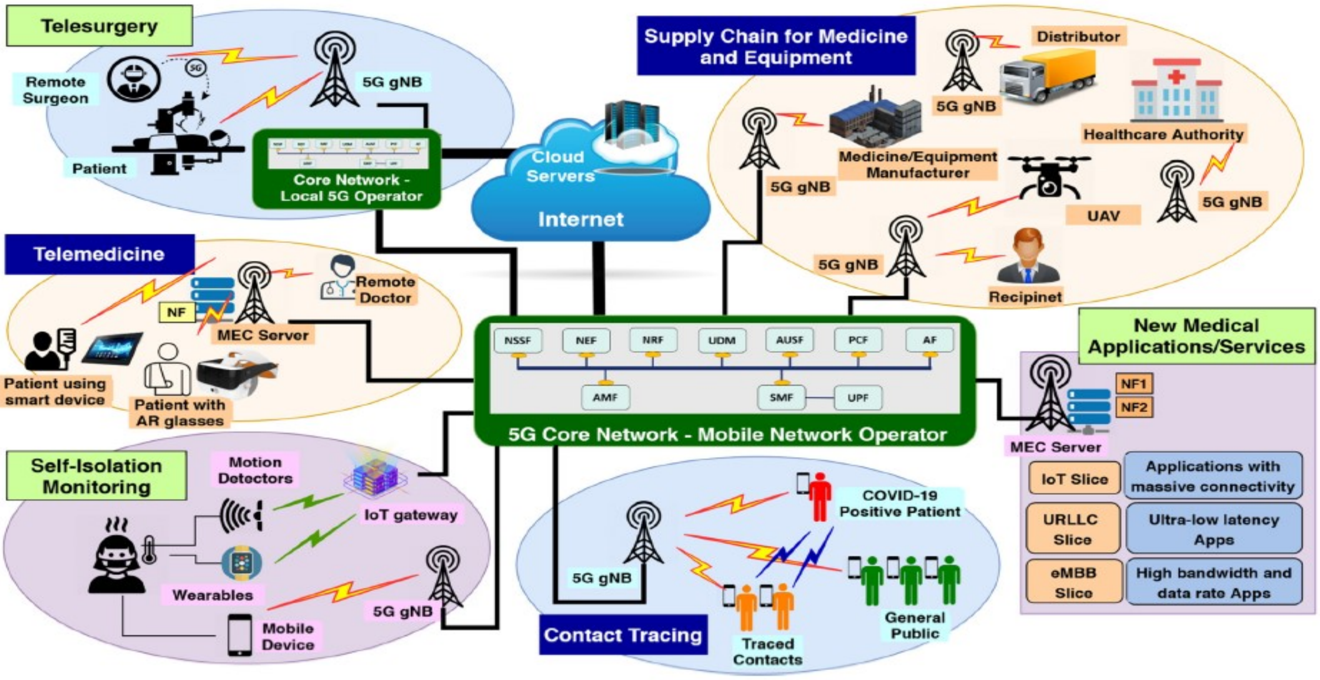


Fig. 2: 5G Telehealth services in COVID-19, [17]

The healthcare providers, such as hospitals, doctors, and nurses, who support the remote monitoring of all types of patients and maintain ubiquitous communication in the event of danger, are also part of our infrastructure. It is based on MEC as an IoT infrastructure and C-RAN in 5G cellular networks structure for efficient patients-doctors dual real-time communication which is divided into a physical infrastructure scheme and a virtual control and management scheme. (CoronaCare) intelligently maintains integrity between the smartphone and the edge servers to ensure real-time detection. This integration is achieved by using Network Virtualization Function (NVF) to achieve a centralized management scheme that controls operations and resource allocation of the infrastructure.

The system contains four main components: (1) real-time symptom video recording via smartphones, (2) a data analysis center that uses artificial intelligence (AI) algorithm, (3) a cloud infrastructure, and (4) virtual control and management scheme.

A video recording of a telemedicine session may contain personal information that the patient wishes to keep private. Furthermore, without the knowledge of the owners, automated contact tracing tools accumulate sensitive location data. It is a major privacy infringement to share such sensitive user data with unauthorized parties such as third-party advertisements. To address the privacy issue, solutions like software-defined privacy [23] must be implemented early in the design phase of 5G health applications. Edge computing is useful for reducing data transmissions over various network elements and enabling local processing, as well as improving privacy.

In addition to that, the virtual network function to simulate the manager is implemented. The proposed infrastructure is capable to achieve an accurate result which makes it more dependable. The simulation of the system is established and the performance of the infrastructure is evaluated to verify the feasibility and effectiveness of the system and to meet the Quality of Service (QoS) requirements. The results demonstrate that the scheme can effectively improve system performance.

This paper presents a proposal for a real-time MEC-based healthcare infrastructure for monitoring COVID-19 in 5G networks. The salient features of the proposed system can be summarized as:

- This paper proposes a monitoring real-time healthcare infrastructure designed to facilitate remote ePrescribe medicines and treatments and detect fluctuations in patients' medical conditions through remote consultations based on a live video conferencing-based interactive system that enables healthcare professionals to discuss with patients and help them.
- The patients in self-isolation or self-quarantine can send daily health symptoms and challenges to doctors via their mobile phones videos.
- Using edge computing provides ultra-low latency, high bandwidth, reduces the influx of data to the backbone, and applications can access heterogeneous networks in real-time where MEC provides the capabilities of cloud computing within the C-RAN at the edge of the network.
- By using the 5G networks, the proposed system can deliver a high number of connected devices, high mobile data volume per area, and long battery life for low power massive machine communications, high user data rate, and improved overall system latency.
- The utilization of the hierarchical IoT-MEC framework enables the reduction of bandwidth required to deliver a significant amount of misalignment data. It makes use of a smartphone to track and report COVID-19 symptoms, resulting in multiple datasets.
- It facilitates a connection between a MEC server and the cloud via control and management systems, allowing data analytics to be visualized on the front-end monitoring tool.

- In pandemics like COVID-19, automating the technique of data collecting, storage, interoperability, and data analytics using a real-time system will be an effective tracking solution.

The rest of this paper is organized as follows. Some previous works of literature are introduced in section 2. Section 3 presents an overview of the system architecture including the physical infrastructure scheme and the control and management scheme. Section 4 introduces the simulation of the system. Section 5 presents the results and discussion. Finally, Section 6 introduces the conclusion of the paper.

II. Related Work

In this section, some previous literature that focused on health surveillance systems is proposed. Li et al. [24] have presented a secure and efficient data management system for mobile healthcare systems. Local authorities are established to schedule edge servers for processing healthcare data and facilitating data trading.

Alabdulatif et al. [25] have proposed real-time health surveillance for the early detection of life-threatening diseases through sensing and communication technology. It reduces medical expenses and saves the lives of community residents.

Verma et al. [26] have proposed a model that uses distributed storage, embedded data mining, and notification services at the edge of the network to process the patient's real-time data at the Fog Layer.

Ray et al. [27] have introduced an edge-IoT-based architecture for e-healthcare called EH-IoT and developed a demo test-bed. The results of the test showed promising results in minimizing dependency over IoT cloud analytics.

Kaur et al. [28] have used various machine learning techniques to develop a system that enables real-time and remote health tracking based on IoT infrastructure and associated with cloud computing, and have considered public health care datasets stored in the cloud.

Mohapatra et al. [29] have developed a prototype model that uses the Internet of Things (IoT) and cloud computing for healthcare monitoring systems. These technologies make it possible to track and evaluate, in real-time, different health parameters. The IoT activated device consists of different patient-attached bio-sensors. Data is read and registered by sensors and transmitted to the database, i.e. to the cloud server. The collection, analysis, and decision-making of the stored data are the responsibility of a cloud server. The cloud that serves as an interface for the various actors involved with the healthcare system hosts a web portal.

Dumka et al. [30] have implemented a smart ambulance system based on technology. Technology such as wireless body sensor networks (WBANs), the Internet of Things (IoT), big data analytics, and artificial intelligence are used in the proposed design (AI).

Rathee et al. [31] implemented a healthcare multimedia data protection system through blockchain technology by generating the hash of each data so that any modification or alteration of data or violation of drugs can be mirrored in users of the entire blockchain network.

Onasanya et al. [32] have implemented an IoT-based cancer care services and business analytics/cloud services healthcare framework and have also recommended the adoption and deployment of IoT/WSN technologies to expand the current opportunities for treatment to deliver healthcare solutions. Market analytics/cloud platforms are the enablers of actionable insights, decision-making, the transmission of information, and reporting to enhance cancer therapies. Besides, a range of frameworks and architectures have been proposed to demonstrate and support the practical IoT-based approach that is being considered or used for cancer care services in the smart healthcare solution.

Coincidence with that, different related techniques used to track the COVID-19 pandemics are presented in Table 1. Support Vector Machine (SVM), Neural Network, Nave Bayes, K-Nearest Neighbor (K-NN), Decision Table, Decision Stump, OneR, and ZeroR are the eight machine learning techniques proposed by Otoom et al. [33]. After choosing the appropriate symptoms, an experiment was done to test these eight algorithms on an actual COVID-19 symptom dataset. The results show that five of these eight algorithms achieved an accuracy of more than 90 %.

To predict body temperature from a sequence of facial photographs, Zheng et al. [34] employed a CNN plus support vector machine (SVM) technique (CNN-SVM). Multiple pictures or video frames were taken with a smartphone camera that could be used to create the sequence images. First, a face detection algorithm, which can be implemented on the smartphone or in the cloud, is used to crop the facial region out of a digital image. Second, using a pre-trained CNN model, normalize the batch of facial photos and extract the facial features. Finally, using a multiclass SVM classifier, train a body temperature prediction model utilizing CNN features.

Feriani et al. [35] used a shared representation learning method to extract actionable data from massive amounts of high-dimensional data collected from IoT edge devices. The tri-sensors on these edge devices allow for real-time monitoring of COVID-19 symptoms. Real datasets are used to test the feasibility of the proposed system.

Based on the patient's X-ray scan images and transfer learning, El-Rashidy et al. [36] proposed a convolutional neural network-based deep learning model for COVID-19 identification.

Hossain et al. [37] developed a B5G framework that uses 5G networks to detect COVID-19 using chest X-ray or CT scan pictures, as well as a mass surveillance system that monitors social distancing, mask wear, and body temperature. The framework investigates three deep learning models: ResNet50, Deep Tree, and Inception v3. Additionally, blockchain technology is employed to secure healthcare data.

Ionescu et al. [38] demonstrated how smaller, inexpensive sensors can be merged into a bigger array of sensors to provide better coverage and be utilized for shape detection and object tracking. The AMG8833 Feather Wing sensors were employed, and the Raspberry Pi platform was used.

To execute collision-free navigation in a crowd and estimate the distance between all identified individuals in the camera's field of view, Sathyamoorthy et al. [39] used a mobile robot with commodity sensors, specifically an RGB-D camera and a 2-D lidar. Furthermore, we outfit the robot with a thermal camera that wirelessly communicates thermal images to security/healthcare personnel who monitors whether somebody has a temperature that is greater than normal.

Chatrati et al. [40] presented a smart home health monitoring system for people with diabetes and high blood pressure. The system assists in assessing the patient's blood pressure and glucose readings at home, providing an alert to the caregiver or healthcare practitioner if an irregularity is discovered, and forecasting the status of hypertension and diabetes in patients via training results obtained from the readings. Support vector machine classification was used to provide effective and efficient training jobs for the model. The technology can also send alerts and real-time updates regarding the patient's health to a licensed physician or clinic from the patient's home.

Taiwo et al. [41] presented a remote smart home healthcare support system for monitoring patients' health status and obtaining prescriptions from doctors while at home. Besides, doctors can diagnose illnesses using data collected remotely from the patient. For effective patients-doctors dual real-time communication, an Android-based mobile application that is connected with a web-based application is built. Sensors are built into the system to capture the physiological health parameters of patients automatically.

Din et al. [42] provide an IoT-based intelligent health monitoring and management architecture. The architecture is made up of three layers: (1) data production and processing from battery-powered medical sensors; (2) Hadoop processing; and (3) applications. Because of the battery's limitations, the experiment used an energy-harvesting method including piezoelectrical devices connected to the human body.

Al-Humairi et al. [43] developed a COVID-19 real-time system for tracking and identifying suspected instances, which uses an Internet of Things platform to capture user symptoms and alert authorities.

By using IoT-based smart solutions to monitor, contract trace, and detect the COVID-19 pandemic, Arun et al. [44] aided in the fight against COVID-19. The Internet of Things (IoT) is a web of interconnected smart devices, sensors, actuators, and data that is collected in raw form and delivered via the internet. The goal of this study is to offer a method for detecting and monitoring asymptotic patients using IoT-based sensors.

Multi-Access Edge Computing (MEC) of the edge paradigms was considered by Ranaweera et al. [45] for developing contact-less ways that aid COVID-19 mediation and the future of healthcare. They introduced three use cases and explain their application in the MEC environment to establish this ideology. In addition, the prerequisites for implementing these services are outlined.

III. Architecture Overview

CoronaCare healthcare infrastructure is designed as real-time surveillance and automated infrastructure of community residents' such as a hospital or home-based patients. The architecture of the infrastructure consists of two main schemes which are the physical scheme and the virtual control and management scheme. The physical infrastructure scheme provides the original information to the control and management scheme and executes the commands issued by the control and management scheme. The control and management scheme has a centralized controller and orchestrator that controls the operations and allocates resources of the physical infrastructure scheme elements. The control and management scheme includes different control functions to ensure the Quality of Services (QoS) requirements.

A. The Physical Infrastructure Scheme

The overview of CoronaCare healthcare physical infrastructure is presented in Figure 3 which consists of four main categories. The first category is patients in the smart city. The second category is the three-layered MEC architecture: (1) the front-end layer (edge devices); (2) mobile edge computing (MEC) edge nodes layer; (3) back-end layer (the cloud). The third category is the Authorized Healthcare Provider (AHP), and finally, the fourth category is the operators and third parties.

a. First Category (The Patients in Smart City)

The first category in (CoronaCare) healthcare physical infrastructure is the patients in smart cities where Billions of edge devices, smartphones, which are geographical, dispersed producing Billions of data every day. In it, fog data streams are mostly created from people by front-end smartphones for single or multiple signs and symptoms indicate the progression of coronavirus disease (COVID-19). The patient's signs and symptoms such as increased body temperature and fever; coughing and sneezing; sore throat; headache; difficulty in breathing; heart rate; and blood pressure are collected by smartphones. These symptoms start within 14 days of being infected as shown in Figure 4.

b. Second Category (MEC)

The MEC is designed as three-layered architecture: the front-end layer; the edge node layer; and finally the back-end layer. The layers will be described in detail in the following sections:

- *The front-end layer (edge devices)*

The edge devices layer represents mobile devices and User Equipment (UE) such as smartphones. Smartphones are normally containing many types of sensors. Some of the sensors that are included in a smartphone are the wireless sensor, Fingerprint sensor, Bluetooth module, Barometer, Gyroscope, Magnetometer, Accelerometer, Proximity, GPS tracker, and Near Field Communication (NFC) sensor which are widely used in developing health monitoring systems. In our proposal, we use the smartphone camera to make a live video conference. The generated massive data has multiple features such as larger size, higher velocity, more modes, higher data quality, and heterogeneity. The massive data is then transmitted from front-end devices to the edge network servers. It can be achieved by the MEC acting as an IoT gateway between mobile devices and the cloud. MEC enables smartphones to collect patient physiological information and send it to the edge servers.

- *The edge node layer*

A large set of sensing and communication techniques can be utilized for IoT data collection in the Wireless Local Area Network (WLAN), including Wi-Fi access point, Mobile Crowdsensing (MCS), femto access point (low power cellular base station), and base stations for fifth-generation (5G) cellular networks as in our proposal. Coinciding with that, MEC is composed of geo-distributed servers or virtual servers installed directly at the premises of mobile users.

TABLE 1: The comparison of the characteristics in the related work

Authors	Ref.	Technique	System type	Methodology
Otoom et al. (2020)	[33]	IoT-based (Machine Learning)	Surveillance	Presented eight machine learning algorithms based on Support Vector Machine (SVM), Neural Network, Naïve Bayes, K-Nearest Neighbor (K-NN), Decision Table, Decision Stump, OneR, and ZeroR and test the eight algorithms on an actual COVID-19 symptom dataset.
Zheng et al. (2020)	[34]	Convolutional Neural Network	Facial and thermal	Used a CNN plus support vector machine (SVM) approach (CNN-SVM) to estimate body temperature from a sequence of facial images.
Feriani et al. (2020)	[35]	IoT-based (Machine Learning)	Surveillance	Utilized a shared representation learning process to extract actionable information from massive high-dimensional data obtained from IoT edge devices.
El-Rashidy et al. (2020)	[36]	Convolutional Neural Network	X-ray scan images	Introduced a convolutional neural network-based deep learning model for COVID-19 detection based on patient’s X-ray scan images and transfer learning.
Hossain et al. (2020)	[37]	5G framework	Surveillance and thermal	Developed a framework that uses 5G networks to detect COVID-19 using chest X-ray pictures. The framework investigates three deep learning models: ResNet50, Deep Tree, and Inception v3.
Ionescu et al. (2021)	[38]	AI-based	Thermal-body	Demonstrated how smaller, inexpensive sensors can be merged into a bigger array of sensors to provide better coverage and be utilized for shape detection and object tracking.
Sathyamoorthy et al. (2020)	[39]	Deep Reinforcement Learning (DRL) method	Vision-guided mobile robot	used a mobile robot with commodity sensors, specifically an RGB-D camera and a 2-D lidar To execute collision-free navigation in a crowd and estimate the distance between all identified individuals in the camera's field of view
Chatrati et al. (2019)	[40]	Convolutional Neural Network	Diabetes and blood pressure	A smart home health monitoring system for remote diabetes and blood pressure monitoring in patients was demonstrated. The technology aids in the analysis of a patient's blood pressure and glucose measurements while they are at home.
Taiwo et al. (2020)	[41]	AI-based	Physiological parameters	Introduced a remote smart home healthcare support system for monitoring patients’ health status.
Din et al. (2020)	[42]	AI-based	Surveillance	Presented an IoT-based intelligent health monitoring and management architecture. Using piezoelectrical devices, the researchers were able to harvest energy.
Al-Humairi et al. (2020)	[43]	AI-based	Facial and thermal	Introduced a COVID-19 real-time system for tracking and identifying suspected cases, which uses an Internet of Things platform to capture user symptoms and alert the appropriate authorities.
Arun et al. (2020)	[44]	AI-based	Surveillance	By connecting with IoT-based smart solutions, the authors were able to aid in the fight against COVID-19 by monitoring, contract tracing, and detecting the COVID-19 pandemic.
Ranaweera et al. (2020)	[45]	Multi-Access Edge Computing (MEC)	Surveillance	MEC of the edge models were considered for implementing contact-less techniques that aid COVID-19 mediation and the future of healthcare.
The proposed system		MEC as an IoT infrastructure	Real-time surveillance	Design a healthcare infrastructure called (CoronaCare). In CoronaCare; signs and symptoms data of (COVID-

	and C-RAN in 5G cellular networks	via live video-conferencing	19) generated by smartphones via live videos are processed in real-time**.** It is divided into a physical infrastructure scheme and a control and management scheme. (CoronaCare) intelligently maintains integrity between the smartphone and the edge servers to ensure real-time detection. This integration is achieved by using Network Virtualization Function (NVF) to achieve a centralized management scheme that controls operations and resource allocation of the infrastructure.

MEC deployed at a base station of a multi-technology (5G/LTE) cell aggregation site. 5G has extended coverage, higher throughput, lower latency, and connection density of massive bandwidth, paving the way for the connection of billions of sensors over the Internet. Furthermore, some potential methods and technologies have been proposed, such as millimeter-wave (mm-Wave), massive Multiple-Input Multiple-Output (MIMO). To push intelligence at the base station and to effectively optimize RAN services, MEC technology develops an energetic ecosystem and a new value chain that allows intelligent and smart services at nearby locations to mobile subscribers.

The massive collected data from billions of smartphones were to be analyzed. Afterward, the data is filtered to check the efficiency of the data. Also, this stage classifies the received data into static data reflecting sensors' status and real-time data streaming. Static data are directly stored in a database, while the real-time data stream is broken down into various layers. Based on these levels, a data analyzing level reorganizes data into a neighborhood structure. The data filtering and classifying based on several local servers to analyze collected data. Computation offloading usually happens across the layers from outside in or inside specific layers. The healthcare infrastructure enables real-time application. In which smartphones can directly migrate the execution of the application to the edge nodes servers to perform the computation offloading for latency reduction.

- *The back-end layer (the Cloud)*

The cloud, standing at the core of the network, is a critical centralized node, and it can help to discover edge nodes, conduct resource management, and perform global big data analytics. This stage carries out application-specific processing tasks based on the collected data streams at multiple individual fog servers. Here, some processing tasks are specific for fog stream applications, such as the networked control and real-time tasks. The processing results are consumed by applications and may also be stored for offline batch processing. It is worth noting that applications may also produce data streams, resulting in loops in the typical life cycle.

c. Third Category: The Authorized Healthcare Provider (AHP)

It shows how health advisers having access to the server can immediately diagnose patients and assist the patients, independent of their geographical location accordingly. The healthcare provider, such as hospitals, doctors, and nurses, who support the remote monitoring of all types of patients and maintain ubiquitous communication in the event of danger monitors and in case of increasing trends in signs and symptoms of Covid-19 which are considered as seriously anomalies. Such trends are computed using smart decisions (e.g., notifications) are sent to the health professionals upon detection of such trends.

d. Fourth Category: The Operators and Third Parties

The operators and third parties such as E-government and the World Health Organization (WHO), to be part of a system where patient records are stored in a database. It allowing access to patients' information and analyzing a huge amount of big data from the database. Such data is first pre-processed and analyzed at the MEC. The pre-processed data is, then, sent to central servers for further analysis. The scenario of the CoronaCare Healthcare infrastructure processing is described in the flowchart shown in Figure 5.

B. Control and Management Scheme

In this section, the description of the CoronaCare control and management scheme will be introduced in detail as shown in Figure 6. It centrally controls and orchestrates the virtual resources to solve the problem of integrating heterogeneous access networks. It dynamically schedules the data flows to access the networks and edge servers through SDN and builds virtual networks according to different data traffic characteristics. Network Function Virtualization (NFV) orchestrator allocates the computing and storage resources according to various edge service QoS requirements to each isolated slice, which carries scalable network functions and corresponding service flows. The orchestrator performs management of the virtual infrastructures and Virtual Machines (VM), including create, initialize, reveal, start, stop, scale-up, and scale-down. The interfaces are provided to configure the platform based on our scheme. The control and management scheme has various function modules, such as resource orchestration, mobility management, and application orchestration management. Network Virtualization (NV) creates separate virtual networks (slices) for different users on a particular physical infrastructure. Each network slice can be created with the specified resource allocation. When the resource slice is no longer needed, it is deleted and the corresponding reserved physical resources are released.

a. Resource Orchestration Management

First, the resource orchestration plane manages physical resources, including infrastructure discovery and monitoring the status of types of equipment (e.g., network elements such as number of mobile devices, number of patients, and edge cloud servers). Virtualization abstracts the physical resources into the virtual network, edge storage, and computing resources. Then, the resource orchestration orchestrates virtual resources. The SDN controller manages network resources by scheduling service flows by dynamically configuring the flow entries of the SDN controller, and the NFV orchestrator allocates IT resources. Virtual network resources include heterogeneous virtual network entities, radio spectrums, and bandwidth resources. The SDN controller slices the diversity resources and embeds the virtual networks on physical networks. The NFV orchestrator is responsible for determining whether to consume the virtual resources or not, how much virtual resource to occupy to create VMs, and which server to place VNFs. When a user accesses services deployed at the network edge, it requires the network together with edge computing or storage resources, which requires the SDN controller to coordinate with the NFV orchestrator to flexibly orchestrate and manage all of the resources.

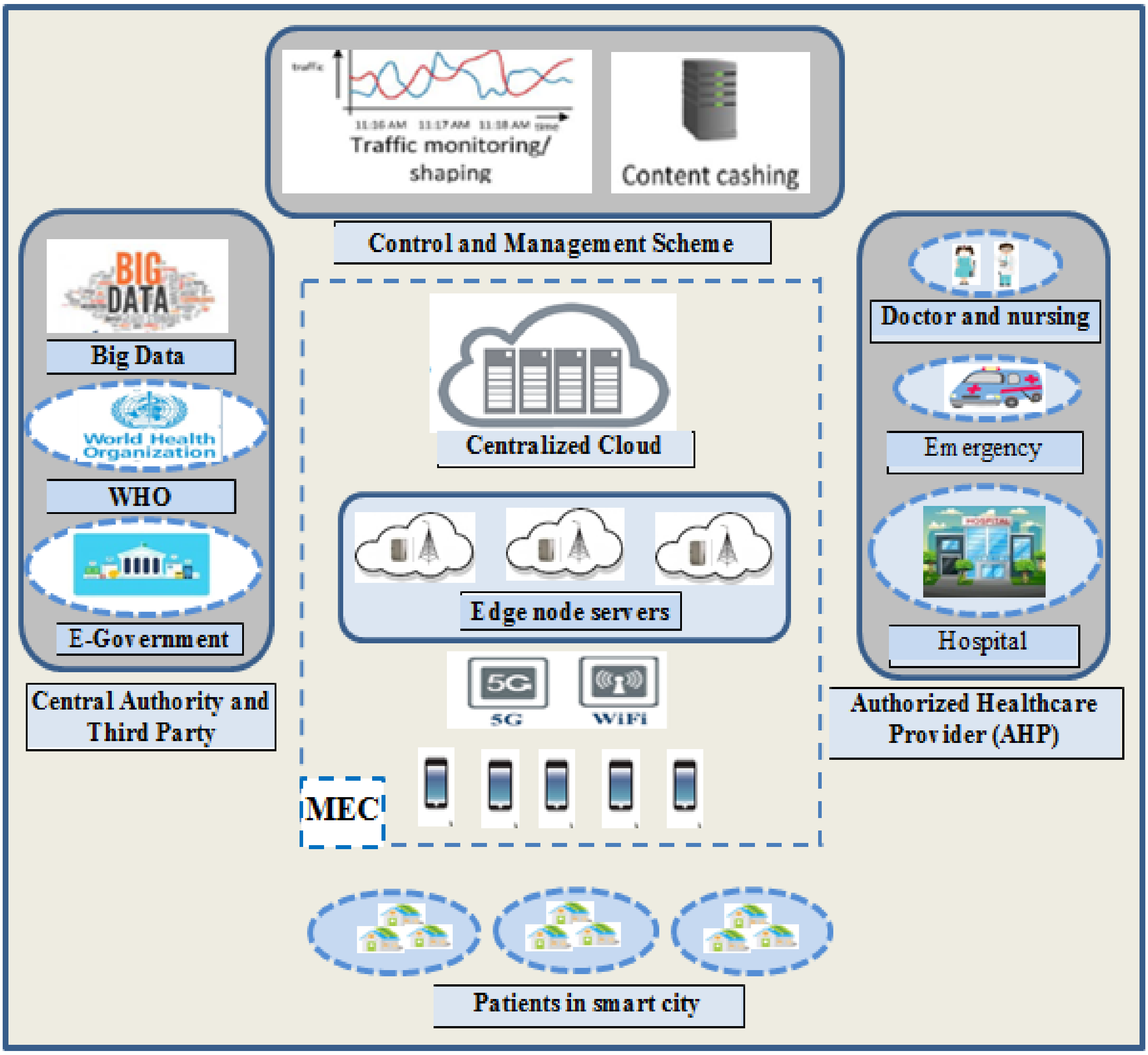


Fig. 3: The architecture of CoronaCare healthcare infrastructure

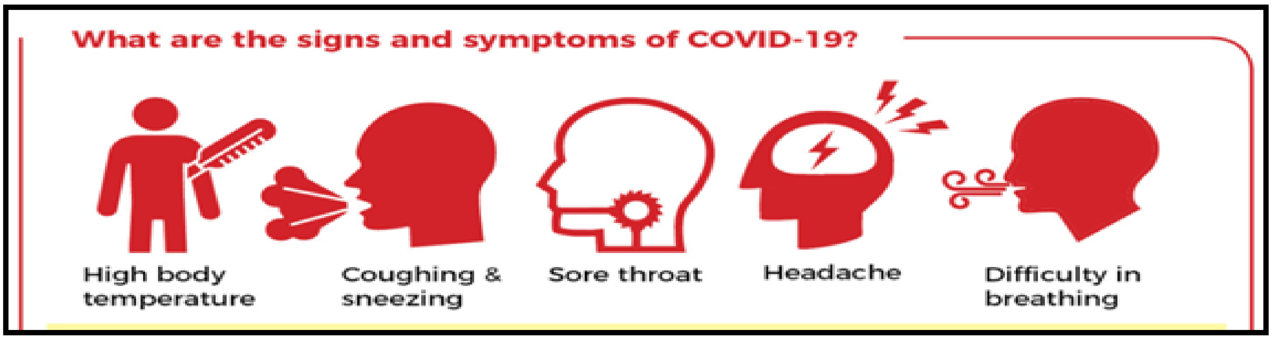


Fig. 4: Signs and symptoms of COVID-19

b. Mobility Management

MEC should provide service continuity, application and VM mobility, and application-specific user-related information. Mobility management (e.g., mobile user mobility and its predictability and handover optimization) is important. When the user moves, his VM should be seamlessly sent between the MEC servers. VM mobility is sensitive to a variety of factors, such as data volume, processing speed, compression ratio, and bandwidth. A typical method of mobility management is that users report their location information to the mobility management entity (MME) of BSs. A novel solution to this problem is to collect users' mobility information, such as locations and times, by BSs. Then, a large amount of data is used to analyze and obtain the movement law of the user. The VM of a user can migrate according to his law, and the management module can preserve bandwidth and other factors.

c. Application Orchestration Management

MEC service is open to third parties such as the World Health Organization and E-government. These applications and services are hosted in various VMs. that are used to share the information of mobile user terminals with the applications. The ultra-low end-to-end response latency for emerging cloud applications makes the services on a distributed edge cloud close to the user, and the connectivity of the access networks facilitates direct communication of the edge clouds without the core network. The dynamically controlled routing of the access networks provides an effective solution for VM migration and service transmission link failure to ensure the high reliability and availability of the service.

IV. THE SIMULATION OF THE SYSTEM

In this section, we provide simulation results for the QoS parameters: average throughput and processing time as well as service time results using the proposed CoronaCare healthcare infrastructure that is based on MEC using a 5G cellular network. The simulation includes 200 to 2000 user devices that are located at different distances from the serving 5G base stations. Simulations are adopted to evaluate the proposed parameters of the control and management scheme. All the experiments are run on Matlab R2020a. Table 2 summarizes the list of main simulation parameters and their default values.

TABLE 2: Main Simulation Parameters

Parameters	Value
Usage percentage (%)	20
Task interarrival time (s)	10
Idle period duration (s)	20
Active period duration (s)	40
Upload data size (kB)	1250
Download data size (kB)	250
Task length (Giga instruction)	2.5
Virtual machine utilization of tasks (%)	4

We design a virtual network that is similar to a smart city in our experiments. Patients in homes or hospitals are moving around and request services from the edge servers that are located at the base stations. Each building in the smart city is also serving a wireless access point; hence, the mobile users are connected to the related access point and offload their tasks via this connection. In our simulations, the mobile devices utilize a healthcare application and the edge and cloud servers provide corresponding services. Normally, mobile devices do not generate service requests continuously. We use an idle/active task generation pattern to simulate real-life properly. According to this pattern, the users create tasks during the active period, and then, they wait during the idle period. When the mobile user moves to the coverage area of the access point, they join the related WLAN. Then, the mobile devices start sending tasks to the edge server. If a task is decided to be offloaded to the global cloud, the WAN connection provided by the Wi-Fi access point is used.

In the simulation, comparing three different architectures levels occurred are (i) edge layer, (ii) core layer, and (iii) manager layer. In our simulation, the offloading ratio to the cloud is decided as 20%, and hence, approximately four out of 20 tasks are offloaded to the cloud. The manager layer has a considerable advantage, because, for the tasks that are executed on the edge layer, only the manager layer can offload the tasks to other edge servers located in different base stations. In the simulation, the manager layer uses the least-loaded algorithm while selecting an edge server to offload in the edge layer.

V. RESULTS AND DISCUSSIONS

In our simulation, important performance metrics are shown. In Figure 7, the average task failure values concerning the number of mobile devices are given for different edge computing architectures. The devices in the edge-layer architecture can only offload to the nearest edge server, and as a result, the number of failed tasks in the edge-layer architecture is observed higher than the other architectures.

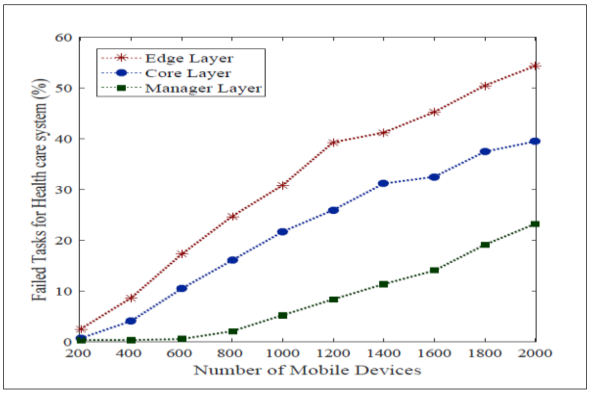


Fig. 7: Evaluation of average failed tasks for different edge computing architectures

In Figure 8, the average service time concerning the number of mobile devices is shown. When it comes to the core-layer architectures, they present better results than the edge-layer architecture because some of the tasks can be offloaded to the cloud servers. In this simulation, a basic probabilistic approach is used to decide offloading tasks to the cloud. Roughly, 20% of the tasks are sent to the cloud, so the core-layer architecture is slightly better than the edge-layer. The edge-manager architecture outperforms the others since the edge orchestrator makes it possible to send the tasks to any edge server in the same LAN. Therefore, it can balance the load of the edge servers efficiently and avoids the congestion occurred in the edge layer where too many users are present.

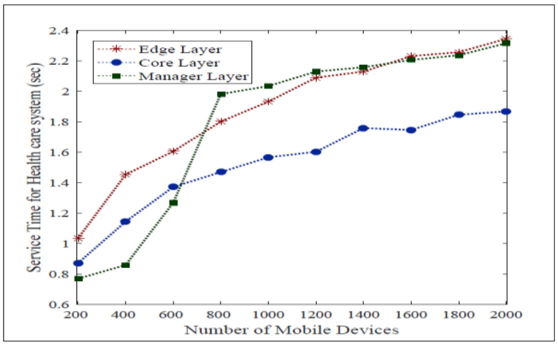


Fig. 8: Evaluation of service time for different edge computing architectures

The average processing time of the tasks generated for different edge computing architectures is shown in Figure 9. The processing time is the duration spent on the server while executing a task request. As a result, the manager layer architecture outperforms the others, since it can distribute tasks among the edge servers. The core-layer architecture provides slightly better performance than the edge-layer architecture since it can relay some tasks to the cloud servers.

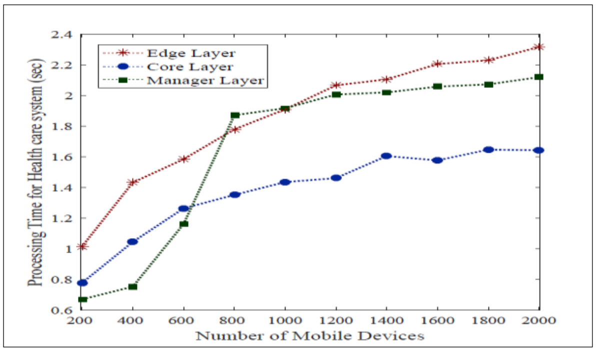


Fig. 9: Evaluation of processing time for different edge computing architectures

The average VM utilization is shown in Figure 10 where the effect of the edge server capacity on the results is investigated.

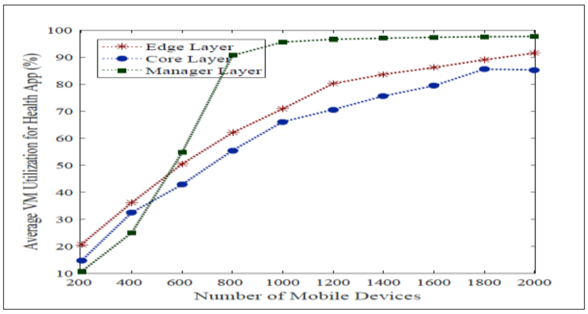


Fig. 10: Average VM utilization for different edge computing architectures

Table 3 shows the comparison of the average latency between the proposed system and the similar previous works which show that the proposed system demonstrates high throughput and extremely low latency compared with similar works.

TABLE 3 Comparison of the average latency between the previous work and the proposed system

Ref. Year	Technique	Latency
[37] (2020)	5G framework (surveillance and thermal)	2.5 seconds
[45] 2020	Multi-Access Edge Computing (MEC) (surveillance)	3.3 seconds
The proposed system	MEC as an IoT infrastructure and C-RAN in 5G cellular networks **(**Real-time surveillance via live video-conferencing**)**	2 seconds

VI. Conclusion

In this paper, we use mobile edge computing to present an efficient healthcare infrastructure system, called by CoronaCare to help patients affected by the Coronavirus (COVID-19). The architecture of CoronaCare is designed to enable medical practitioners to evaluate, diagnose patients, facilitate remote ePrescribe medicines and treatments, and detect fluctuations in their medical conditions through remote consultations through a live video conferencing-based interactive system. Deploying multi-access edge computing (MEC) servers over 5G cellular networks is designed to reduce the heavy traffic load and the end-to-end latency. Resource allocation management among multiple users served by one base station to achieve the optimal system-wide user utility and ensure the feasibility of efficient data management is introduced. Centralized control for data management using virtual function networks and specialized schedules edge servers are designed. The interaction between a data collector and edge server and central cloud is formulated by virtual functions to closely approach the real data trading environment. Finally, numerical results with analysis of the system are provided to demonstrate that CoronaCare has significant advantages for healthcare data, and supports efficient data management to meet QoS requirements. The system is simulated and the results demonstrated high throughput and low latency as the evaluation of service time is approximately 2 seconds and the average utilization of Virtual Machines (VMs) is approximately 98% for different edge computing architectures which effectively improved the system performance.

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