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Fuzzy-logic-based IoMT framework for COVID19 patient monitoring

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ABSTRACT

Smart healthcare is an integral part of a smart city, which provides real time and intelligent remote monitoring and tracking services to patients and elderly persons. In the era of an extraordinary public health crisis due to the spread of the novel coronavirus (2019-nCoV), which caused the deaths of millions and affected a multitude of people worldwide in different ways, the role of smart healthcare has become indispensable. Any modern method that allows for speedy and efficient monitoring of COVID19-affected patients could be highly beneficial to medical staff. Several smart-healthcare systems based on the Internet of Medical Things (IoMT) have attracted worldwide interest in their growing technical assistance in health services, notably in predicting, identifying and preventing, and their remote surveillance of most infectious diseases. In this paper, a real time health monitoring system for COVID19 patients based on edge computing and fuzzy logic technique is proposed. The proposed model makes use of the IoMT architecture to collect real time biological data (or health information) from the patients to monitor and analyze the health conditions of the infected patients and generates alert messages that are transmitted to the concerned parties such as relatives, medical staff and doctors to provide appropriate treatment in a timely fashion. The health data are collected through sensors attached to the patients and transmitted to the edge devices and cloud storage for further processing. The collected data are analyzed through fuzzy logic in edge devices to efficiently identify the risk status (such as low risk, moderate risk and high risk) of the COVID19 patients in real time. The proposed system is also associated with a mobile app that enables the continuous monitoring of the health status of the patients. Moreover, once alerted by the system about the high risk status of a patient, a doctor can fetch all the health records of the patient for a specified period, which can be utilized for a detailed clinical diagnosis.

1. Introduction

Since the size and the population of cities are ever-growing all over the world (Kirimtat, Krejcar, Kertesz, & Tasgetiren, 2020), providing essential services such as healthcare, transportation, energy, education, etc., to the urban population is becoming a significant challenge. A technology-driven solution to this problem has been proposed in terms of the smart city. The smart city, an IoT-based solution, promises sustainability in delivering different services in urban areas and ensuring collaborations among different components and layers of the city. As per Attaran, Kheibari, and Bahrepour (2022) the smart city has six dimensions – a smart environment, smart economy, smart living, smart people, smart government, and smart transportation. Hamid and Bawany (2022) proposed a framework which divides the smart city into five layers to improve its management and overall security. As reported by Hamid and Bawany (2022) the smart-city layers are — application, communication, infrastructure, data, and stakeholders. Smart healthcare is an integrated part of the smart city. Cook, Duncan, Sprint, and Fritz (2018) discussed how information and communication technologies (ICTs) used in a smart city can significantly scale up healthcare effectiveness and also reduce the cost of healthcare services. Tuncer, Dogan, Özyurt, and Bensmail (2020) utilized a massive amount of smart sensors (or bio-sensors) connected in several body sensor networks (BSNs), smart devices, massive amounts of biological data and media content, an efficient communication framework, and intelligent decision support to build a framework which logically connects stakeholders such as the patients, patient's relatives, doctors, and medical assistants who may be physically located in different locations.

The outbreak of COVID19 (He, Deng, & Li, 2020) in late December 2019 scaled up as a pandemic and threatened the entire world. Huang et al. (2020) summarized the symptoms of 41 COVID19 cases on

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January 24, 2020, showing that flu-like symptoms, coughing, muscle aches, pain, and weakness were perhaps the most frequent initiation signs. The World Health Organization (WHO) declared COVID19 as a pandemic on March 11, 2020, and requested immediate international intervention (Rubin et al., 2020). Doctors and healthcare staff were badly affected due to the infectious nature of the disease. The situation urges a unique solution that can address the problem of fulfilling the urgent need for medical supplies, medical assistance, and therapies within a constrained environment. The emergence of this COVID19 crisis has magnificently escalated the demand for more efficient and responsive smart healthcare systems.

Furthermore, every front-line professional, such as medical staff, relies upon personal protective equipment (PPE) to safeguard themselves from the transmission. However, the lack of gloves, face masks, gowns, and other medical necessities left front-line healthcare workers woefully unprepared to handle an infected individual. The world's sole option for dealing with this virus is to halt its transmission. On the other hand, science and technology may be able to assist in reducing the spread of the disease by early detection (or prediction) and surveillance of reported cases (Hlaing, Nopparatjamjomras, Nopparatjamjomras, et al., 2018). New technologies, like the IoT, are gaining international attention and have become more accessible for predicting and tracking the progression of severe diseases (Christaki, 2015).

Healthcare service (Ray, 2014; Goyal, Garg, Rastogi, & Singhal, 2018) is a system that aids in improving health and preventing different diseases with appropriate medical treatments. In the healthcare sector, IoT has brought about several remote health-monitoring solutions. Numerous bio-sensors may be used to collect health data in IoT-based solutions. A specialized area of IoT in the medical domain is referred to as IoMT (Internet of Medical Things) (Christaki, 2015). IoMT is becoming more evident in healthcare-related solutions, and it is also a perfect option for screening, forecasting, and monitoring new infectious illnesses such as COVID19. The schemes presented in Gozes et al. (2020), Bai et al. (2020), Vaishya, Javaid, Khan, and Haleem (2020) are based on artificial intelligence (AI). Rajees. Kumar et al. (2022) used IoT for the detection and monitoring of asymptotic COVID19 patients. However, most of the proposed methods are either inefficient in dealing with real time data and hence unable to provide real time response, or they are not cost-effective systems. The main challenges that are identified in the several frameworks and models proposed to address the problem of monitoring COVID19 patients are as follows.

- COVID19 patients staying at home or at COVID care centers need to be monitored remotely to prevent the spread of the infection and safeguard the doctors and medical staff.
- In high risk situations for patients, it will generate alerts in real time, notifying all concerned parties so that preventive actions can be taken.
- The majority of existing frameworks are inefficient at generating real time responses and require extensive training during the learning process. At the same time, some frameworks require costly hardware. Thus, the challenge is to develop a framework that is cost-effective but at the same time efficient.
- The solution is required to provide a user-friendly mobile app to monitor patients' medical status.
- Since the medical data are highly sensitive, sufficient security measures have to be considered, so the patients' privacy cannot be compromised.

1.1. Our contributions

This paper mainly concentrates on designing and implementing an IoMT-based framework along with a light-weighted fuzzy analysis system that monitors and generates the risk status of COVID patients. More specifically, the main contributions are as follows:

1. Designing and implementing a cost-effective, remote, and real time health monitor system for COVID19 patients based on the IoMT framework along with edge computation.
2. Developing a fuzzy system to detect patients' health status at the edge layer in real time and in high risk situations generates a text alerts to attract the attention of the designated personnel like relatives, doctors, or medical staff.
3. Using the fuzzy logic controller to ensure a quick response with little computational cost (no training is required). Moreover, the use of low cost hardware along with low-cost sensors to collect real time health (or medical) data of the patients makes the overall framework cost-effective.
4. Implementing a mobile application that enables continuous as well as on-demand monitoring of the patient's health information.
5. Designing and implementing an approval-based mechanism to ensure secure access to the health information in the cloud.

This approach aims to minimize death rates by monitoring, correctly understanding the level of risk associated with the patients and reducing the contamination rate throughout the associated persons in the healthcare sector.

The paper is organized as follows – Section 2 provides a study on the existing solutions, the proposed framework is presented in Section 3, while in Section 4, the experiment and the experimental results are reported, and Section 5 includes the discussion about the proposed system and the utilization of the developed system. Section 6 concludes the paper by presenting the scope of future works.

2. Related study

As per Ting, Carin, Dzau, and Wong (2020), the versatility of the IoT allows remote monitoring of a significant number of patients from their care homes. The patients' health data include heart rate and blood pressure, which may be transferred to the cloud for processing without putting healthcare professionals at risk of contamination. In current scenarios, the use of IoT to supply healthcare assistance has received much attention. Said and Tolba (2021) proposed a IoT healthcare architecture. The proposed health architecture has three layers. The first layer collects the user's health data, the second part is responsible for managing the administration's function, and the third one has the most important task, i.e., to classify the collected data, depending on the priority. As reported by Singh, Javaid, Haleem, and Suman (2020), the advantages of applying IoT to combat the COVID19 outbreak involve lower healthcare costs and better treatment outcomes for affected patients. Based on this, Darwish, Hassanien, Elhoseny, Sangaiah, and Muhammad (2019) presented a CloudIoT-Health paradigm that blends cloud services using IoT in the healthcare sector.

The relevance of Radio-Frequency IDentification (RFID) technology for managing affected people's medical information and surveillance devices without being contaminated is highlighted by Huang and Xie (2014). Alshraideh, Otoom, Al-Araida, Bawaneh, and Bravo (2015) presented an IoT-based method for detecting cardiovascular disease. The authors have applied several machine learning methods to implement their scheme. Rao and Vazquez (2020) presented a machine learning-based approach for the detection of COVID. The scheme is based on information collected from respondents via a pre-defined series of questions that can be viewed on a smartphone. Madurai Elavarasan and Pugazhendhi (2020) studied the significant role of technologies in controlling the COVID19 pandemic and discussed different technologies that assist the healthcare systems, government, and public sectors to fight against COVID19. Kumar, Raut, and Narkhede (2020) reported different ways to properly utilize technological domains such as AI and IoT in healthcare sectors. Singh et al. (2020) described the implementation of IoT as a crucial part of the system for tracking and reporting real time data about infections.

Vaishya et al. (2020) reported how AI could be used to detect COVID19 patients. The authors compared different AI-based and non-AI-based applications. The authors also proposed seven different ways AI can fight against COVID19, including early detection, treatment monitoring, contact tracing, mortality projection, development of drugs and vaccines, minimizing the workloads of healthcare persons, and prevention of this disease. In Gozes et al. (2020), Gozes et al. presented an AI-based automated CT image analysis system for COVID19 identification, measurement, tracking, and distinguishing COVID19 patients from non-COVID19 patients. Further, Rajees. Kumar et al. (2022) proposed a technique for finding and tracking asymptotic patients by collecting data about them using IoT devices, as well as monitoring their health status after separating them using IoT-based technologies. Google and Apple[1] developed an app for exposure notification using contact tracking methods, which can assist and enhance these efforts by allowing public health officials to instantly warn anyone who may have been in close contacted with someone who has caught COVID19. Bai et al. (2020) proposed an IoT-based diagnosis and treatment assistant program by utilizing a set of questionnaires and automatically generating conclusions about confirmed or suspected COVID19 patients. A. Bassam et al. (2021) designed and implemented a system for COVID19 patient monitoring. Three system layers include wearable sensors, a cloud-based API, and an Android web application for mobile devices. The data from the IoT sensor layer are initially used to characterize the signs and symptoms of the disease. The next layer saves data in a cloud database to prevent, alert, and respond quickly to threats. This layer is responsible for contacting and alerting the family members of patients who are most likely affected. In addition, the technology immediately notifies the relevant health practitioners of quarantine breaks for possibly infected people using real time location information.

Dhiman, Vinot. Kumar, Kaur, and Sharma (2021) proposed that X-rays could be used to identify the patients contaminated with COVID19 using a deep learning algorithm and a multi-objective optimization strategy. The authors used the J48 DT approach to detect infected individuals by successfully classifying their characteristics. This research built 11 CNN models to diagnose COVID19 from X-ray scans. Sodhi et al. (2022) reviewed the technologies that assist governments in their efforts to combat the pandemic. In Poongodi et al. (2022), Poongodi et al. proposed a hybrid deep learning method to diagnose COVID19. The layered approach is used here to measure the symptom level of the patients and to analyze the patient image data to confirm whether he/she is positive for COVID19. This work utilizes smart AI techniques to rapidly predict and diagnose the COVID19 by the Oura smart ring within 24 h. In the laboratory, a rapid coronavirus test is prepared with the help of a deep learning model using the recurrent neural network (RNN) and convolutional neural network (CNN) algorithms to diagnose COVID19 rapidly and accurately. Sharma, Tomar, Chilamkurti, Kim, et al. (2020) explored the idea of blockchain combined with smart contracts and analyzed its use in IoMT. They also analyzed the IoMT's decentralization and the usage of smart contracts. Furthermore, the authors also proposed a unique architecture of IoMT and outlined its benefits, drawbacks, and future developments.

Aman et al. (2021) proposed the basic architecture of the IoMT. The main functional tasks associated with this architectures are common such as data collection, storage, transmission, and analysis, which may assist in restricting the spread of infectious diseases. Furthermore, the architecture has been enhanced by integrating the cloud platform to analyze the collected dataset and make decisions by end-user devices such as smartphones or monitoring devices. Therefore, this paper provides an IoMT-based solution that can help to prevent the spread of COVID19 infection. The proposed framework comprises biosensors, edge devices, and a fuzzy system that can remotely monitor the COVID19 patients in real time. In an alarming situation, the system generates alert messages to the person associated with the patient so that preventive actions can be carried out.

[1] https://www.google.com/covid19/exposurenotifications/

3. Proposed framework

The proposed framework enables continuous monitoring of specific health parameters of COVID19 patients using wearable sensors. It analyzes the collected data to find the risk status associated with the patient and, when the risk is high, it generates text alerts. The IoMT system comprises four basic layers: (1) sensor layer, (2) edge layer, (3) cloud layer, and (4) interface layer. Fig. 1 depicts the basic IoMT architecture. In this proposed system, the sensors are connected with a Raspberry Pi system to collect real time data from COVID19 patients remotely. In the implementation, the Raspberry Pi systems are used as edge devices. After collecting data with edge devices, the fuzzification and decision-making occur at the edges so that an alert in real time can be generated (in the form of a text alert) about the patients' high risk health conditions. Further, the collected data would be finally accumulated in the cloud through edge devices for storage and could be accessed by authorized users for health monitoring purposes. COVIMONI, a mobile app that serves as an interface layer, has been proposed and developed for health monitoring purposes.

This proposed framework comprises five main components, as presented in Fig. 2.

1. The wearable body sensors collect health-related data from the target COVID19 patients (at **sensor layer**).
2. The real time data are stored in edge devices (at **edge layer**).
3. Fuzzification: fuzzy logic is applied to analyze the collected data (at **edge layer**).
4. Decision-support mechanism: the fuzzy logic system generates risk status associated with the patients in terms of high risk, moderate risk, and low risk (at **edge layer**).
5. Alert generation: if the associated risk is high, it generates text alerts (at **edge layer**).
6. Data accumulation in the cloud: the edge devices forward the collected data to some cloud server.
7. The cloud server provides secure access to the data and risk status information (at **cloud layer**).
8. Data monitoring: a dedicated mobile app can be used for data monitoring. An approval-based mechanism implements the data access security (at the **interface layer**).

3.1. Sensors collecting data

Tharakan, Nomoto, Miyashita, and Ishikawa (2020) reported that the COVID19 patients with high body temperatures have high mortality risk. Therefore high body temperature is one of the significant symptoms, and it is considered one of the key parameters. Furthermore, Alzubaidi, Otoom, Otoum, Etoom, and Banihani (2021) identified the prominent symptoms of COVID19 patients, which are pulse rate and oxygen saturation in the blood. Thus, these are also considered dominant parameters for monitoring COVID19 patients in this proposed system. Some sensors are required to collect real time health data from the COVID19 patient under monitoring. For this purpose, the proposed framework uses an LM35 temperature sensor for sensing body temperature (in degrees centigrade) and a MAX30102 heart rate sensor for measuring the pulse rate and oxygen saturation level of the COVID19 patients. A brief description of the sensors is presented as follows:

- **LM35 temperature sensor:** The LM35 (Liu, Ren, Zhang, & Lv, 2011) is a low-cost temperature sensor that produces an analogue reading of temperature. The output voltage is expressed as an equivalent temperature value in degrees centigrade. Unlike the thermistors, the external calibration for accuracy is not required for the LM35. The LM35 can detect temperatures ranging between -55° to 150° centigrade.

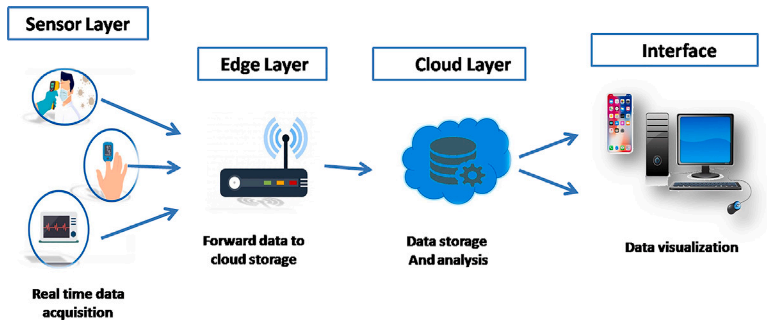


Fig. 1. Basic Architecture of IoMT. Pustokhina et al. (2020).

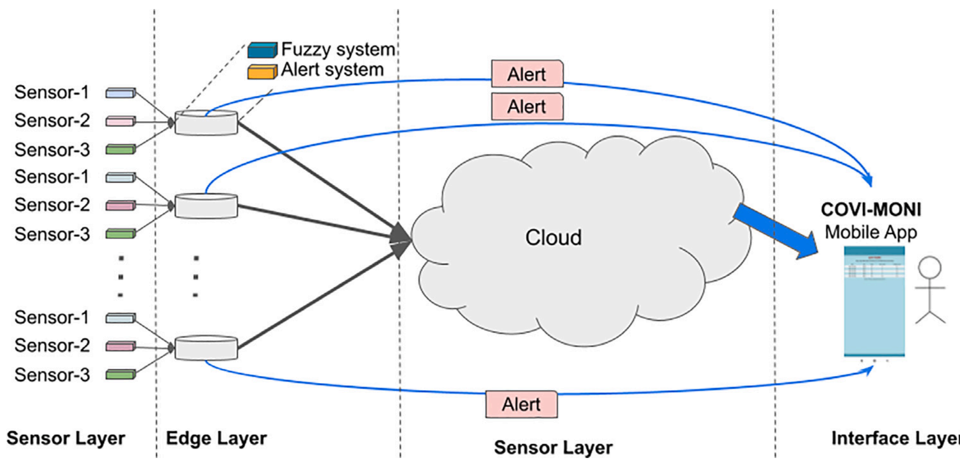


Fig. 2. Layered architecture for the proposed framework where sensor-1 is the LM35 temperature sensor, sensor-2 is the MAX30102 heart rate sensor and sensor-3 is the MAX30102 oxygen saturation sensor.

In this proposed system, the LM35 (Datasheet, 2017) has been used because it is an inexpensive and readily available temperature sensor. The LM35 sensor requires no further calibration or trimming for normal accuracy. As a stand-alone tool, it is particularly precise.

- **MAX30102 heart rate sensor:** The MAX30102 sensor[2] measures blood oxygen levels as well as pulse rate. The quantity of oxygen in the blood is calculated by measuring the wave amplitude after the infrared light is transmitted and reflected by striking the finger. The MAX30102 is an integrated component that works with Arduino and STM32 microcontrollers. It combines a red and infrared LED, a photoelectric sensor, an optical device, and a low-noise electrical circuit to block ambient light. The proposed framework uses the MAX30102 sensor since it has a higher sensitivity to the changes in infrared receiver voltage. Its capacity to store more data while using less power is a significant advantage.

3.2. Intelligent edges

In the proposed scheme, the fuzzy logic is applied to the collected data to determine the patient's risk level, and the entire process takes place at the edges. If the fuzzy system indicates a high risk associated with a patient, the edges use a text alert system to notify almost in real time the patient's relatives, doctors, or medical staff about the situation.

3.2.1. Real time collected data

The real time health data are collected through sensors from the patient in one minute intervals and every consecutive five data are collected as a window. The proposed fuzzy system will analyze the data at edge devices, and an alert will be generated if the patient is at risk. Further, the collected data combined with generated risk status would be passed to the cloud from the edge device for storage.

3.2.2. Fuzzy logic system

During the fuzzification process, knowledge-based information (Barro & Marín, 2002) is employed to turn input values into fuzzy ones, which is accomplished via the application of fuzzy logic. Fuzzy logic (FL) can significantly simplify the development and deployment of the system. It does not require complex mathematical or statistical techniques, but requires a realistic grasp of the functionalities of the entire system. Higher precision with efficient computation (Patyra & Mlynek, 2012) can be achieved using FL techniques. Fuzzification (Zadeh, Klir, & Yuan, 1996) can be used to translate any ambiguous input, like "joyful", "lovely", or "excellent", into the mathematical model. In this proposed system, the role of fuzzification is very significant since the alert system performs based on its output. The proposed system works with real time collected data, so generated alerts must be sent to the concerned doctors as soon as possible. Therefore, the fuzzification process is carried out at the edges of the IoMT framework. In the implementation, Raspberry Pi systems are used as edge devices. Fig. 13 depicts the overall idea of the FL system implemented in this study.

Substantial human knowledge of and experience with the physical system are required for developing fuzzy rules. The promising area of fuzzy sets resembles human reasoning and system knowledge. Fuzzy logic is used to overcome the inefficiencies of both table-based and formula-based control systems. A look-up table is used to determine the consequence of one or more inputs in table-based controllers. The disadvantage of using a table-based controller is that it could grow quite lengthy, especially if there are a lot of entries or results. Thus,

[2] https://datasheets.maximintegrated.com/en/ds/MAX30102.pdf

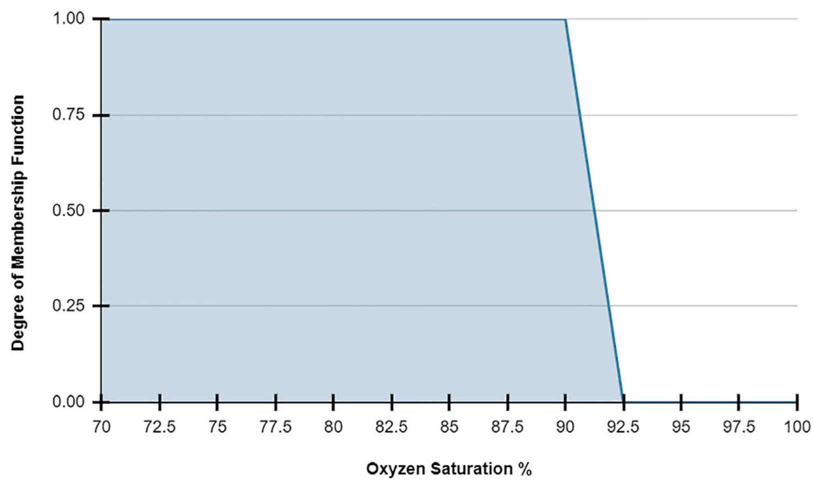


Fig. 3. Membership Function of O_L.

a large memory capacity is required. The output of a formula-based controller is expressed as a function of the input. The controller's ability to execute the formulae may be limited. As a result, both table-based and formula-based approaches are ineffective because it is impossible to develop a suitable mathematical model at the very first stage.

This proposed framework is based on fuzzy logic because it assesses the confidence of an issue, and the algorithms are resilient, meaning that they can quickly adapt to changing circumstances. Moreover, the framework does not require any training to operate. It is possible to implement similar systems with the help of ML. However, the target is to develop a cost-effective system. ML algorithms are designed to take out information from vast amounts of data and provide conventional techniques for the classifying and grouping processes, among other things. ML algorithms are capable of handling a wide range of data types and may be employed in big contexts. Furthermore, extra training time is necessary for the algorithms to improve accuracy and relevance as time goes on. Due to the above reasons, ML has been avoided. When it comes to fuzzy logic, it assesses the confidence of an issue, and the algorithms are resilient, meaning that they can quickly adapt to changing circumstances.

This proposed system considers three attributes: oxygen saturation percentage, body temperature, and pulse rate, as inputs and generates risk levels associated with the COVID19 patient as an output. To generate a more accurate risk level, the Mamdani fuzzy inference system has been followed here. Inference implies obtaining a specific judgement based on certain data related to a logical concept.

Oxygen saturation percentage: When a particle of haemoglobin carries four oxygen particles, it is said to be (Myatt, 2017) saturated with oxygen. The maximum saturation of a haemoglobin molecule is 100%. Therefore, a healthy person with normal lungs should have an oxygen saturation of 95% to 100% (saturated oxygen level refers to the range of 95%–100%). If the blood oxygen is between 90% and 95%, the person is hypoxic and should be adequately treated immediately (moderate oxygen, 90%–95%). A saturation level of less than 90% is considered a medical emergency (low oxygen, < 90%).

The verbal phrases (Chakraborty, Banik, Mondal, & Alam, 2020) of oxygen saturation attribute are low oxygen (O_L), moderate oxygen (O_M), and saturate oxygen (O_S). According to our verbal phrase setting the best fitted uncertain number is a triangular fuzzy number as it can handle three different membership values of a real problem. The membership function of (O_L) is represented by $\mu_{O_L}(x)$ in Eq. (1), where three cases are presented. If oxygen saturation < 90 then degree of membership function is 1, which will be calculated from first case of Eq. (1). If oxygen saturation is ≥ 90 and < 92.5 then degree of membership function will be calculated from the second case of Eq. (1). For any other values of oxygen saturation, the degree of the membership function is zero, which is calculated from the third case of Eq. (1). The visualization of membership function is given in Fig. 3.

$$\mu_{O_L}(x) = \begin{cases} 1, & \text{if } x < 90. \\ \frac{92.5-x}{92.5-90}, & \text{if } 90 \geq x < 92.5. \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

The membership function of (O_M) is represented by $\mu_{O_M}(x)$ in Eq. (2), where three cases are presented. If oxygen saturation > 90 and ≤ 92.5 then degree of membership function will be calculated from the first case of Eq. (2). If oxygen saturation > 92.5 and < 95 then degree of membership function will be calculated from the second case of Eq. (2). For any other values of oxygen saturation, the degree of membership function is zero, which is calculated from the third case of Eq. (2). The visualization of membership function is given in Fig. 4

$$\mu_{O_M}(x) = \begin{cases} \frac{x-90}{92.5-90}, & \text{if } 90 < x \leq 92.5. \\ \frac{95-x}{95-92.5}, & \text{if } 92.5 < x < 95. \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

The membership function of (O_S) is represented by $\mu_{O_S}(x)$ in Eq. (3), where three cases are presented. If oxygen saturation > 95 then the degree of membership function will be 1, from the first case of Eq. (3). If oxygen saturation is > 92.5 and ≤ 95 then the degree of membership function will be calculated from the second case of Eq. (3). For any other values of oxygen saturation, the degree of membership function is zero, which is calculated from the third case of Eq. (3). The visualization of membership function is given in Fig. 5.

$$\mu_{O_S}(x) = \begin{cases} 1, & \text{if } x > 95. \\ \frac{x-92.5}{95-92.5}, & \text{if } 92.5 < x \leq 95. \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Body temperature: The relationship (Drewry, Hotchkiss, & Kulstad, 2020) between body temperature and COVID19 fatality is evident, and exhibits a strong trend. Given the significant degree of fatality seen in individuals with high temperatures, it is critical to look at all options to find the best temperature control measures. In proposed system, the range of body temperature is divided into three sub-ranges i.e; risk temperature (20°–34°C and 42°–45 °C), moderate temperature (34°–36 °C and 38°–42 °C) and normal temperature (36°–38 °C). All temperatures are in degrees centigrade.

The verbal phrases of body temperature attribute are risk body temperature (T_R), moderate body temperature (T_M), normal body temperature (T_N). According to our verbal phrase setting the best fitted uncertain number is a triangular fuzzy number as it can handle three different membership values and an uncertain number is an asymmetric

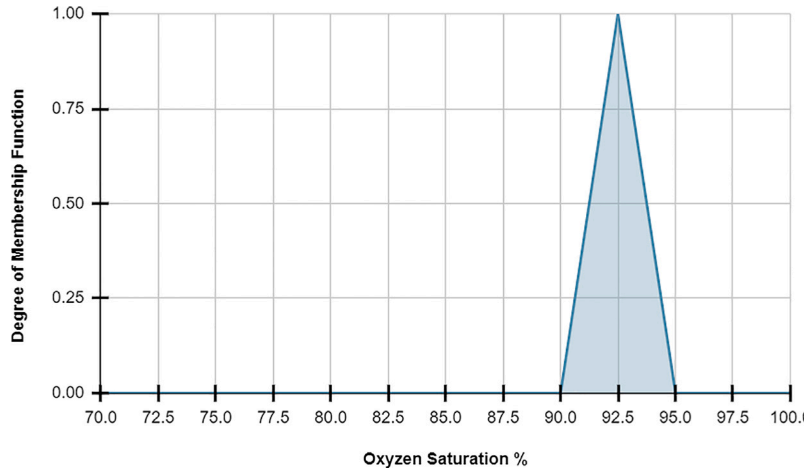


Fig. 4. Membership Function of O_M.

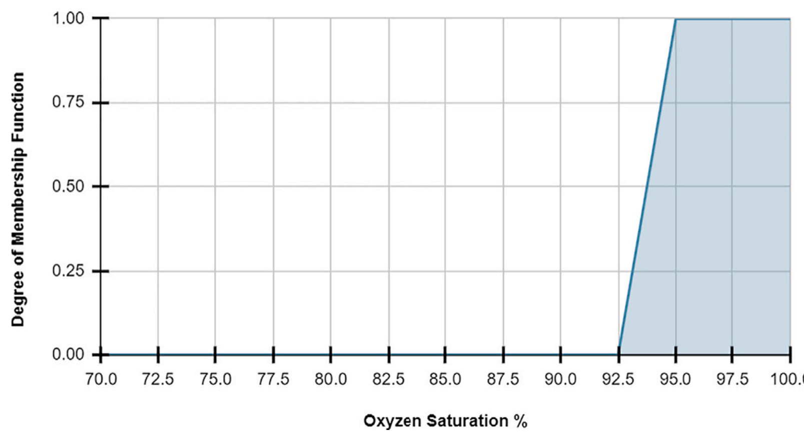


Fig. 5. Membership Function of O_S.

trapezoidal fuzzy number as it can handle four different membership values of a real problem. The membership function is represented by $\mu_{T_R}(x)$, which is shown in Eq. (4). There are four cases in this membership equation. If body temperature $\leq$ 34 and $\geq$ 41, then the degree of membership would be 1. If body temperature is between 34 and 35, the second case of Eq. (4) would calculate the degree of membership. If the body temperature is between 39.5 and 41, then the degree of membership value would be calculated from the third case of Eq. (4). The degree of membership in other values of body temperature will be calculated as zero from the $\mu_{T_R}(x)$ membership function. The visualization of the membership function is given in Fig. 6.

$$\mu_{T_R}(x) = \begin{cases} 1, & \text{if } x \leq 34 \text{ and } x \geq 41 \\ \frac{35-x}{35-34}, & \text{if } 34 < x < 35 \\ \frac{x-39.5}{41-39.5}, & \text{if } 39.5 < x < 41 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The membership function for the moderate body temperature (T_M) is represented by $\mu_{T_M}(x)$, which is shown in Eq. (5). Here, the degree of membership function will be calculated from five cases of Eq. (5). If body temperature > 34 and $\leq$ 35, then the first case of Eq. (5) would calculate the degree of membership. If body temperature > 35 and $\leq$ 36, then the second case of Eq. (5) would calculate the degree of membership. If body temperature > 38 and $\leq$ 39.5, then the third case of Eq. (5) would calculate the degree of membership. If body temperature > 39.5 and $\leq$ 41, then the fourth case of Eq. (5) would calculate the degree of membership. For any other values of body temperature, then the fifth case of Eq. (5) would calculate 0 as the degree of membership. The visualization of membership function is given in Fig. 7.

$$\mu_{T_M}(x) = \begin{cases} \frac{35-x}{35-34}, & \text{if } 34 < x \leq 35 \\ \frac{x-35}{36-35}, & \text{if } 35 < x \leq 36 \\ \frac{39.5-x}{39.5-38}, & \text{if } 38 < x \leq 39.5 \\ \frac{x-39.5}{41-39.5}, & \text{if } 39.5 < x \leq 41 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The membership function for normal body temperature is represented by $\mu_{T_N}(x)$, which is shown in Eq. (6). If body temperature $\geq$ 36 and < 38 then degree of membership function will be calculated as 1 from the first case of Eq. (6). If body temperature $\geq$ 35 and < 36 then degree of membership function will be calculated from the second case of Eq. (6). If body temperature $\geq$ 38 and < 39.5 then degree of membership function will be calculated as 1 from the third case of Eq. (6). For other values of body temperature the degree of membership function will be calculated from the fourth case of Eq. (6). The visualization of membership function is given in Fig. 8.

$$\mu_{T_N}(x) = \begin{cases} 1, & \text{if } 36 \leq x < 38 \\ \frac{x-35}{36-35}, & \text{if } 35 \leq x < 36 \\ \frac{39.5-x}{39.5-38}, & \text{if } 38 \leq x < 39.5 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Pulse rate: Heart disease is the leading cause of mortality worldwide. It (Diller et al., 2021) also increases the risk of mortality among

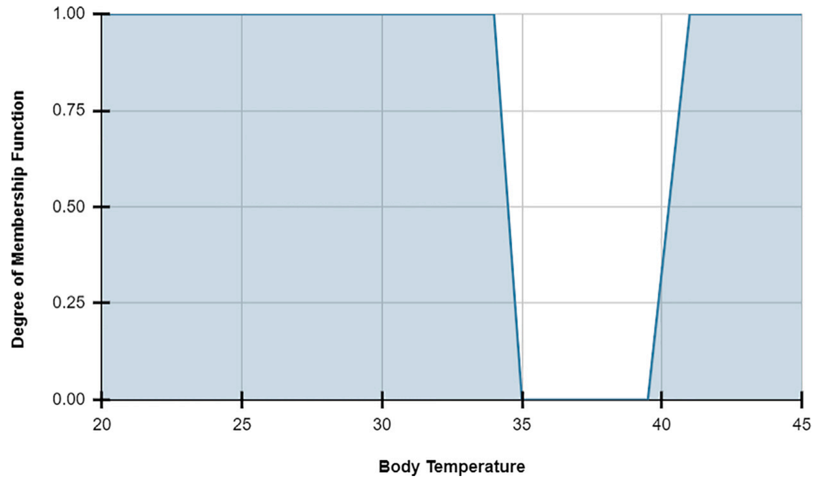


Fig. 6. Membership Function of T_R.

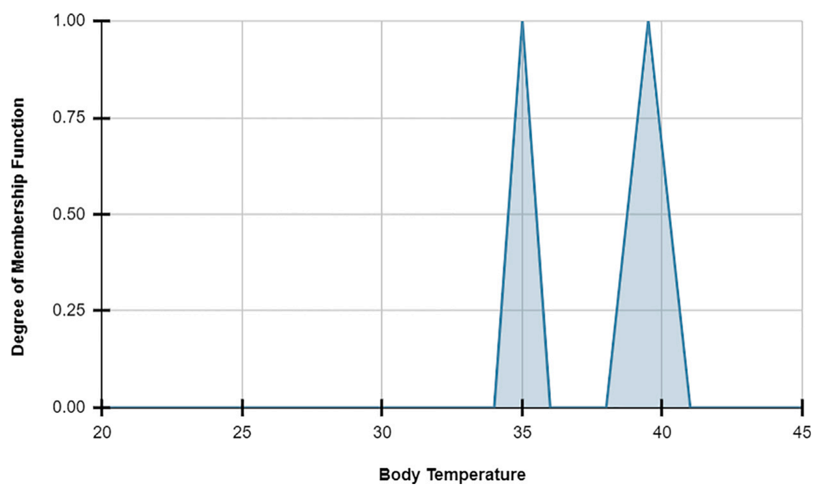


Fig. 7. Membership Function of T_M.

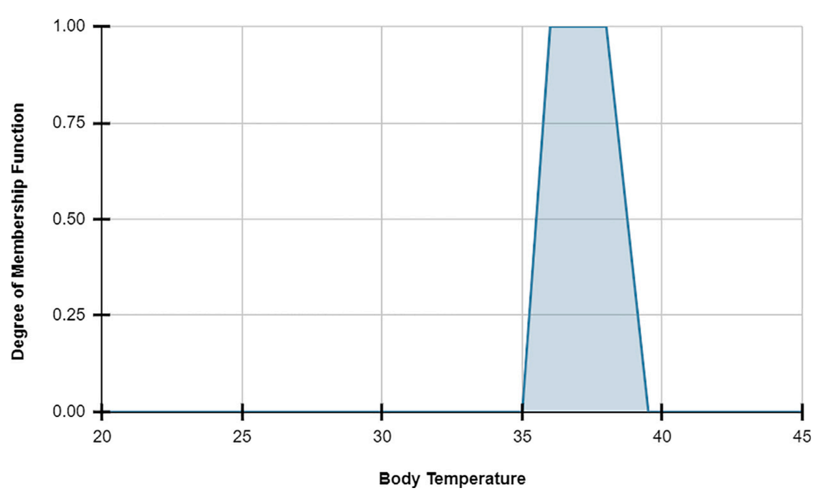


Fig. 8. Membership Function of T_N.

those affected with COVID19. Therefore, pulse rate is also an important factor for COVID19 patients. As per WHO guidelines, Feinmann (2021) total pulse rate range is 30–240 bpm. In this proposed system, the range of pulse rate is divided into three sub-ranges, risk pulse rate (30–50, 140–200 bpm) moderate pulse rate (50–70, 100–140 bpm) and normal pulse rate (70–100 bpm). Here it has been considered the minimum and maximum pulse rate to be between 30 bpm and 200 bpm respectively.

The verbal phrases for different pulse rate levels are risk pulse rate (R_R), moderate pulse rate (R_M) and normal pulse rate (R_N). According to verbal phrase setting, the best fitted uncertain number is a triangular

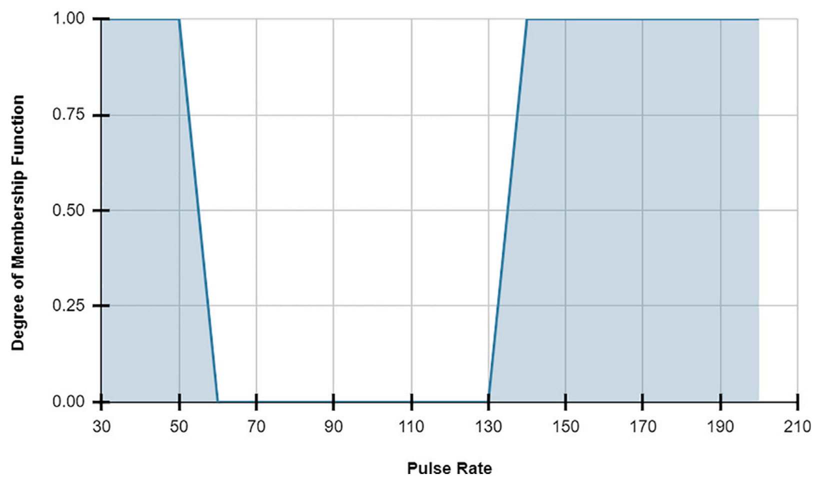


Fig. 9. Membership Function of R_R.

fuzzy number as it can handle three different membership values and a trapezoidal fuzzy number for four different membership values of a real problem.

The membership function is represented by $\mu_{R_R}(x)$, which is shown in Eq. (7). There are four cases in this membership equation. If the pulse rate $\leq$ 50 and $\geq$ 140, then the degree of membership would be 1. If the pulse rate > 50 and < 60 then $\mu_{R_R}(x)$ will be calculated from the second case of Eq. (7). If the pulse rate > 130 and < 140 then degree of membership value would be calculated from the third case of Eq. (7). In all other cases, the degree of membership pulse rate will be calculated as zero from the $\mu_{R_R}(x)$ membership function. The visualization of membership function is given in Fig. 9.

$$\mu_{R_R}(x) = \begin{cases} 1, & \text{if } x \leq 50 \text{ and } x \geq 140 \\ \frac{60-x}{60-50}, & \text{if } 50 < x < 60 \\ \frac{x-130}{140-130}, & \text{if } 130 < x < 140 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The membership function for R_M is represented by $\mu_{R_M}(x)$ shown in Eq. (8). There are six cases in Eq. (8). If pulse rate > 50 and $\leq$ 60 then degree of membership function will be calculated from the first case of Eq. (8). If pulse rate > 60 and < 70 then degree of membership function will be calculated from the second case of Eq. (8). If pulse rate > 100 and $\leq$ 110 then degree of membership function will be calculated from the third case of Eq. (8). If pulse rate > 110 and $\leq$ 130 then degree of membership function will be 1 from the fourth case of Eq. (8). If pulse rate > 130 and < 140 then degree of membership function will be calculated from the fifth case of Eq. (8). From the sixth case of Eq. (8), the degree of membership function will 0 for all other values of pulse rate. The visualization of membership function is given in Fig. 10.

$$\mu_{R_M}(x) = \begin{cases} \frac{x-50}{60-50}, & \text{if } 50 < x \leq 60 \\ \frac{70-x}{70-60}, & \text{if } 60 < x \leq 70 \\ \frac{x-100}{110-100}, & \text{if } 100 < x \leq 110. \\ 1, & \text{if } 110 < x \leq 130. \\ \frac{x-130}{140-130}, & \text{if } 130 < x < 140 \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

The membership function for R_N as represented by $\mu_{R_N}(x)$ is calculated by Eq. (9) and graphically presented in Fig. 11. This membership function has four cases. If pulse rate > 60 and $\leq$ 70 then degree of membership function will be calculated from the first case of Eq. (9). If pulse rate > 70 and $\leq$ 100 then degree of membership function will be 1 from the second case of Eq. (9). If pulse rate > 100 and $\leq$ 110 then degree of membership function will be calculated from the third case of Eq. (9). From the fourth case of Eq. (9), the degree of membership function will 0 for all other values of pulse rate.

$$\mu_{R_N}(x) = \begin{cases} \frac{x-60}{70-60}, & \text{if } 60 < x \leq 70 \\ 1, & \text{if } 70 < x \leq 100 \\ \frac{x-100}{110-100}, & \text{if } 100 < x \leq 110 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

Fig. 12 represents the graphical visualization of the membership function for risk. In the diagram, the X-axis denotes the risk value of the patient, and the Y-axis denotes the degree of membership between 0 and 1. Risk can present in three different levels: High (0–10), Moderate (10–20), and Low (20–30). The database of the fuzzy logic controller are given in Table 1.

Table 1
Database of the fuzzy logic controller.

Symbols	Types of uncertain parameter	Descriptions
O	–	Oxygen saturation
T	–	Body temperature
R	–	Pulse rate
O_L	Triangular fuzzy number	Low oxygen
O_M	Triangular fuzzy number	Moderate oxygen
O_S	Triangular fuzzy number	Saturated oxygen
T_N	Trapezoidal fuzzy number	Normal body temperature
T_M	Triangular fuzzy number	Moderate body temperature
T_R	Triangular fuzzy number	Risk body temperature
R_M	Triangular and Trapezoidal fuzzy number	Moderate pulse rate
R_R	Triangular fuzzy number	Risk pulse rate
R_N	Trapezoidal fuzzy number	Normal pulse rate

Then, after figuring out the degree of membership function for a given set of crisp values, the fuzzy inference rules help to find out the type(s) of membership function of risk and turn them active. Fuzzy inference rules are a set of language statements that specify how the fuzzy inference system (FIS) should make a judgement on whether to categorize an input or control output. In this proposed system, at any instance time values of three attributes will be taken from the patients – O for oxygen saturation, R for pulse rate, and T for body temperature. Since each attribute has three different verbal phrases, a total of $3 \times 3 \times 3 = 27$ rules have been developed for this system. These 27 fuzzy rules are given in Table 2.

For each fuzzy rule, the strength of the rules that were fired and their associated membership in the output were calculated. The final crisp value of risk was computed using the Mamdani fuzzy inference technique. All the fuzzy output functions were aggregated on the same axis to get the final crisp value of risk, which is given in Fig. 14 for three different sample inputs.

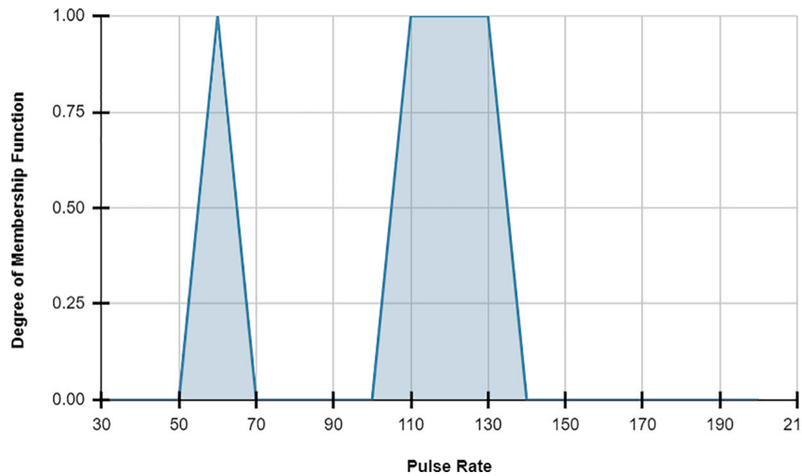


Fig. 10. Membership Function of R_M.

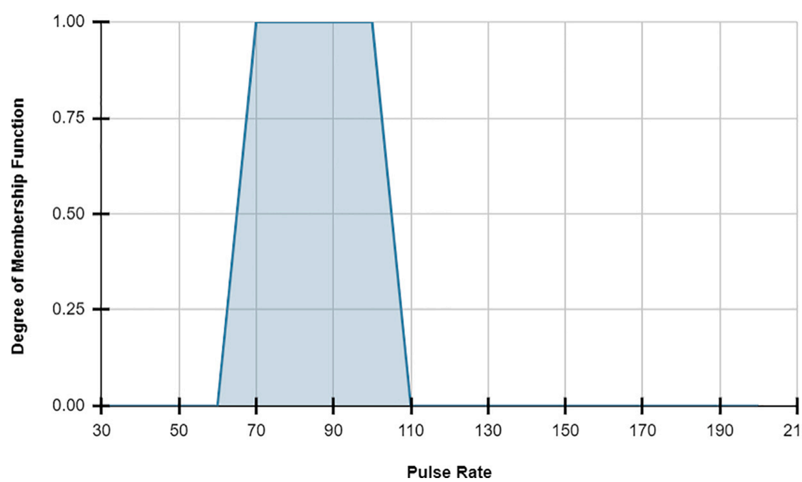


Fig. 11. Membership Function of R_N.

Table 2
Rule set for the proposed fuzzy model.

No.	Rules
RULE 1 :	IF O IS O_L AND T IS T_N AND R IS R_N THEN risk IS high;
RULE 2 :	IF O IS O_L AND T IS T_M AND R IS R_N THEN risk IS high;
RULE 3 :	IF O IS O_L AND T IS T_R AND R IS R_N THEN risk IS high;
RULE 4 :	IF O IS O_L AND T IS T_N AND R IS R_M THEN risk IS high;
RULE 5 :	IF O IS O_L AND T IS T_M AND R IS R_M THEN risk IS high;
RULE 6 :	IF O IS O_L AND T IS T_R AND R IS R_M THEN risk IS high;
RULE 7 :	IF O IS O_L AND T IS T_N AND R IS R_R THEN risk IS high;
RULE 8 :	IF O IS O_L AND T IS T_M AND R IS R_R THEN risk IS high;
RULE 9 :	IF O IS O_L AND T IS T_R AND R IS R_R THEN risk IS high;
RULE 10 :	IF O IS O_M AND T IS T_N AND R IS R_N THEN risk IS moderate;
RULE 11 :	IF O IS O_M AND T IS T_M AND R IS R_N THEN risk IS moderate;
RULE 12 :	IF O IS O_M AND T IS T_R AND R IS R_N THEN risk IS high;
RULE 13 :	IF O IS O_M AND T IS T_N AND R IS R_M THEN risk IS moderate;
RULE 14 :	IF O IS O_M AND T IS T_M AND R IS R_M THEN risk IS high;
RULE 15 :	IF O IS O_M AND T IS T_R AND R IS R_M THEN risk IS high;
RULE 16 :	IF O IS O_M AND T IS T_N AND R IS R_R THEN risk IS high;
RULE 17 :	IF O IS O_M AND T IS T_M AND R IS R_R THEN risk IS high;
RULE 18 :	IF O IS O_M AND T IS T_R AND R IS R_R THEN risk IS high;
RULE 19 :	IF O IS O_S AND T IS T_N AND R IS R_N THEN risk IS low;
RULE 20 :	IF O IS O_S AND T IS T_M AND R IS R_N THEN risk IS low;
RULE 21 :	IF O IS O_S AND T IS T_R AND R IS R_N THEN risk IS moderate;
RULE 22 :	IF O IS O_S AND T IS T_N AND R IS R_M THEN risk IS low;
RULE 23 :	IF O IS O_S AND T IS T_M AND R IS R_M THEN risk IS moderate;
RULE 24 :	IF O IS O_S AND T IS T_R AND R IS R_M THEN risk IS high;
RULE 25 :	IF O IS O_S AND T IS T_N AND R IS R_R THEN risk IS moderate;
RULE 26 :	IF O IS O_S AND T IS T_M AND R IS R_R THEN risk IS high;
RULE 27 :	IF O IS O_S AND T IS T_R AND R IS R_R THEN risk IS high;

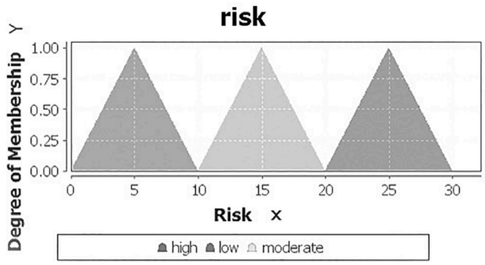


Fig. 12. Membership Function of Risk.

In the proposed system to defuzzify the 'risk level' of a person, the identified three outputs are 'low', 'moderate', and 'high', where the default value is '0' for no rule activation. The risk level is quantified using a discrete membership function, and the defuzzified value x^* is stated as follows.

$$x^* = \sum_{i=1}^{n} x_i \cdot \mu\left(x_i\right) / \sum_{i=1}^{n} \mu\left(x_i\right), \tag{10}$$

where n is the number of elements and $\mu(x_i)$ is the membership function.

3.2.3. Illustrative example

Let us consider a patient whose parameters are $O = 93$, $T = 42$, and $R = 84$. The input value $O = 93$ is a member of two fuzzy sets called O_M and O_S, whereas $T = 42$ is a member of T_R. The third variable $R = 84$ is a member of the R_N. As per the rule table, Rule no. 12 and Rule no. 21 are found to be applicable to this condition and these rules are fired. The corresponding membership function for each fuzzy rule has been aggregated as per the Mamdani fuzzy inference method. This aggregated fuzzy output function on the same axis has been displayed in Fig. 14(a). Then from the aggregated fuzzy output function defuzzification is carried out using the center of gravity (COG) method to get a risk value of 7.73. To double-check the defuzzification methods, the Center of Sums method is also applied to get a risk value of 7.80. It is observed that the risk values from both the defuzzification methods are similar.

3.2.4. Alert system

If the fuzzy system indicates a high risk for a patient, the edge devices send text alerts to the designated persons. The designated persons can be the patient's relatives, doctors, or medical staff already registered in the system.

3.3. Data accumulation at cloud and secure data access mechanism

The data collected at edge devices are forwarded to a cloud data server. Those data can be fetched using a specific mobile app for monitoring purposes. The proposed mobile app considers two different scenarios when the data stored in the cloud needs to be accessed: (1) *continuous monitoring* by the patient's relatives or the medical staff, and (2) on-demand monitoring as well as retrieval of patient's historical data (which may be from the last few hours) by the doctor for clinical diagnosis, once he/she is alerted by the system about the high risk status of the patient. Since the collected medical data are highly sensitive, a secure approval-based data access system is designed to develop a threshold access structure for data usage.

The mobile app COVI-MONI (which has been designed for health data monitoring in the proposed framework and will be discussed in the next section) installed on the users' mobile phones can be used to monitor a patient's health information and risk status. Since the health information and risk status derived from the data analysis are considered sensitive, delivering the message in a plain-text format is not safe. However, the traditional encryption processes are computationally expensive and unsuitable for resource-constrained devices like mobile phones. Thus, here we apply the secret sharing technique to deliver the secret message among a group of participants. Someone within the group accesses the message with approval from a number of participants which meets or exceeds a particular threshold of participants. For the proposed applications, the doctors, clinicians, patients' relatives, etc., belong to the group of the participants. Each of them has to carry out a specific procedure to register to the group (each group is associated with a patient). The (t, n) multi-secret sharing scheme by Yang, Chang, and Hwang (2004) uses for sharing the secret message, where a cloud app server (acting as the dealer or distributor) encodes the secret message into n pieces called shares so that with any t or more shares one can compute the secret message. However, the same is not possible with $t - 1$ or fewer shares. The method of secure access to the message through the mobile app COVI-MONI is discussed in the following section.

3.4. Monitoring system

COVI-MONI has been presented to provide secure access to sensitive medical data for health data monitoring purposes. It shows the five most recent values of the parameters collected by the sensors, along with the risk status of the patients. More details of the output are discussed in Section 4. The app can also retrieve all the records pertaining to a patient for a certain time period, allowing doctors to perform clinical diagnosis.

3.4.1. Approval-based access to health information

The steps for secure access to the medical data and the risk status are presented as follows.

Step 1: Each record to be fetched by the mobile app is first converted into a collection of integers, which are known as secrets. An example is presented in Section 4.1.

Step 2: The mobile app server applies the multi-secret sharing scheme proposed by Yang et al. (2004) to encode the secrets into n public shares, and publishes them in the cloud in some authenticated manner. It also privately transfers a secret shadow (similar to a secret key) to each participant belonging to the group of participants associated with a patient. The participants can reuse the same secret shadows during multiple secret sharing processes, which also ensures the participants do not need to ask for approval each time they use the mobile app.

Step 3: The participant seeking the secret message through the mobile app sends a message to request approval from all other $n - 1$ participants.

Step 4: All other $n - 1$ participants receive the approval request through the mobile app. If any $t - 1$ or more participants (out of the $n - 1$) approve the request, the secrets can be reconstructed.

Step 5: The secrets, which are the integer numbers, are assembled to recreate the secret record. However, if fewer than $t - 1$ participants send the "Approval", the secret record cannot be recovered.

4. Experiment and results

The following have been considered for the implementation of the proposed model.

- LM35 temperature sensors to measure body temperature and MAX30102 heart rate sensors to measure pulse rate and oxygen saturation percentage.
- All the sensors are registered to the framework to ensure that no intruder enters the system.
- Sensors are connected to an Arduino Uno board, which transfers the collected data to the edge device implemented using Raspberry Pi.

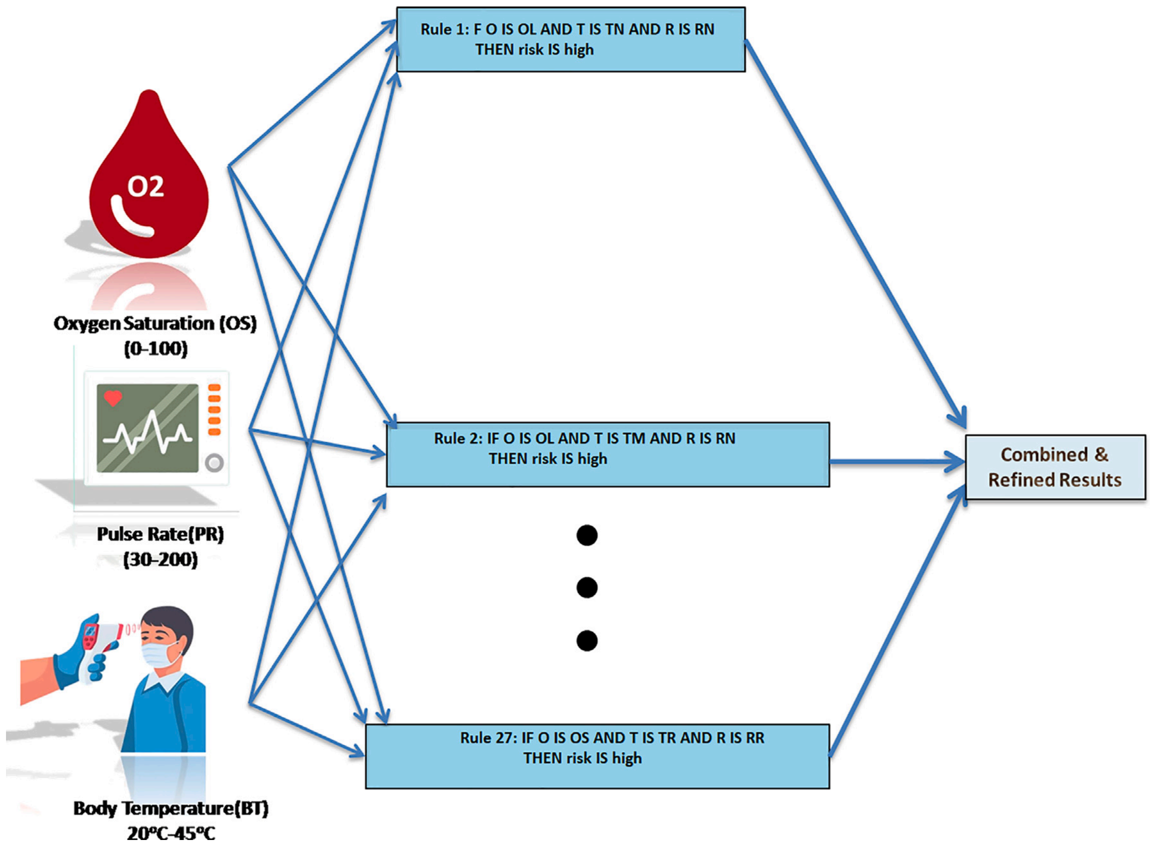


Fig. 13. Fuzzy Evaluation System of Proposed Model.

- The collected data are stored with the Raspberry Pi in CSV format.
- The fuzzy system is implemented in the edge devices using Java programming.
- Data gets accumulated on a cloud server in CSV format.
- The COVI-MONI app needs to be authenticated (the authentication mechanism assumed to be provided by the CSP) itself to access the medical data stored in the cloud server.
- An approval-based security mechanism has been designed and implemented to ensure data access security.
- All participants such as doctors, relatives, and medical staff associated with a patient need to register for the system, and they form a group of participants for a patient.

Fig. 15 presents the screenshots of the mobile app in all three different cases. In this proposed system, after defuzzification, if the crisp value of the risk factor lies in the 0–10 range, the patient's risk level is identified as 'high' (Fig. 15(a)), if the crisp value of the risk factor lies in the 10–20 range the patient's risk is identified as 'moderate' (Fig. 15(b)), and if the crisp value of the risk factor lies in the 20–30 range the patient's risk is identified as 'low' (Fig. 15(c)). The corresponding output membership function is shown in Fig. 14(a), Figs. 14(b) and 14(c) respectively.

Figs. 14(a)–14(c) denote graphical visualization of the membership function of three different risk values: 7.73 means high risk, 12.27 means moderate risk, and 25.00 means low risk, obtained from the risk membership function.

Fig. 14(a) depicts an example case where the risk value was calculated to be 7.73 which is 'High Risk' when the input value was Oxygen saturation (O) = 93, Body temperature (T) = 42, and Pulse rate (R) = 84. In Fig. 14(b) another case is presented where the risk value was calculated to be 12.27 which is 'Moderate Risk' when the input value was Oxygen saturation (O) = 92, Body temperature (T) = 36, and Pulse rate (R) = 71. One more example is shown in Fig. 14(c) where the risk value was found to be 25.00 which is 'Low Risk' when the input value was Oxygen saturation (O) = 97, Body temperature (T) = 35, and Pulse rate (R) = 98.

In cases of high risk, the application sends a text alert to the designated persons, a snapshot of which is shown in Fig. 16.

4.1. Results of secure data access implementation

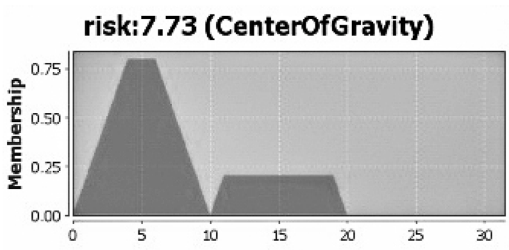
We considered a typical example of $(3, 5)$, i.e., 3-out-of −5 scenario, where the participant group related to patients has size five participants, and anyone from the group who wants to access the patient's health information from the cloud requires approval from at least two other participants. Table 3 presents the results of a secure data access mechanism implemented to access health data from the cloud. The parameters for Table 3 are as follows:

- **Record** represents a row from the CSV file (in the cloud) with the following information:
  - **Case ID** is mapped to the **Patient Id** which represents each patient to be monitored.
  - **Date** and **Time** when the sensor data are recorded.
  - **Temperature**, **Heart Rate** and **Oxygen** store the corresponding values collected from the sensors.

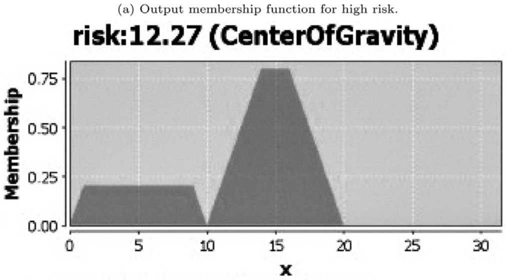
  The **records** are kept as private information in the cloud. The **records** are encoded (using the secret sharing algorithm (Yang et al., 2004)) before they are published and can be accessed by the members.
- The **records** are first converted into *secrets*, which are integers to be encoded.
- **Public Values** are the encoded versions of the secrets using the secret sharing algorithm (Yang et al., 2004). These are published to be accessed by the members.

Table 3
Results of security results - sample **record**, **record** is converted into **secrets**, **secrets** encoded into **public values**.

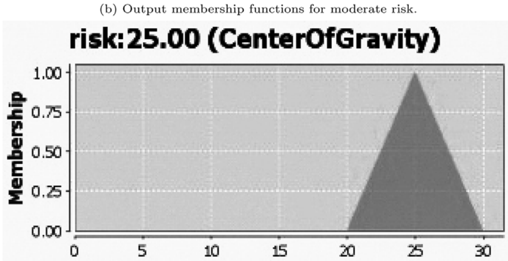
	Case ID	Date			Time		Temperature	Heart rate	Oxygen
Record	1013	2021-05-30			16:30		42	86	93
Secrets	1013	2021	5	30	16	30	42	86	93
Public values	{335, 1052, 298, 182, 416, 914, 2804, 1586, 336, 851, 843}								



(a) Output membership function for high risk.



(b) Output membership functions for moderate risk.



(c) Output membership functions for low risk.

Fig. 14. Output membership function for three sample cases.

Let the secret shadows privately held by the members be — 168, 170, 172, 180, 190. In the specific case of the 3-out-of −5 scenario, the member who wants to access the health information of his/her patient (corresponding to a given *Case ID*) sends an approval request to the other four members from the same group using the COVI-MONI app. Any two (the member and at least two other) members sending approval enables the requesting member to access the health information for his/her patient using COVI-MONI.

The approval system implemented based on the multi-secret sharing scheme by Yang et al. (2004) ensures the following security aspects:

- **Confidentiality:** In a t-out-of-n scenario, the member seeking the data access requires approval from at least $t-1$ other members (total t including himself/hrself), and this is implemented using the (t,n)-threshold structure along with specified (Yang et al., 2004) secret sharing scheme. Since the sharing scheme by Yang et al. (2004) is a perfect secret sharing scheme, it ensures that without having approval from $t-1$ other members, it is impossible to access the data from the cloud.
- **Robustness:** In the t-out-of-n scenario, the member seeking the data access can do so if he/she gets approval from at least $t-1$ other members in the same group. Since the secret sharing algorithm (Yang et al., 2004) used in this implementation is based on Lagrange interpolation polynomial which, ensures a $(t-1)^{\text{th}}$ degree polynomial $f(x)$ can be uniquely reconstructed with t or more values of $f(x)$, our approval mechanism guarantees data access facility to the seeker with approval from $t-1$ other members of the group (plus his/her own).
- **Multi-use-ness:** During the approval process, the approving member transmits his/her pseudo shares to the member seeking the approval. The pseudo shares (Yang et al., 2004) are computed from secret shadows and a public value using a one-way two-variable function. Therefore, an attack scenario to be considered is that the member who gets approval may attempt to disclose the actual secret shadows of the members who provided the approval (the actual owner of the secret shadows) and reuse those secret shadows or transmit them to others without the knowledge or permission of the owners. However, this attack is infeasible due to the one-way-ness of the function that generates the pseudo shares from the secret shadows. Thus, the members can reuse the same secret shadows during several sharing processes.

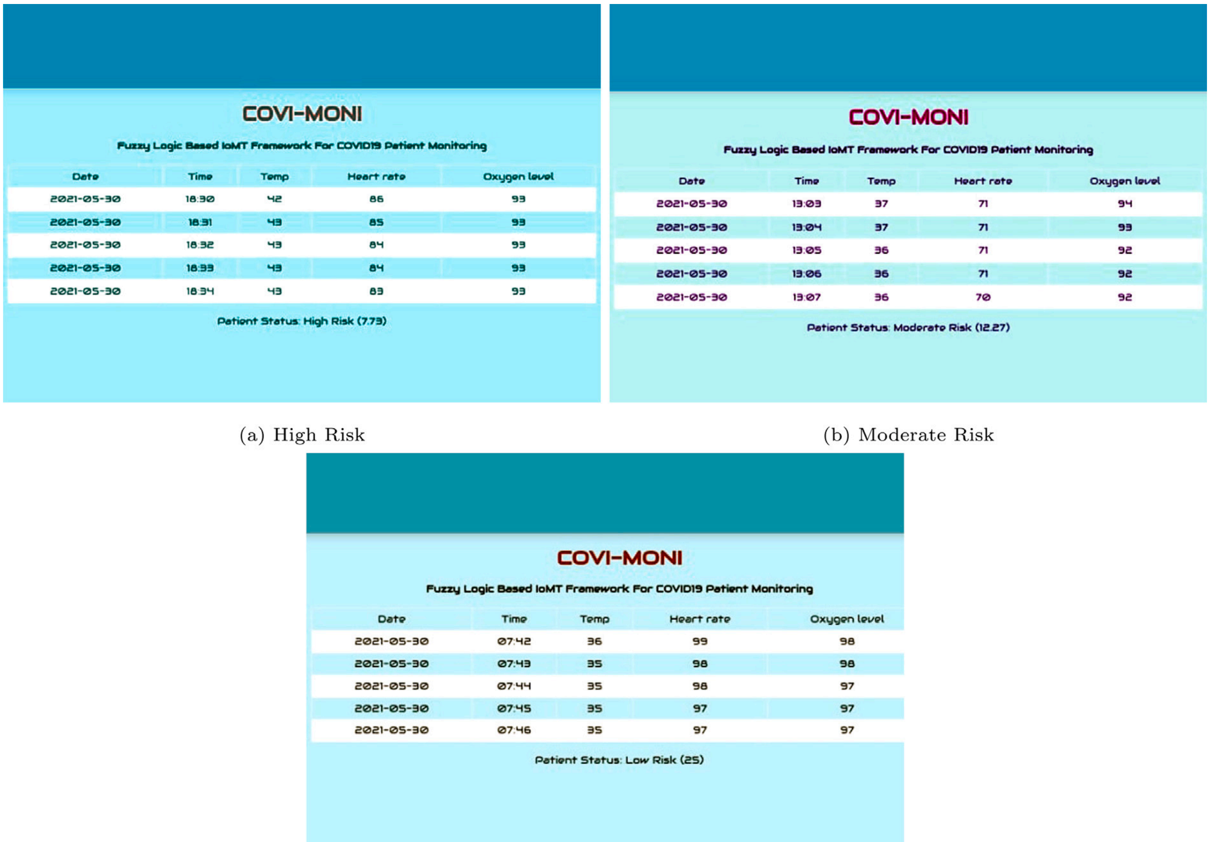
Many researchers presented several schemes and/or frameworks for early detection of COVID19 symptoms, tracking the movement of COVID19-infected people, remotely monitoring the COVID19 patients, and so on. A comparative study has been presented in Table 4. It compares the proposed framework with some recently proposed similar frameworks such as Gozes et al. (2020), Bai et al. (2020), Vaishya et al. (2020), Rajees. Kumar et al. (2022) with respect to the following parameters : main objectives, technology used, and availability of monitoring and/or diagnosis.

The schemes presented in Gozes et al. (2020), Bai et al. (2020), Vaishya et al. (2020) used AI technologies. Rajees. Kumar et al. (2022) used IoT to detect and monitoring the asymptotic COVID19 patients. The main objective of the proposed scheme is to monitor the COVID19 patients in real time. For real time COVID19 patient monitoring, the proposed system has integrated IoT and fuzzy logic with a mobile app. As a result, the proposed system can efficiently and effectively monitor COVID19 patients in real time.

5. Discussion

Since the most effective way to control infectious diseases like COVID19 is to reduce the transmission of the virus as much as possible, remote and real time monitoring of the patients is very important. Remote and real time monitoring of the health data of the patients can be effective to safeguard the doctors and medical staff who are the critical workers in the fight against COVID19 and efficiently reduce the crunch of resources like medical PPE kits. An IoT system comprises sensors mounted on the patients' bodies to enable continuous health data monitoring.

The data from sensors are collected at the edge devices, and then further analyzed using a fuzzy-based system at the edge layer, which identifies risks associated with a particular patient in real time, and alerts the doctors and other concerned parties. This paper proposes an IoMT-based framework that can help all stakeholders, such as patients, the relatives of the patients, doctors, and medical staff. This system enables remote and real time monitoring of health parameters related to COVID19 for the target patients, significantly reducing the spread of infection among medical staff and patients' relatives. Therefore, the medical staff can serve more confidently; simultaneously, the pa-



(a) High Risk (b) Moderate Risk

(c) Low Risk

Fig. 15. Application outputs.

Table 4
Comparison between COVID19 monitoring or diagnosis related schemes.

Proposed scheme	Main objective	Technology used	Monitor/ Diagnosis	Remarks
Vaishya et al. (2020)	Early detection of COVID	Artificial Intelligence	Yes	It is a proposed work without implementation
Gozes et al. (2020)	To develop AI-based automated CT image analysis tools for detection of COVID patient	Artificial Intelligence	No	High Accuracy but it is for detection. Patient monitoring is not possible
Rajees. Kumar et al. (2022)	Detection and monitoring of the asymptotic COVID19 patients using IoT devices and sensors	Internet of Things	Yes	Mainly depends on SpO2. In case of emergency, notification alerts are not enable in this system
Google and Apple[a]	To help anyone who may have been in close contact with a person who has contracted COVID19	Android App	No	Notification for COVID19 alert
Bai et al. (2020)	Diagnosis and treatment using nCapp	Deep mining and Intelligent processing	Yes	Authenticity and reliability of the uploaded data depends on the user. Diagnosis performed using Q&A method
Proposed model	Monitor the COVID patients	IoT, Fuzzy Logic and Mobile App	Yes	As per different parameter, it provides accurate information. In case of emergency notification message also sent from this system.

[a]https://www.google.com/covid19/exposurenotifications/

tients can stay at home under continuous surveillance. Moreover, the data collected will be analyzed by the proposed fuzzy system without any human intervention, which continuously generates the conclusive health status of the patients concerning COVID19 on a mobile app (named COVI-MONI). The medical data analysis takes place at the edge. It ensures the sending of a text alert in real time to the registered persons in a high risk situation so that protective measures can be carried out. The COVI-MONI app operates in two modes:

- A participant belonging to a group associated with a patient may want to monitor the health parameters continuously. COVI-MONI fetches and shows five records at a time.
- After receiving an alert from the proposed IoMT system, a doctor may seek to get a patient's information for a specific time period in order to conduct a comprehensive clinical diagnostic. In this case, COVI-MONI fetches all the records collected for the specified duration on demand.

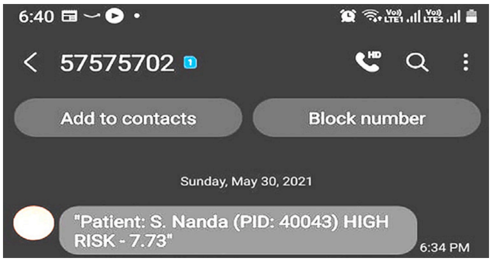


Fig. 16. Screenshot of a sample SMS alert.

Since the health data of the patients are considered very sensitive, protecting data confidentiality is a major concern. Thus, we have designed and developed an approval-based secure data access mechanism using the secret sharing technique, which ensures that the health data are published in an encoded form. A participant (a member of a patient's group) can decode the information after getting approval from enough other participants in the group.

6. Conclusion

The proposed IoMT framework comprises several sensors to collect the health data of COVID19 patients, which are collected and undergo processing in the edge devices. The processes that occur at edge devices to identify the risk status of the target patient are fuzzification of the data, application of fuzzy rule base, and finally, inferencing and defuzzification. If the risk status of the patient is high, the doctors and other concerned parties like medical staff and relatives would be alerted immediately by sending a text alert. Finally, the patient's health data and health status, along with the timestamp, are forwarded and stored on a cloud server. The members associated with the patients often want continuous monitoring of the patient's health data, which can be done using the proposed mobile app, COVI-MONI. Furthermore, after receiving a text alert for a patient, the doctors and medical staff may want to look up the immediate history of the health parameters of the patient and can also access the same from the cloud. Since health data are extremely sensitive, an approval-based data access mechanism has been presented and implemented.

The proposed framework, being a part of a smart healthcare system, may be integrated with other infrastructure elements in a smart city like transport, energy management, etc. Further, the privacy preservation of the health data collected from the patients is a major concern since any unauthorized person getting access to the information regarding COVID19 infected users from the edge or cloud storage poses major privacy issues. Thus, in the future, more security components can be added to ensure the privacy of patients' data. Therefore, the scope of future works are identified as follows:

1. In the proposed IoMT framework, only three parameters are considered. Further, a similar but more robust IoMT framework can be presented with more parameters to achieve better accuracy.
2. An approval-based security system has been applied for accessing and monitoring the medical data stored in the cloud. However, the data in communication between the sensors and edge devices and between the edges and the cloud are not secure. Since medical data are very sensitive, the scheme can be enhanced further to implement some security mechanisms to ensure the privacy of the medical data.

CRediT authorship contribution statement

Subir Panja: Conceptualization, Methodology, Original draft preparation, Visualization, Software, Investigation. **Arup Kumar Chattopadhyay:** Conceptualization, Methodology, Original draft preparation, Visualization, Software, Investigation. **Amitava Nag:** Conceptualization, Visualization, Methodology, Writing – review & editing. **Jyoti Prakash Singh:** Supervision, Software, Investigation, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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