Heliyon 10 (2024) e22454

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

# An IoT-fuzzy intelligent approach for holistic management of COVID-19 patients

Muhammad Zia Ur Rahman [a], Muhammad Azeem Akbar [b], Víctor Leiva [c,*], Carlos Martin-Barreiro [d,e,*], Muhammad Imran [a,f], Muhammad Tanveer Riaz [a], Cecilia Castro [g]

[a] Department of Mechanical, Mechatronics and Manufacturing Engineering, University of Engineering and Technology Lahore, Faisalabad, Pakistan
[b] Department of Software Engineering, LUT University, Lappeenranta, Finland
[c] Escuela de Ingeniería Industrial, Universidad Católica de Valparaíso, Valparaíso, Chile
[d] Facultad de Ciencias Naturales y Matemáticas, ESPOL, Guayaquil, Ecuador
[e] Facultad de Ingeniería, Universidad Espíritu Santo, Samborondón, Ecuador
[f] Department of Mechanical Engineering, Tsinghua University, Beijing, China
[g] Centre of Mathematics, Universidade do Minho, Braga, Portugal

A R T I C L E I N F O

*Keywords:*
Arduino microcontroller
Fuzzy logic
Internet of things
Mobile application
Personalized medicine
SARS-Cov2
Telemetry

A B S T R A C T

In this study, an internet of things (IoT)-enabled fuzzy intelligent system is introduced for the remote monitoring, diagnosis, and prescription of treatment for patients with COVID-19. The main objective of the present study is to develop an integrated tool that combines IoT and fuzzy logic to provide timely healthcare and diagnosis within a smart framework. This system tracks patients' health by utilizing an Arduino microcontroller, a small and affordable computer that reads data from various sensors, to gather data. Once collected, the data are processed, analyzed, and transmitted to a web page for remote access via an IoT-compatible Wi-Fi module. In cases of emergencies, such as abnormal blood pressure, cardiac issues, glucose levels, or temperature, immediate action can be taken to monitor the health of critical COVID-19 patients in isolation. The system employs fuzzy logic to recommend medical treatments for patients. Sudden changes in these medical conditions are remotely reported through a web page to healthcare providers, relatives, or friends. This intelligent system assists healthcare professionals in making informed decisions based on the patient's condition.

## 1. Introduction

The advent of modern technology has greatly enhanced communication worldwide. One of the most revolutionary technological advancements is the Internet of Things (IoT), a network of interconnected devices that can exchange data without the need for human interaction [1]. IoT technology has found applications in various fields, including business, domotics (home automation), education, healthcare, and transportation [2,3]. In the healthcare sector, timely and accurate medical diagnosis and treatment are essential for saving lives. However, daily check-ups in healthcare facilities can be costly and inconvenient for patients [4].

* Corresponding authors.
*E-mail addresses:* victorleivasanchez@gmail.com (V. Leiva), cmmartin@espol.edu.ec (C. Martin-Barreiro).

https://doi.org/10.1016/j.heliyon.2023.e22454
Received 30 May 2023; Received in revised form 13 November 2023; Accepted 13 November 2023

Available online 20 November 2023

In this context, the IoT has emerged as a transformative solution that allows continuous remote monitoring of patients' health. IoT-enabled systems can connect patients with healthcare professionals, permitting the transmission of real-time health data over the internet, and reducing the need for in-person check-ups. This can be particularly beneficial for patients who are located in remote areas where access to healthcare facilities is limited. The IoT has not only enhanced patient care and remote monitoring but it has also presented new challenges and opportunities in fields such as blockchain and data privacy [5,6].

Telemetry and data analytics are critical technologies of IoT-enabled healthcare systems. These technologies facilitate continuous monitoring of patients, which can be invaluable in providing timely medical interventions. In such systems, various sensors can be integrated with microcontrollers to monitor patients' vital signs, and the collected data can be transmitted to healthcare professionals for further analysis. For example, a system equipped with sensors and a microcontroller can monitor heart rate, blood pressure (BP), and temperature, sending these data to a doctor via protocols such as Raspberry Pi with an ESP8266 Wi-Fi module. The medical doctor can then view the results remotely through platforms like LabVIEW [7].

As the IoT continues to advance, its applications in healthcare are becoming increasingly diverse. For instance, when patients enter a hospital, radio-frequency identification sensors can be attached to them to record biomedical data such as BP, temperature, and weight. These data may then be transmitted to doctors via a Zigbee protocol. Doctors can monitor patients' conditions and provide appropriate treatments based on the received data [8]. Other monitoring systems that measure heartbeats, saline levels, and temperature have been developed using sensors interfaced with a PIC16F877A controller. The data collected by these systems can be transmitted to the IoT Gecko webpage, where doctors can access it by entering their username and password [9].

The convergence of IoT technology and fuzzy logic has the potential to revolutionize patient monitoring and healthcare delivery. Fuzzy logic employs linguistic variables to build rules and truths, allowing for more nuanced and probabilistic decision-making compared to traditional binary logic [10–13]. In the medical field, fuzzy logic has been applied to decision-making in intensive care units, patient monitoring during anesthesia, and diagnostic systems for detecting lung cancer [14–16]. Despite the significant advancements in IoT-based health monitoring systems, the existing literature still presents several challenges and limitations. The majority of these systems offer a narrow focus on specific vital signs or lack comprehensive real-time monitoring of multiple health indicators. Additionally, data privacy and security concerns have not been comprehensively addressed, especially in the context of varying noise levels in health data. Moreover, most systems do not provide flexible room control features or global positioning system (GPS) integration, indicating gaps that must be covered.

Motivated by these gaps, the main objective of our study is to design a versatile health monitoring system that combines comprehensive monitoring of vital signs such as heart rate, blood oxygen saturation (SpO2), and electrocardiogram (ECG) with advanced room control features, GPS integration, and robust data privacy measures. In particular, our designed system leverages the novel approach to data differential privacy based on regression models under heteroscedasticity, as introduced in [17], to handle varying levels of noise in data more effectively. By providing a holistic solution for patient monitoring, we aim to enhance patient care, enable timely interventions by healthcare providers, and improve the overall quality of life for patients with chronic conditions. However, despite the advantages of IoT-enabled healthcare systems and the potential of fuzzy logic, there is a gap in the current literature regarding the integration of these technologies for remote health monitoring, diagnosis, and treatment, especially for COVID-19 patients in remote areas [18]. Our research aims to fill this gap by proposing an intelligent health monitoring system that combines IoT technology with fuzzy logic to provide prompt diagnosis and medical treatment. This system can help reduce costs, eliminate human errors, and improve access to healthcare for patients in remote areas.

In summary, in this article, we present a comprehensive IoT-based health monitoring system that incorporates fuzzy logic for intelligent decision-making. Our system is designed to capture data from various sensors related to BP, ECG, and temperature. These data are then transmitted to doctors via an online platform, allowing them to view the information obtained from the data and provide feedback to patients. The proposed system offers a cost-effective and accurate solution for remote health monitoring and diagnosis, especially for COVID-19 patients [19–21]. By harnessing the power of fuzzy logic, our approach aims to account for the inherent uncertainty and vagueness in human health conditions, allowing for more nuanced and adaptable recommendations. Furthermore, our methodology stands out for its potential to be tailored to the specific needs and preferences of individual patients, offering a more holistic approach to healthcare management. Therefore, the novelty of our work lies in the integration of an automated health monitoring system with fuzzy logic-based algorithms to provide personalized health recommendations.

The remainder of the article is organized as follows. Section 2 presents related work on health monitoring systems and the application of fuzzy logic in the medical field. In Section 3, we build the proposed methodology and presents an algorithm that summarizes this methodology. In Section 4, the numerical aspects of the present investigation and their discussion are provided. Lastly, Section 5 states conclusions, limitations of our study, and ideas for further research.

## 2. Related work

Several techniques have been employed to provide continuous monitoring of patients [22–24]. Systems can be designed with various sensors interfaced with microcontrollers to monitor patients. The data generated by this system can be sent to a doctor using a protocol such as Raspberry Pi with an ESP8266 Wi-Fi module. Consequently, the doctor can view the results through LabVIEW [7].

When patients enter the hospital, radio-frequency identification sensors can be attached to them to record biomedical data, such as BP, temperature, and weight. Subsequently, these data can be sent to the doctor through a Zigbee protocol. If the patient is normal, the doctor can record the patient's data using a local server. However, if the patient is unwell, the doctor can prescribe treatments and monitor their condition accordingly [8].

**Table 1**
Functionality comparison of various health monitoring systems in the literature.

| Reference | NET | System | Heart rate | App | ECG | GSM | LCD | Email alert | Room control | GPS |
|---|---|---|---|---|---|---|---|---|---|---|
| Our proposal | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Krishnan, 2018 [28] | ✓ | ✓ | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ |
| Guk, 2019 [29] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ |
| Manas, 2019 [30] | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Misran, 2019 [31] | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Queralta, 2019 [32] | ✓ | ✗ | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Dampage, 2021 [33] | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Khan, 2021 [34] | ✓ | ✓ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Taloba, 2021 [35] | ✗ | ✓ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| Bhardwaj, 2022 [36] | ✓ | ✓ | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |

Other monitoring systems can measure variables such as heartbeats, saline levels, and temperature using sensors. These sensors can be interfaced with a PIC16F877A controller, and the data can be transmitted through ESP8266 to the IoT Gecko webpage. Doctors would need to enter a username and password to access the data [9]. Devices may be designed based on BP, ECG, and temperature sensors that interact with an Arduino microcontroller. Consequently, the data can be sent to a server where both doctor and patient can access the observed data using a digital mobile application (app). Another system may be designed employing a ZigBee technology [25], which is cost-effective and preferred over Bluetooth, as it supports infrared wireless communication [26]. ECG, finger flip, and temperature sensors can be used, and their data sent to a server where a doctor may access it by entering digital credentials. A device based on biomedical sensors related to BP, heart rate, and temperature can be utilized to measure and transmit data through a wireless network [27].

Fuzzy logic uses linguistic variables to build rules and truths by working with probabilities ranging from zero to one, as opposed to a straightforward yes-or-no range [10–13]. Intelligent fuzzy logic finds numerous real-time applications, particularly in the field of medicine. For instance, it is employed in medical decision-making for intensive care units [14], implementing patient monitoring and diagnostic alert systems in the case of a serious occurrence during anesthesia administration [15], and creating diagnostic systems for detecting lung cancer [16].

Existing literature [28,30,31,34,36] showcases several health monitoring systems that utilize IoT-based procedures, as shown in Table 1. Furthermore, other studies [29,32,33,35,37] have expanded IoT-based health monitoring by incorporating remote diagnosis using artificial intelligence (AI). Recent advancements in data privacy approaches have also been explored in the context of health monitoring systems. In [17], a novel approach was introduced to data differential privacy based on regression models under heteroscedasticity, offering a promising solution for handling varying levels of noise in data. In addition, recent studies have employed machine learning and deep learning techniques for the analysis of heart disease [38–40].

Our literature review reveals that several health monitoring systems have been developed. However, these systems often employ either IoT or fuzzy logic, but not both simultaneously. The integration of both technologies could potentially offer improved functionality and more sophisticated health monitoring capabilities. The reviewed health monitoring systems encompass diverse approaches, including IoT, AI, and data privacy techniques. Table 1 summarizes and compares the functionalities of various health monitoring systems from the literature. As technology advances, health monitoring systems are expected to become more sophisticated, with enhanced functionality and security features to better serve patients and healthcare professionals. Table 1 shows a wide range of functionality available in current health monitoring systems. Nevertheless, many of these systems lack certain features, such as real-time data analysis and comprehensive health monitoring, which could be beneficial for both patients and healthcare providers. In the next section, we outline our proposed health monitoring system, designed to address these gaps and offer a more robust solution.

## 3. Methodology, inputs, and outputs

### 3.1. Fuzzy logic

Fuzzy logic offers a valuable approach for dealing with the inherent uncertainties and complexities of health monitoring data. By employing fuzzy sets and their corresponding membership functions, fuzzy logic allows us to express commonly understood information, particularly of a qualitative linguistic nature, in a mathematical framework [10]. Fuzzy logic, unlike crisp and single-valued classical logic, is a non-crisp and multi-valued paraconsistent logic that allows linguistic variables assigning real numerical values between zero and one using probabilities. This assignment permits for the handling of partial truths, where truth values can range from completely true to completely false. The Boolean logic (classical or crisp), however, restricts truth values to either zero or one for variables. Fuzzy logic recognizes that human reasoning often relies on imprecise and non-numerical information. It enables decision-making based on varying degrees of agreement with a premise, which aligns well with the relative nature of our opinions and the complexities of the real world we inhabit.

Fuzzy models or fuzzy sets are mathematical tools used to handle imprecise and ambiguous information, often present in health monitoring data. These models are particularly well-suited for representing, understanding, and capitalizing on uncertain and vague

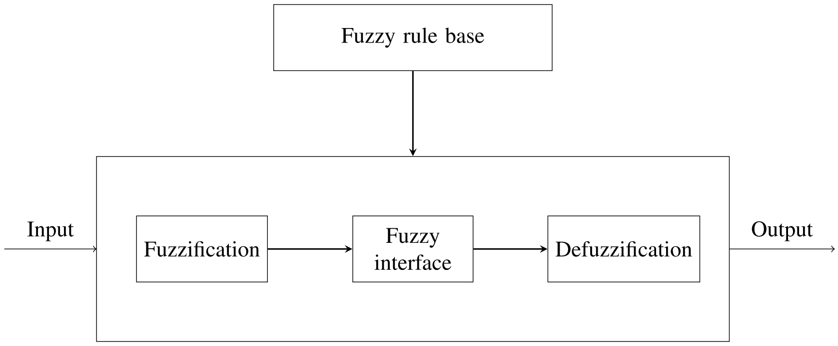


**Fig. 1.** Block diagram representation of the fuzzy logic.

data. Fuzzy set theory involves various operations on fuzzy sets, such as complement, difference, union, negation, and intersection, among others. Each fuzzy set is associated with a membership function that indicates the degree to which an element belongs to that set. These membership functions can take various shapes, including curved, linear, triangular, and trapezoidal [41].

Fuzzy logic relies on heuristic principles, using antecedents (IF) and consequents (THEN), both of which are fuzzy sets, either in their original form or as a result of operations on them. Heuristic norms such as "very much", "drastically", "a bit", and "slightly" can be incorporated into fuzzy logic. The inferential method for such a rule should be adaptable and efficient, often resulting in an area that corresponds to overlapping regions, each representing the outcome of an inference rule. The centroid method, which utilizes the center of gravity of the final overlapping area as the output, is typically employed to select a specific output from multiple premises. Experts may establish the rules for the fuzzy system's inferential engine, and sensors typically collect the input data for the system's input variables.

In our study, we used multiple sensors to gather health data from patients. These sensors were strategically placed to measure variables such as BP, heart rate, and SpO2 accurately. The sensors wirelessly transmitted the collected data to an Arduino microcontroller, which processed the data and fed it into our fuzzy logic approach for further analysis. For example, a patient's heart rate can be represented as a fuzzy set, where the membership function determines the degree to which this rate is considered "normal" or "abnormal". This approach allows for more nuanced assessments of health variables, accommodating the inherent variability in health data.

Fuzzy logic has found applications in various domains, including control theory [15], medicine [15], and AI. Its relevance in medical decision-making is particularly significant. Given the individual nature of healthcare and medical data, fuzzy logic-based approaches have the potential to greatly benefit applications in the health field. The application of a similar approach can be extended to various fields of the medical decision-making system. Nonetheles, an ongoing debate revolves around the extent to which valuable data can be derived through fuzzy logic. A key challenge lies in obtaining the necessary data, especially when it involves eliciting fuzzy data from humans. The process of eliciting fuzzy data and assessing their accuracy is still a work in progress, closely tied to the use of fuzzy logic. Detecting the quality of ambiguous data presents a difficult issue. Despite the promise of fuzzy logic in medical decision-making applications, further research is needed before it can be fully utilized. The employment of fuzzy logic when medical decision-making is intriguing, but fuzzy techniques still face challenges within the medical decision-making framework.

The standard methodology typically follows guiding principles: (i) converting the values of all input linguistic variables into fuzzy membership functions through fuzzification; (ii) applying the appropriate rules from the rule base to calculate the fuzzy output functions; and (iii) deconstructing these output functions to obtain precise output values. For a visual representation, see Fig. 1.

Fuzzification involves the process of transforming numerical inputs from a system into fuzzy sets, which exhibit varying degrees of membership denoted by values within the range between zero and one, denoted as $[0,1]$. A zero value signifies no association with the given fuzzy set, while a one value indicates complete membership in the fuzzy set. Values between zero and one represent the level of uncertainty or ambiguity regarding the correspondence of the value to the set. By linking the system inputx to fuzzy sets, often characterized by linguistic terms, reasoning can be conducted in a linguistically appropriate manner. Fuzzy sets are commonly depicted utilizing triangular curves that feature an ascending slope, reaching a peak at the one value, and then the values go descending. These values can be defined utilizing a logistic function expressed as

$$S(x) = \frac{1}{1 + \exp(-x)}, \tag{1}$$

as outlined in existing methodologies [41], that has the property of symmetry $1 = S(x) + S(-x)$, generated from (1).

Fuzzy logic operates in a similar manner to Boolean logic, but it requires alternative operators to replace the traditional NOT, AND, and OR operators. Additionally, linguistic modifiers known as hedges can be employed. Hedges are typically adverbs such as "extremely" or "somewhat" that modify the meaning of a set employing a mathematical formula. By combining any two of the operators AND, OR, and NOT, a new operator may be created. In cases where an output variable appears in multiple THEN sections, the values from the corresponding IF parts are combined using the OR operator.

Defuzzification involves converting fuzzy truth values into continuous variables. This process would be straightforward if the output truth values aligned perfectly with a specific set of integers obtained during fuzzification. However, since the output truth

**Table 2**
Rules for minimum fuzzy inference with a generalized structure.

| Rule | Input($x$) | Input($y$) | Output($z$) |
|---|---|---|---|
| 1 | if $x =$ low | if $y =$ high | then $z =$ low |
| 2 | if $x =$ low | if $y =$ low | then $z =$ low |
| 3 | if $x =$ high | if $y =$ high | then $z =$ high |
| 4 | if $x =$ high | if $y =$ low | then $z =$ low |

values are independently calculated, they often do not precisely correspond to a defined set of integers. Therefore, it is necessary to select the number that best represents the "intention" conveyed by the truth value. Algorithm 1 provides a standardized explanation of the defuzzification process.

**Algorithm 1** Defuzzification method.

1: Cut the membership function at each truth value.
2: Combine the derived curves by applying the OR logic operator.
3: Calculate the region beneath the curve's center of mass.
4: Decide the final result as a centroid based on the x-position of this center.

Fuzzy logic systems can effectively handle situations where input values are unavailable or unreliable because their output is based on the overall agreement of the inputs and rules [42]. In the rule base, each individual rule can be assigned a weighting factor that determines its influence on the output values. The use of weightings can impose limitations on the influence of a particular rule on the ultimate output. These weightings take into account factors such as the consistency, reliability, or significance of each rule. The weightings may be either static or dynamic, depending on whether they are fixed or adjusted based on the outcomes of other rules. By incorporating the rule weightings, fuzzy logic systems offer flexibility in capturing the importance and reliability of individual rules within the decision-making process.

### 3.2. *Fuzzy intelligent system*

Our fuzzy intelligent medical prescription system evaluates the output in real-time by analyzing the data inputs acquired from a sensor. The proposed system utilizes four input linguistic variables and two fuzzy output variables. This system was implemented using the `MATLAB` software, leveraging the intelligent fuzzy toolbox [43]. In this logic, linguistic variables are employed to define facts and rules, using probabilities within the range [0, 1] instead of a binary yes-or-no approach [10]. Unlike traditional binary systems that operate solely on true (1) or false (0) conditions, fuzzy logic allows for multiple truth values within [0, 1]. The adaptability of intelligent fuzzy systems grants them an edge over traditional binary logic systems. As mentioned earlier, triangular membership functions are extensively employed in real-time fuzzy system applications [41]. The methodology under consideration also embraces triangular membership functions, which can be mathematically expressed as

$$u_A(x) = \begin{cases} \dfrac{x-a}{m-a}, & a < x \leq m; \\ \dfrac{b-x}{b-m}, & m < x < b; \\ 0, & x \leq a \vee x \geq b; \end{cases} \tag{2}$$

where $a$, $m$, and $b$ define minimum, medium, and maximum values, respectively.

The fuzzifier component establishes the membership functions for the linguistic variables used as inputs in this intelligent system. These membership functions are defined by the values $a$, $m$, and $b$ stated in (2). These functions are then applied based on the truth values of the linguistic input variables. In the subsequent step, the truth values are determined through the application of fuzzy inference rules. Table 2 provides a general description of fuzzy inference, considering a minimal rule with input variables $x$ and $y$, and an output variable $z$ within [0, 1]. Each fuzzy rule maps a single output variable to a specific fuzzy subset. In the system's final stage, defuzzification takes place to transform fuzzy outputs into crisp outputs. The CENTROID method is typically employed for defuzzification in this context. The proposed system consists of four input variables and two output variables. Fig. 2 provides a visual depiction of the methodology of the designed intelligent system, which is based on fuzzy logic. The process begins with the collection of data, which encompasses four input variables and two output variables. The next step involves categorizing the collected data, whose categorization is performed through two parallel processes. First, the input data are obtained from sensors that measure specific variables relevant to the study. Second, the output data are defined based on the knowledge of prescription strategies. Both input and output data are then utilized to develop a system based on consensus. In our desing, 'consensus' refers to the harmonization of system components, which may involve combining inputs from multiple sensors or aligning multiple data sources. This designed system is evaluated in real-time, producing a prescription as the output. The prescription represents the recommended treatment strategy based on the analyzed data. The process concludes with the implementation of the prescribed treatment.

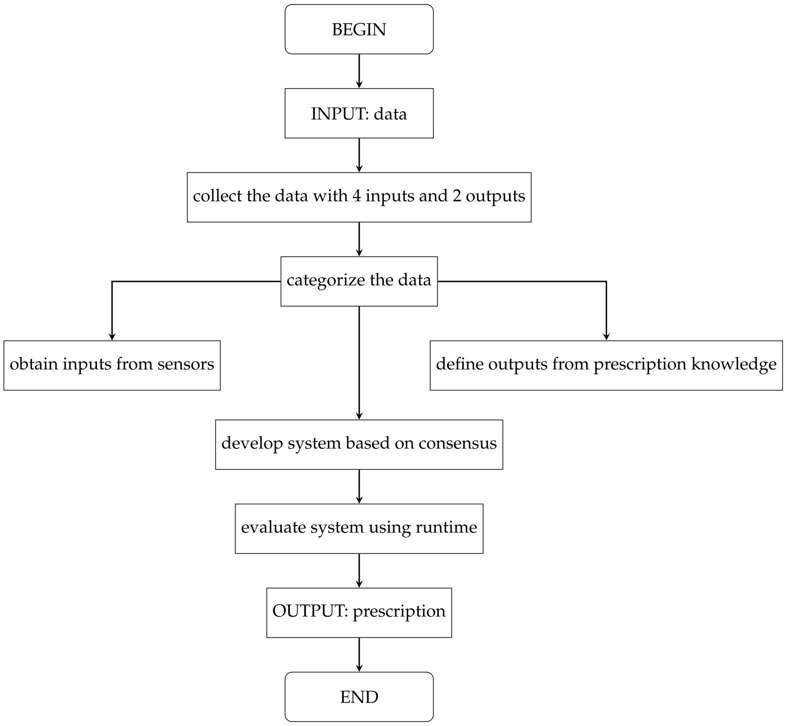


**Fig. 2.** Proposed methodology using an intelligent fuzzy system.

### 3.3. Methodology

Next, we describe how data are collected using sensors:

- Step 1. Sensors are physically connected to the patients in a strategic way.
- Step 2. Patient's data collected by these sensors are then transferred to microcontroller.

Fig. 3 depicts the proposed system, which combines fuzzy logic and the IoT to provide an intelligent medical prescription solution. The system incorporates multiple sensors: a BP sensor, an AD8232 ECG sensor [37], a heart rate sensor, a pulse oximetry sensor, and a temperature sensor. These sensors collect data that are then relayed to an Arduino microcontroller. The system uses the Bylink/Thingspeak IoT platform to enable online data transmission and monitoring, which is accessible through both a mobile app and a webpage. Doctors are given unique login IDs and passwords, enabling them to access patient data and prescribe medication based on the data presented. In situations where a doctor is unavailable or does not have the time to review the data, the intelligent system can recommend appropriate medication utilizing fuzzy logic, particularly in emergency situations. The sequence of steps followed by the system to administer the appropriate medication is presented in Algorithm 2. Additionally, Fig. 4 provides a graphical representation of the steps involved in the proposed methodology.

**Algorithm 2** System steps to generate the patient's medication.

1: Collect data using sensors and transmit them to the Arduino microcontroller.
2: Process the data with the Arduino microcontroller and transfer them to a cloud-based database.
3: Access the data via a web application, allowing a doctor to prescribe medication based on the patient's condition.
4: Suggest the patient's prescription with the intelligent fuzzy system and the aid of medical staff, if the doctor does not respond within a predetermined time.

Further enhancement of Algorithm 2 can be achieved by incorporating a database sensor component. This software component, operating within the database, may respond to new data inputs via triggers, which are code sections that are executed when the sensor sends the command. These triggers are stored in the database alongside the data. Some algorithms utilizing database sensors are discussed in [44–46]. With our methodology, the patient data can be stored in any database regardless of its location. It also maintains a record of the patient's medical history, which can be accessed by healthcare professionals through the online application.

Note that the system may also employ communication tools like email and WhatsApp [47] to keep the doctor and other registered individuals informed about the patient's condition and the intelligent system's medication recommendations. Algorithm 3 details how the proposed system generates the patient's medication, incorporating a database sensor and communication tools.

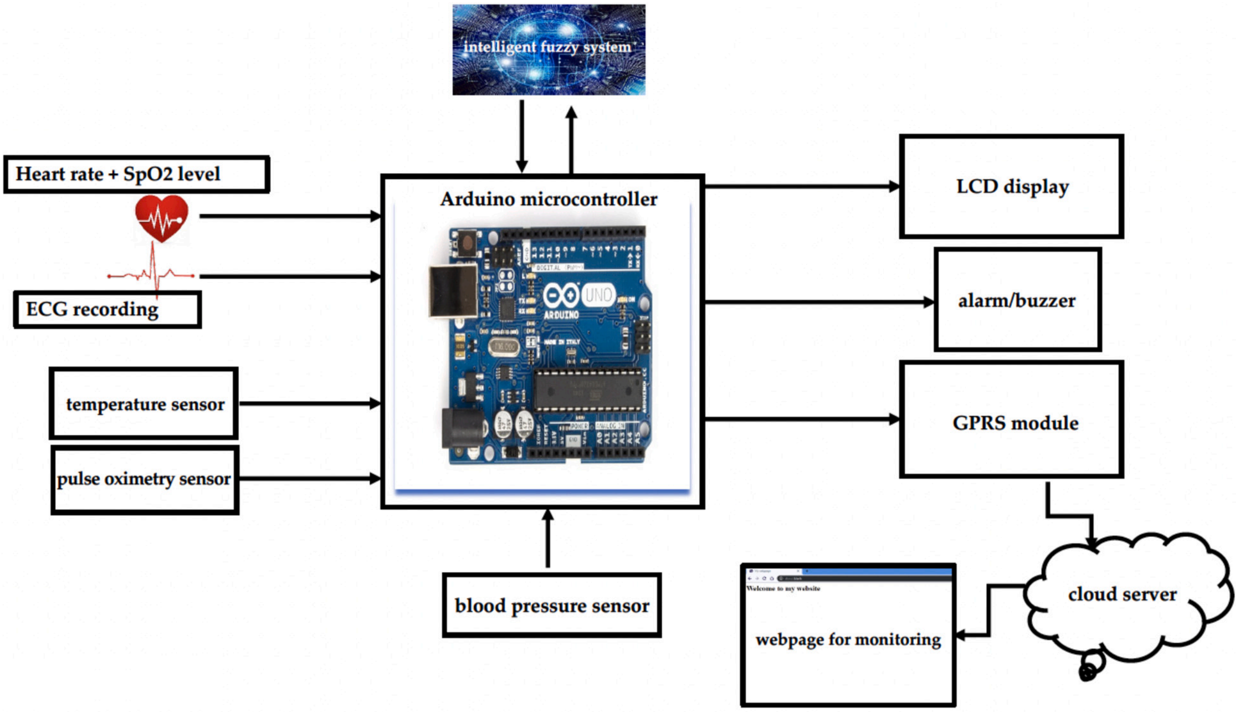


**Fig. 3.** Block diagram of the patient's monitoring system.

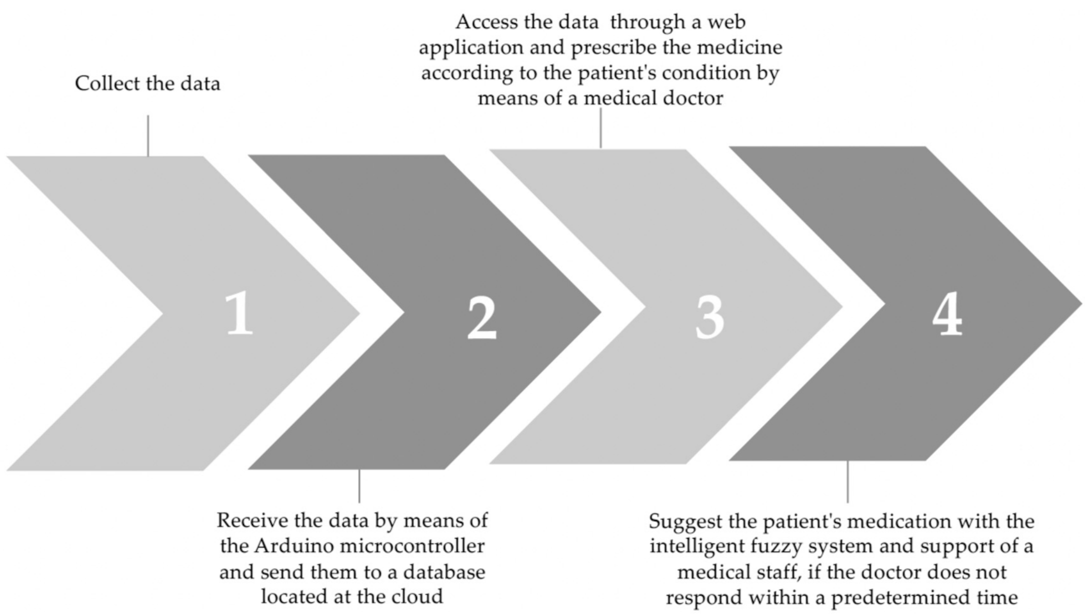


**Fig. 4.** Steps of the proposed methodology to generate the patient's medication.

### 3.4. Inputs

Four inputs constitute the proposed system. All membership values assigned to the inputs are derived from sensor data. Furthermore, the system suggests and administers the appropriate medication dosage based on the patient's condition. Consider factors that are influenced by inputs such as systolic/diastolic BP, temperature, and glucose level as follows:

- Systolic BP: This input is associated with six membership functions. Table 3 reports the variety of systolic BP membership functions, and Fig. 5 displays a graphical representation of them.

**Algorithm 3** System steps to generate the patient's medication with a database sensor and communication tools.

1: Collect data using sensors and transmit them to the Arduino microcontroller.
2: Process the data with the Arduino microcontroller and transfer them to a database.
3: Perform the following actions with the trigger when new data are entered in the database:
   3.1 Timestamp the patient's data.
   3.2 Store the patient's history in a repository.
   3.3 Send the data via email and/or WhatsApp to the attending physician and a second registered individual.
4: Access the data through a web application, have a doctor to prescribe medication based on the patient's condition, and store the prescription details in the patient's medical record.
5: Recommend medication based on fuzzy logic with the intelligent syste and the help of a medical staff, if the maximum waiting time has passed without a response from the doctor, sending this recommendation via email and WhatsApp to the patient's doctor and the second registered individual.

**Table 3**
Membership function for systolic BP ranges.

| Membership function | Systolic range (in mmHg) |
|---|---|
| Low | 70-90 |
| Normal | 90-130 |
| Tension | 130-140 |
| Hypertension | 140-160 |
| High | 160-190 |
| Dangerous | 190-220 |

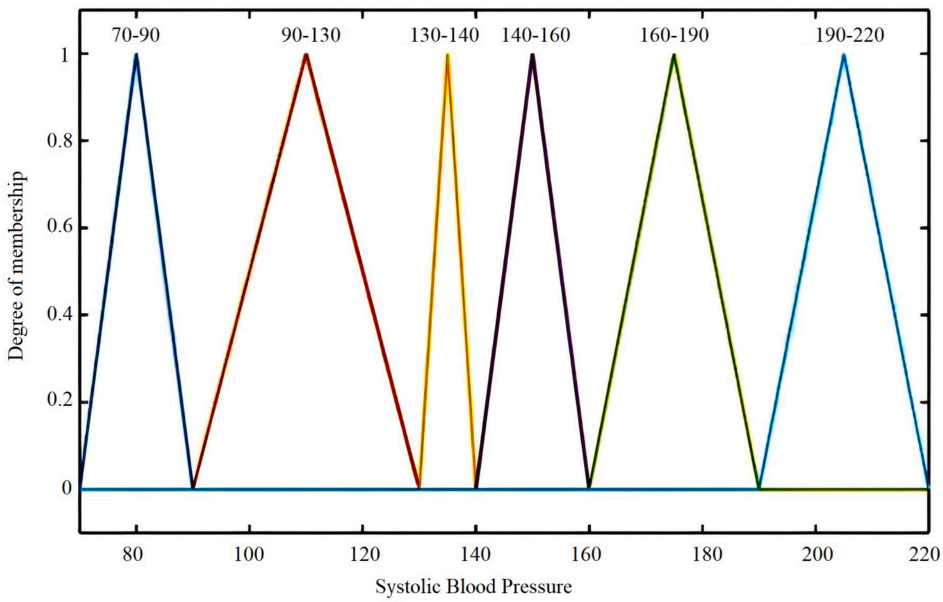


**Fig. 5.** Membership functions of systolic BP.

**Table 4**
Membership function for diastolic BP ranges.

| Membership function | Diastolic range (in mmHg) |
|---|---|
| Low | 40–70 |
| Normal | 70–90 |
| High | 90–100 |
| Dangerous | 100–115 |

- Diastolic BP: This input is connected to four membership functions. Table 4 presents the variety of diastolic BP membership functions, and Fig. 6 shows their graphical depiction.

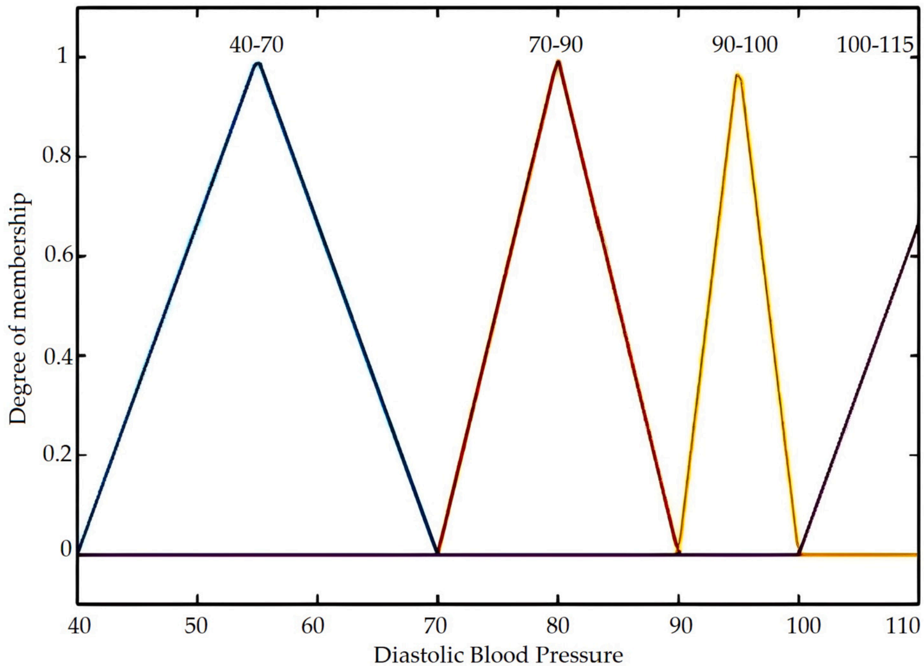


**Fig. 6.** Membership functions of diastolic BP.

**Table 5**
Membership functions for glucose level ranges.

| Membership function | Glucose level range (in milli mols/liter) |
|---|---|
| Low | 50–65 |
| Normal | 65–180 |
| High level 1 | 180–250 |
| High level 2 | 250–310 |
| High level 3 | 310–350 |
| Dangerous | 350–390 |

**Table 6**
Membership function and ranges for temperature.

| Membership function | Temperature range (in ˚F) |
|---|---|
| Normal temperature | 40–70 |
| High temperature | 70–90 |

- Glucose level: Table 5 provides information on the spectrum of membership functions related to blood glucose levels, and Fig. 7 illustrates their graphical representation.
- Temperature: Table 6 displays the spectrum of temperature-related membership functions, and their graphical representation is presented in Fig. 8.

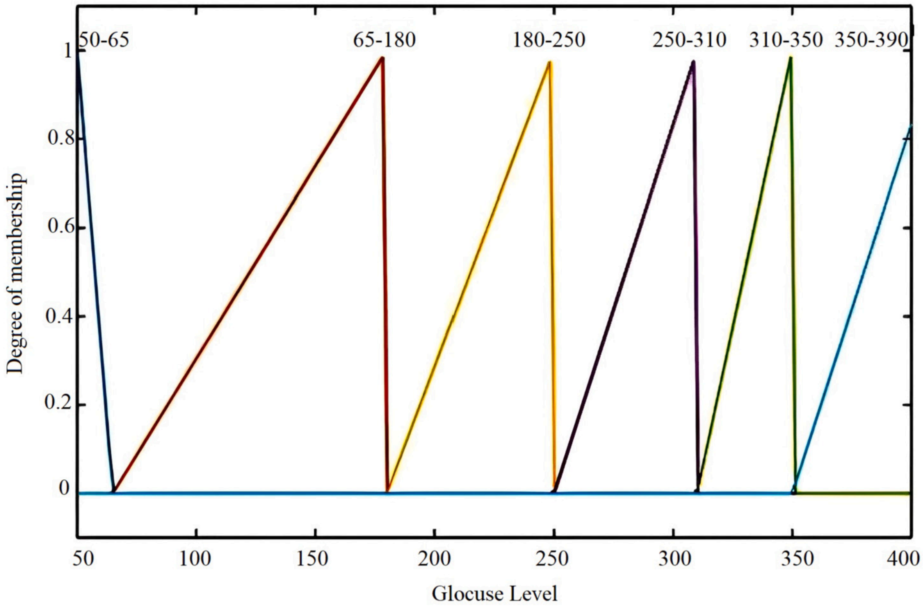


**Fig. 7.** Membership functions of glucose level.

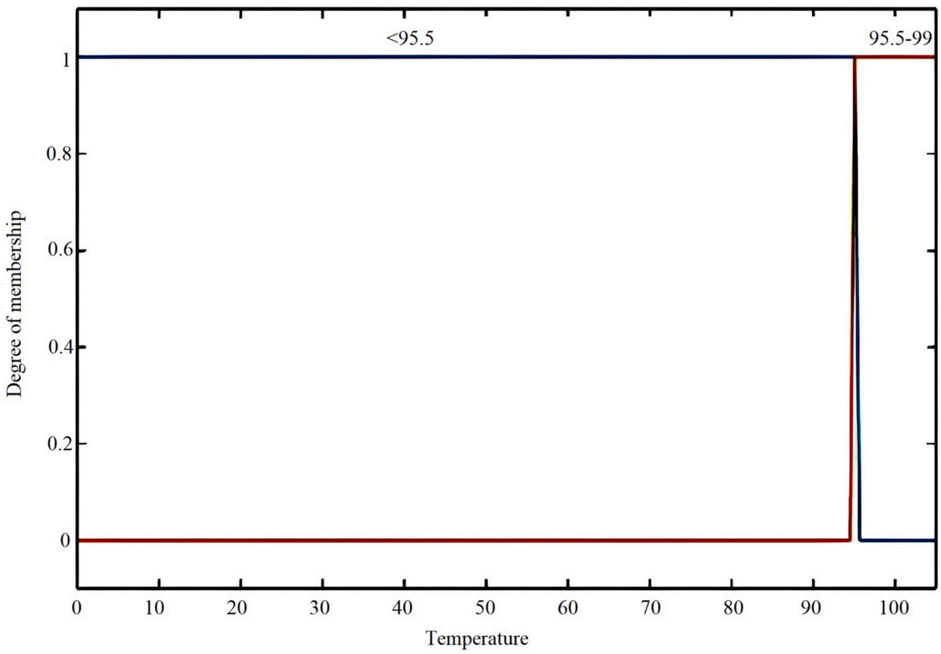


**Fig. 8.** Membership functions of temperature.

The proposed system depends critically on the precision of the data collected from the sensors. Inaccurate or erroneous sensor readings can lead to suboptimal or even harmful medication recommendations. The collected data undergo a pre-processing phase where outliers and erroneous readings are filtered out. Advanced algorithms, such as Kalman filters, are employed to ensure the data are as accurate and noise-free as possible. The pre-processed data are then fed into the fuzzy logic system and IoT platform. It is worth noting that the reliability of the proposed system hinges on the quality of the sensor data, which underscores the importance of proper sensor calibration.

Each sensor was properly calibrated before its inclusion in the proposed system. Calibration was done using appropriate reference equipment. For instance, the BP sensor was calibrated using a standard sphygmomanometer and stethoscope. Calibration ensures that the values obtained from the sensors accurately reflect the patient's condition.

**Table 7**
Prescribed medicine for the treatment of BP.

| Inputs | | Membership function | Prescribed medicine |
|---|---|---|---|
| Systolic | Diastolic | Range | |
| 70–90 | 40–70 | 0–10 | Normal-saline |
| 90–130 | 70–90 | 10–20 | No medicine |
| 130–140 | 90–100 | 20–30 | NM-salt restriction |
| 140–160 | 90–100 | 30–40 | Amiodiphine-5mg+saltR |
| 160–190 | 100–115 | 40–50 | Extra amlodipine + thiazide-diozene |
| 190–220 | 100–115 | 50–60 | Extra amlodipine + thiazide-diozene |

### 3.5. Dataset collection and consent

Data for this study were collected from a total of 100 patients over a period of 12 months. Patients were equipped with two types of sensors for the purpose of this study -the MAX30100 sensor for BP measurements, and the Glucose Sensor –M01 for glucose level measurements. These sensors were carefully calibrated prior to data collection to ensure accuracy.

The data collection process was straightforward. Patients were instructed to wear the sensors as per the guidelines provided by the researchers. The MAX30100 sensor measures both systolic and diastolic BP by using photoplethysmography to detect blood volume changes in the microvascular bed of tissue. The glucose sensor -M01 measures the glucose level through a minimally invasive procedure that draws a tiny amount of blood. The data from these sensors were collected at a sampling rate of 10 times per minute and transmitted to an Arduino microcontroller, which then processes the data into a usable format. The data transmission is achieved utilizing the Bylink communication protocol and the data are stored in one-dimensional arrays format for further analysis.

Each data point in the dataset consists of three features: diastolic and systolic BPs, and glucose level. This dataset was used to train and validate the proposed fuzzy logic-based system for the treatment of BP and glucose levels.

Consent was obtained from all patients involved in this study. All patients were informed on the purpose and procedure of the study and provided written consent, allowing their data to be collected and employed for research purposes. The collected data were anonymized to ensure patient privacy and confidentiality. No personal identification data were included in the dataset.

Due to privacy concerns, the dataset is not publicly available. However, it can be provided upon request for research purposes. Researchers interested in accessing the dataset can contact the corresponding author.

### 3.6. Outputs

The system generates two primary outputs: treatment protocols for BP and glucose level management. These outputs are obtained from the input variables, which include systolic and diastolic BPs, as well as glucose level. Depending on the input values, the system prescribes a range of treatments delineated as follows:

- Treatment of BP: The proposed system recommends different treatments for BP based on the patient's systolic and diastolic BP levels. The prescribed treatments for BP, along with the associated membership function ranges, are reported in Table 7. Each membership function corresponds to a specific range of systolic and diastolic BP values, and the recommended treatment is assigned based on the patient's BP levels falling within these ranges. The membership functions for the prescribed treatments are shown in Fig. 9.

Table 7 categorizes systolic and diastolic BP readings into various ranges. Corresponding therapeutic recommendations are delineated for each categorized range according to BP management protocols. Fig. 9 shows the membership functions for the prescribed medicine in the BP treatment. Each membership function corresponds to a specific range of systolic and diastolic BP values, as described in Table 7.

- Treatment of glucose level: The system prescribes specific treatments for varying blood glucose conditions based on the glucose level input. The medications intended to manage blood glucose levels are detailed in Table 8. Fig. 10 delineates the membership functions for these treatments.

Table 8 presents a stratification of glucose readings into defined ranges. Appropriate pharmacological responses are detailed for each stratified glucose interval. Fig. 10 illustrates the dosing profiles for medications, mapping them to the corresponding glucose level ranges outlined in Table 8.

## 4. Discussion and results

The system presented in this investigation collects data from the human body using ECG and temperature sensors. These data are then transmitted through the IoT to a Blynk/Thingspeak webpage, where a doctor can access and analyze the data by logging into a private Thingspeak account, as depicted in Fig. 11.

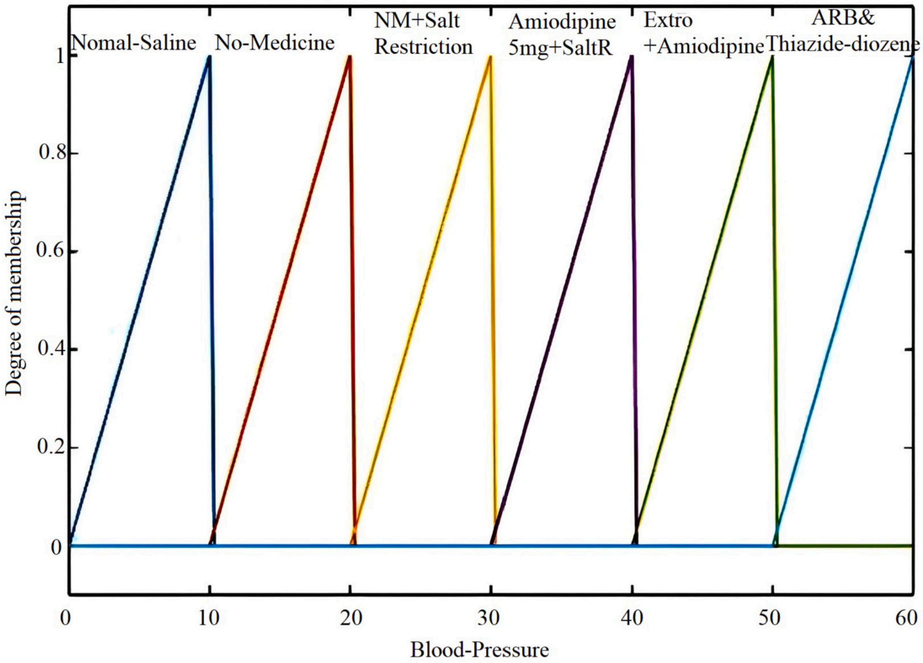


**Fig. 9.** Functional profiles for medication dosing in the BP management.

**Table 8**
Medications prescribed for the treatment of blood glucose level.

| Input Glucose level | Output Range | Prescribed medicine |
|---|---|---|
| 50–65 | 0–10 | Intravenous-glucose |
| 65–180 | 10–20 | No medicine |
| 180–250 | 20–30 | Metformin-500mg |
| 250–310 | 30–40 | Sitagliptin-metformin-50/500mg |
| 310–350 | 40–50 | Stigliptin-metformin/diamacron_MR_60mg |
| 350–390 | 50–60 | M-insulin_5_unit/kg |

The integration with Blynk/Thingspeak enables real-time access to the health data, facilitating prompt medical decisions and reducing the time required for consultations. As mentioned, our intelligent health monitoring system is implemented in the MATLAB software using the fuzzy designer toolbox. It can smartly recommend medicine for patients based on their medical condition, as demonstrated in Fig. 12.

Our system decodes the numeric output from the fuzzy logic to suggest a particular medicine. The fuzzy logic engine processes the inputs and calculates a membership degree for each rule. The corresponding medication is then recommended based on the rule with the highest membership degree. If a patient's BP suddenly exceeds a level of 170 in systolic BP and of 100 in diastolic BP, the device administers a pre-filled dose through an injection linked to the patient's hand via a pipe that serves as a gateway for dose intake. Fig. 12 illustrates the success of this fuzzy logic-based approach.

Our system prescribes medicine in numerical format for specific BP, glucose, and temperature values. After decoding these numbers, the corresponding medicine is identified, as described in Tables 7 and 8 (Subsection 3.6). In Fig. 12, the systolic and diastolic BP inputs are 145 mmHg and 93.3 mmHg, respectively, resulting in an output of BP = 35.6. By decoding this output, we prescribed "Amiodiphine-5mg+SaltR" for the patient. Similar decoding is applied for glucose and temperature. For example, given inputs of glucose = 225 millimoles per liter and temperature = 100 °F, the output values of 26.5 and 26.3 predict "Metformin-500mg" and "Paracetamol" prescriptions, respectively.

For real-time validation of our intelligent health monitoring system using the Blynk platform, we utilized a locally available Max30100 sensor to measure heart rate and SpO2 levels, which were interfaced with a microcontroller, as presented in Fig. 13. These data were sent to the Blynk IoT platform via a Wi-Fi module ESP8266.

The data were taken at our University Campus, and the app operates from a distance of 34 kilometers. These data are continuously available on the cloud for remote health monitoring, as shown in Fig. 14. The data are also displayed on an LCD for the patient's reference, ensuring that the patient and caregivers have immediate access to essential health information.

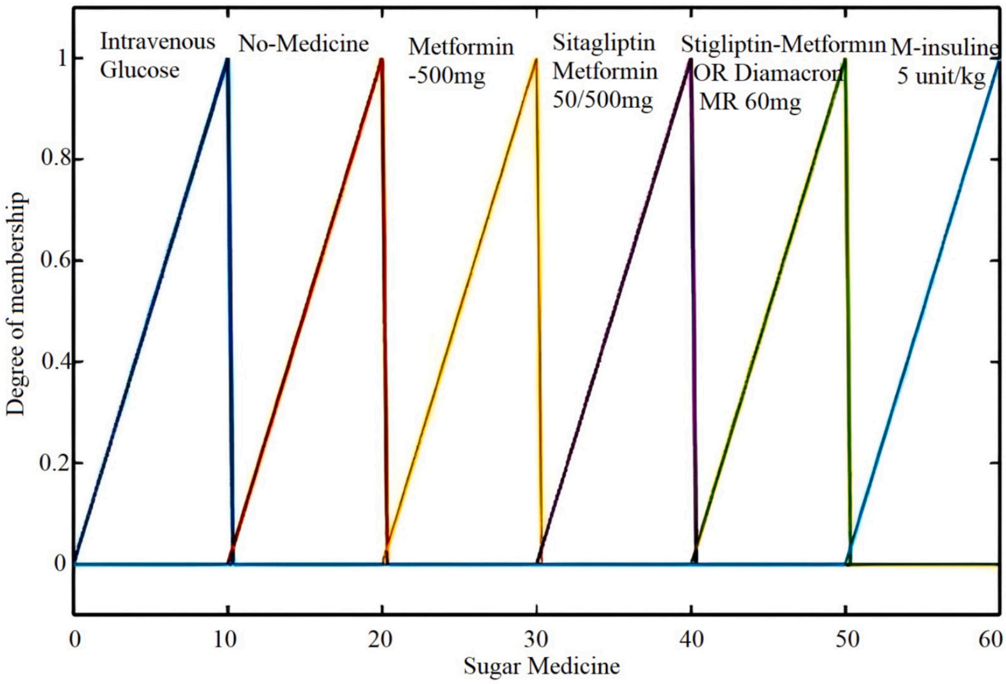


**Fig. 10.** Dosing profiles for pharmacological interventions in blood glucose control.

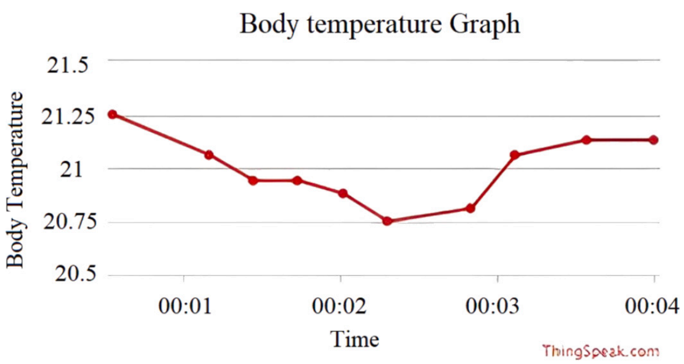


**Fig. 11.** Temperature sensor data on a webpage.

For continuous ECG monitoring and diagnosis purposes, we performed an experiment and generated new ECG data on the webpage using an AD8232 ECG sensor [48]. We delivered 50 ECG data samples to a ThingSpeak webpage and exported the same data samples (representing a complex of QRS curves) from the ThingSpeak online data cloud to MATLAB at another location. Then, data samples were plotted in MATLAB to represent the complex QRS ECG data. We submitted one sample of the QRS complex ECG data for clear depiction. These data are plotted in Figs. 15, 16, and 17, which corresponds to the QRS complex [49], and it can be used for any diagnosis purpose. The AD8232 ECG sensor is also employed in recent research [48,37], where only health monitoring was provided. We propose a system that states intelligent medical prescription plus IoT-based health monitoring in the present investigation.

In summary, this investigation presented a novel approach to real-time health monitoring using IoT-based sensors and an intelligent system implemented in MATLAB with fuzzy logic. Our system provides real-time access to patient data, allowing prompt medical decisions and treatment recommendations. The system's ability to continuously collect and analyze vital health data, coupled with its intelligent medicine recommendation capability, makes it a versatile and practical tool for both patients and healthcare professionals. By providing immediate access to critical health data and prescribing medicines based on individual patient conditions, our system offers a significant advancement in the field of remote health monitoring and personalized medicine. As demonstrated in the results, the proposed system can effectively monitor, analyze, and recommend treatment for various health parameters such as BP, glucose levels, and temperature.

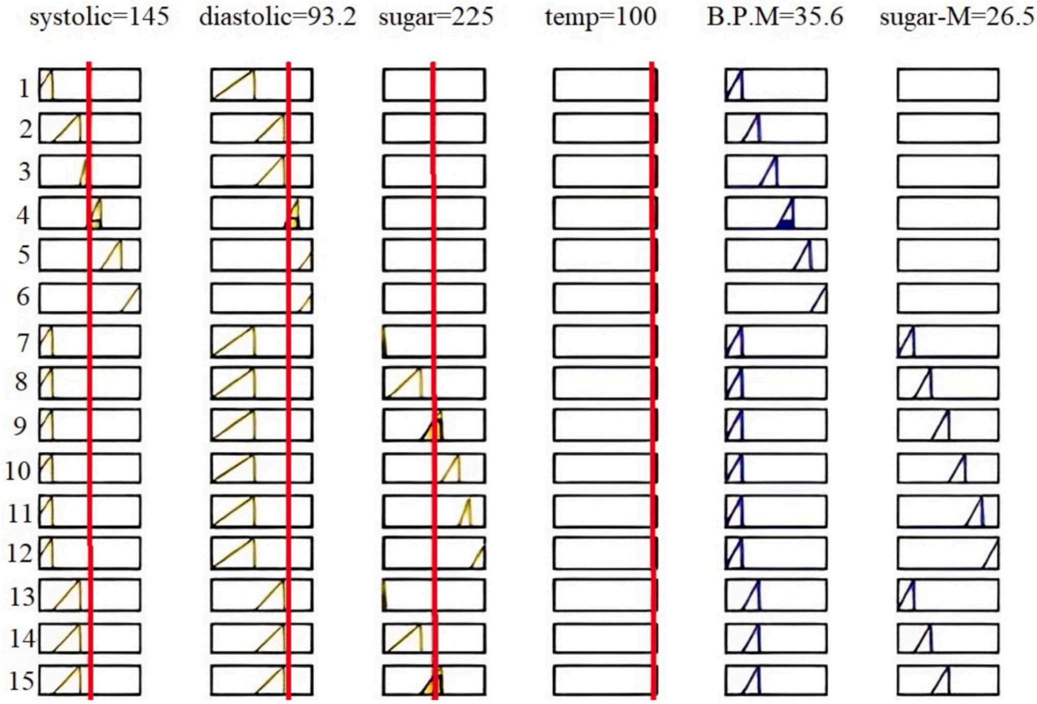


**Fig. 12.** Fuzzy logic outputs.

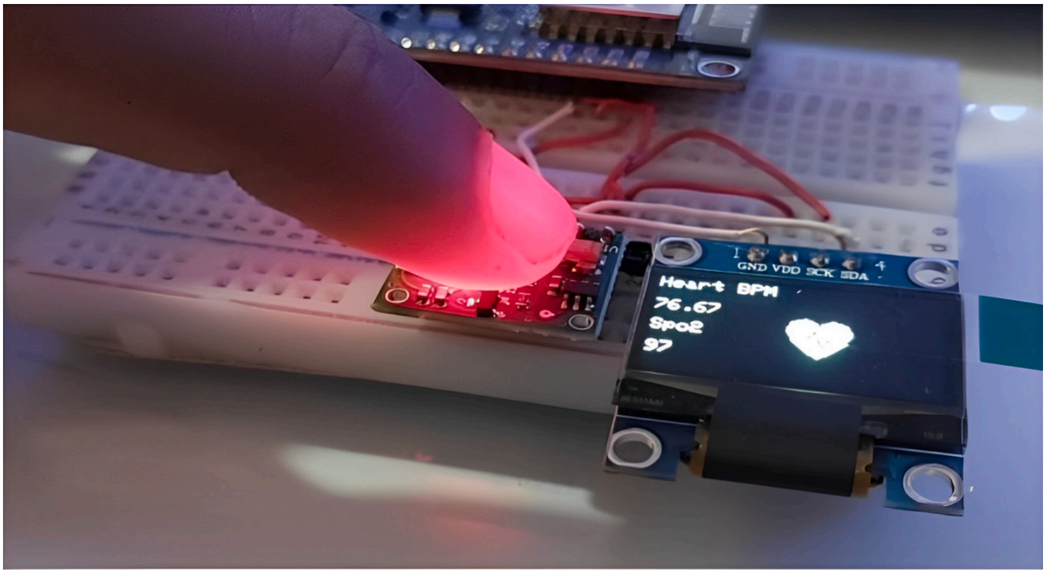


**Fig. 13.** Data recorded at our university campus.

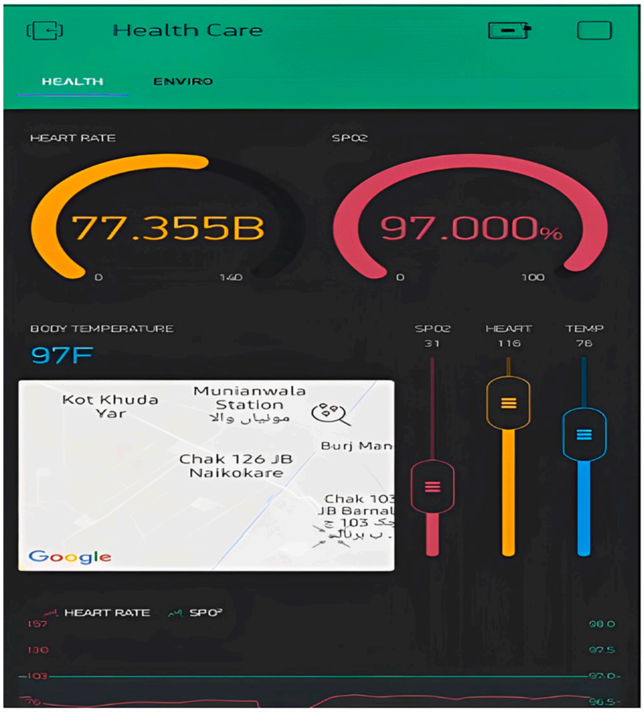


**Fig. 14.** Health monitoring data, including heart rate, SpO2, and body temperature, available remotely from a distance of 34 kilometers.

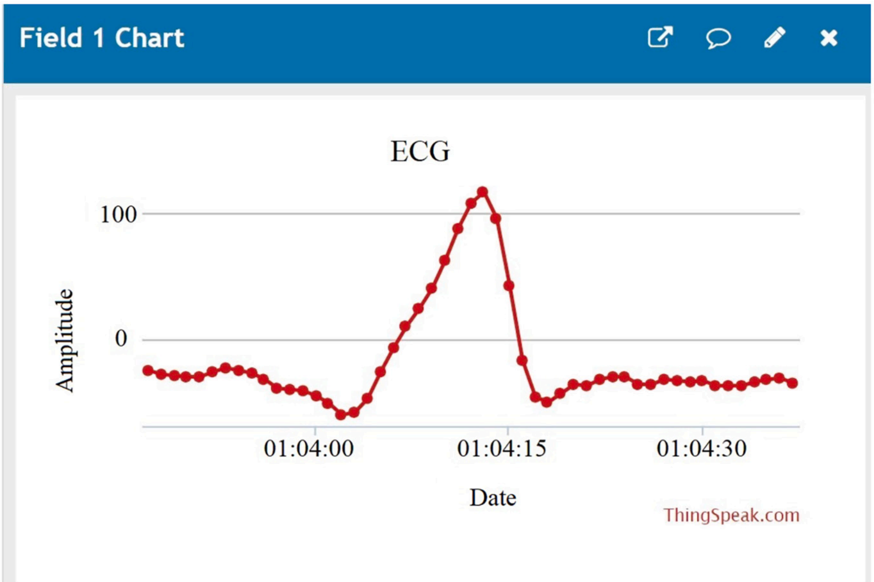


**Fig. 15.** AD8232 ECG QRS complex on a ThingSpeak.

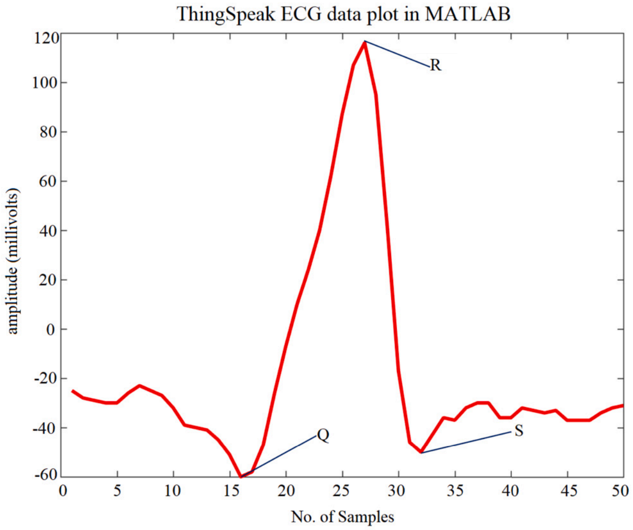


**Fig. 16.** ThingSpeak ECG data samples plot for diagnosis purposes.

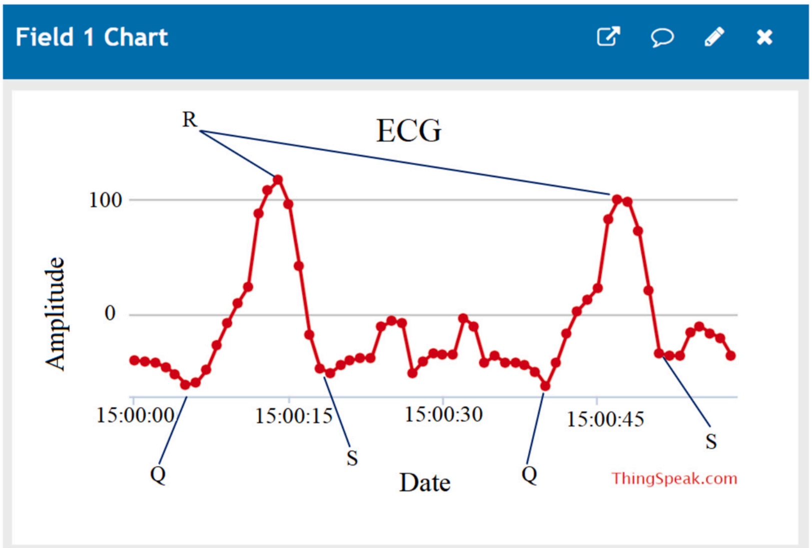


**Fig. 17.** AD8232 ECG sensor data on a webpage for continuous monitoring.

## 5. Conclusions and future work

This study presented an intelligent system combining fuzzy logic and IoT to remotely monitor and diagnose COVID-19 patients, suggesting medical prescriptions, particularly beneficial for areas with limited access to healthcare facilities. The system is portable, suitable for both home and hospital use. While existing systems focus mainly on IoT-based monitoring or employ AI for remote diagnosis, our proposed system uniquely integrates comprehensive IoT-based monitoring with intelligent diagnosis and a fuzzy medical prescription system. By harnessing the power of IoT, our system enables doctors or attendants to monitor patients' health remotely. Moreover, the system's intelligent prescription decisions serve as a valuable tool in situations where doctors or medical staff are unavailable.

We acknowledge some limitations of our system. Adding more rules can increase the processing time for suggesting appropriate medications in COVID-19 patients. The system is currently designed for individual COVID-19 patients, posing potential scalability challenges for the simultaneous monitoring of multiple patients. In addition, we recognize the need for more in-depth validation of the system's performance using metrics such as accuracy, sensitivity, receiver operating characteristic (ROC) curve, or area under the ROC curve (AUC). Despite these limitations, our system is a promising approach to intelligent health monitoring, as it combines the advantages of IoT-based monitoring, fuzzy logic, and remote diagnosis. We have focused on presenting the system's design and functionality in this proof-of-concept study. We intend to address these considerations in future studies and explore the integration of next-generation computing technologies. Therefore, in terms of future research directions, we suggest:

- Expanding the system to simultaneously monitor multiple patients. Although this presents scalability challenges, we are confident that integrating next-generation computing technologies can help address these issues.
- Integrating next-generation computing technologies such as deep learning, machine learning, cloud computing, fog computing, edge computing, serverless computing, and quantum computing, which can significantly improve system performance [50].
- Exploring autonomous computing, which enables computers to function independently, and can be achieved by combining AI and machine learning to enhance our system [37].
- Implementing neural networks as part of AI, which can further improve the accuracy and efficiency of the system [51].
- Identifying and utilizing big data sources, which can provide valuable insights and modify the context of the proposed system [52].
- Employing fuzzy rule-based systems for fusion to enhance system accuracy and incorporating unobserved states of patients using fuzzy designs [53,54].

Our work aligns with other studies in the literature. In [55], fog computing is explored with IoT for real-time processing, particularly relevant for healthcare applications. Similarly, [56] emphasizes smart product-service systems in healthcare, underscoring the role of connected intelligent products and stakeholder communication in digital health adoption. [57] employed deep learning and IoT for teeth lesion detection post-COVID-19, demonstrating the applicability of intelligent systems in healthcare. Likewise, [58] underscored the importance of IoT, cloud computing, AI, and 5G (fifth generation of mobile network technology, known for its higher speeds and lower latency) for self-monitoring of COVID-19. Our work complements these studies by providing an intelligent health monitoring and medical prescription system, particularly crucial for remote areas. The study provided in [59] on peer-to-peer federated learning for COVID-19 detection showcased the potential of advanced machine learning techniques for healthcare, hinting at an exciting direction for future work.

In conclusion, our system introduced new possibilities for comprehensive and advanced AI-based medical treatment recommendations. Despite some limitations, the potential of such systems to transform healthcare, especially in remote or isolated areas, is immense. Ongoing research is currently exploring these areas further, and we eagerly anticipate reporting the findings in future articles.

## CRediT authorship contribution statement

**Muhammad Zia Ur Rahman:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Azeem Akbar:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Víctor Leiva:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Carlos Martin-Barreiro:** Writing – original draft, Methodology, Data curation, Conceptualization. **Muhammad Imran:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Muhammad Tanveer Riaz:** Writing – original draft, Methodology, Data curation, Conceptualization. **Cecilia Castro:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## 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 from the authors.

## Acknowledgements

The authors would also like to thank the Editors and Reviewers for their constructive comments which led to improve the presentation of the article. This research was partially supported by FONDECYT, grant number 1200525 (Víctor Leiva), from the National Agency for Research and Development (ANID) of the Chilean government under the Ministry of Science, Technology, Knowledge, and Innovation; and by Portuguese funds through the CMAT—Research Centre of Mathematics of University of Minho—within projects UIDB/00013/2020 and UIDP/00013/2020 (Cecilia Castro).

## References

[1] M. Mangla, A. Kumar, V. Mehta, M. Bhushan, S.N. Mohanty (Eds.), Real-Life Applications of the Internet of Things: Challenges, Applications, and Advances, CRC Press, Boca Raton, FL, USA, 2022.
[2] L. Atzori, A. Iera, G. Morabito, The Internet of things: a survey, Comput. Netw. 54 (2010) 2787–2805.
[3] A. Deshpande, P. Pitale, S. Sanap, Industrial automation using Internet of Things (IoT), Int. J. Adv. Res. Comput. Eng. Technol. 5 (2016) 266–269.
[4] M. Rana, M. Bhushan, Advancements in healthcare services using deep learning techniques, in: 2022 International Mobile and Embedded Technology Conference (MECON), Noida, India, 2022.
[5] I. Sardar, M.A. Akbar, V. Leiva, A. Alsanad, P. Mishra, Machine learning and automatic ARIMA/Prophet models-based forecasting of COVID-19: methodology, evaluation, and case study in SAARC countries, Stoch. Environ. Res. Risk Assess. 37 (2022) 345–359.

[6] M.A. Akbar, V. Leiva, S. Rafi, S.F. Qadri, S. Mahmood, A. Alsanad, Toward roadmap to implement blockchain in healthcare systems based on a maturity model, J. Softw. Evol. Process 34 (2022) e2500.
[7] R. Kumar, M. Rajasekaran, An IoT-based patient monitoring system using Raspberry Pi, in: Proceeding of the 2016 International Conference on Computing Technologies and Intelligent Data Engineering, 2016, pp. 1–4.
[8] N.S. Palkhede, S.D. Mali, P.M.S. Shelar, IoT-based patient monitoring, Int. J. Trend Sci. Res. Dev. 2 (2018) 971–975.
[9] F. Faisal, S. Hossain, IoT-based remote medical diagnosis system using NodeMCU, in: Proceeding of the 13th Conference on Software, Information Management and Applications, 2019, pp. 1–7.
[10] B. Bede, Mathematics of Fuzzy Sets and Fuzzy Logic, Springer, Berlin, Germany, 2013.
[11] D.N. Nguyen, T.A. Nguyen, Proposing an original control algorithm for the active suspension system to improve vehicle vibration: adaptive fuzzy sliding mode proportional-integral-derivative tuned by the fuzzy (AFSPIDF), Heliyon 9 (2023) e14210.
[12] L.X. Wang, Adaptive Fuzzy Systems and Control: Design and Stability Analysis, Prentice-Hall, New York, NY, USA, 1994.
[13] T. Terano, K. Asai, M. Sugeno, Fuzzy Systems Theory and Its Applications, Academic Press, New York, NY, USA, 1992.
[14] J.H.T. Bates, M.P. Young, Applying fuzzy logic to medical decision making in the intensive care unit, Am. J. Respir. Crit. Care Med. 167 (2003) 948–952.
[15] M. Mirza, H. Gholamhosseini, M.J. Harrison, A fuzzy logic-based system for anaesthesia monitoring, in: Proceeding of the 2010 International Conference of the Engineering in Medicine and Biology Society, 2010, pp. 3974–3977.
[16] O.T. Jones, N. Calanzani, S. Saji, et al., Artificial intelligence techniques that may be applied to primary care data to facilitate earlier diagnosis of cancer: systematic review, J. Med. Internet Res. 23 (2021) e23483.
[17] C. Manchini, R. Ospina, V. Leiva, C. Martin-Barreiro, A new approach to data differential privacy based on regression models under heteroscedasticity with numerical applications, Inf. Sci. 627 (2022) 280–300.
[18] S.A. Almutairi, A multimodal AI-based non-invasive COVID-19 grading framework powered by deep learning, manta ray, and fuzzy inference system from multimedia vital signs, Heliyon 9 (2023) e16552.
[19] V. Leiva, E. Alcudia, A. Montano, C. Castro, An epidemiological analysis for assessing and evaluating COVID-19 based on data analytics in Latin American countries, Biology 12 (2023) 887.
[20] R. Ospina, J.A.M. Gondim, V. Leiva, C. Castro, An overview of forecast analysis with ARIMA models during the COVID-19 pandemic: methodology and case study in Brazil, Mathematics 11 (2023) 3069.
[21] C. Martin-Barreiro, X. Cabezas, V. Leiva, P. Ramos de Santis, J.A. Ramirez-Figueroa, E. Delgado, Statistical characterization of vaccinated cases and deaths due to COVID-19: methodology and case study in South America, AIMS Math. 8 (2023) 22693–22713.
[22] Y. Udara, S. Udara, H.M. Harish, H.C. Hadimani, Health monitoring system using IoT, Int. J. Eng. Manuf. Sci. 8 (2018) 177–182.
[23] S. Patil, S. Pardeshi, Health monitoring system using IoT, Int. Res. J. Eng. Technol. 5 (2018) 1678–1682.
[24] S.N. Singh, M. Bhushan, Smart ECG monitoring and analysis system using machine learning, in: 2022 IEEE VLSI Device Circuit and System (VLSI DCS), Kolkata, India, 2022.
[25] D.J. Singh, M. Tiwari, M. Shelar, ZigBee-based patient monitoring system, Int. J. Comput. Appl. 51 (2012) 17–20.
[26] K. Navya, M.B.S. Murthy, A Zigbee based patient health monitoring system, Int. J. Eng. Res. Appl. 3 (2013) 483–486.
[27] U. Ahmed, G. Rasool, S. Zafar, H.F. Maqbool, Fuzzy rule based diagnostic system to detect the lung cancer, in: Proceeding of the 2018 International Conference on Computing, Electronic and Electrical Engineering, 2018, pp. 1–6.
[28] D.S.R. Krishnan, S.C. Gupta, T. Choudhury, An IoT-based patient health monitoring system, in: Proceeding of the 2018 International Conference on Advances in Computing and Communication Engineering, 2018, pp. 1–7.
[29] K. Guk, G. Han, J. Lim, K. Jeong, T. Kang, E.K. Lim, J. Jung, Evolution of wearable devices with real-time disease monitoring for personalized healthcare, Nanomaterials 9 (2019) 813.
[30] M. Manas, A. Sinha, S. Sharma, M. Mahboob, An approach for IoT-based wearable health monitoring and messaging system, J. Ambient Intell. Humaniz. Comput. 10 (2019) 2817–2828.
[31] N. Misran, M.S. Islam, G.K. Beng, N. Amin, M.T. Islam, IoT-based health monitoring system with LoRa communication technology, in: Proceeding of the 2019 International Conference on Electrical Engineering and Informatics, 2019, pp. 514–517.
[32] J.P. Queralta, T.N. Gia, H. Tenhunen, T. Westerlund, Edge-AI in LoRa-based health monitoring: fall detection system with fog computing and LSTM recurrent neural networks, in: Proceeding of the 42nd International Conference on Telecommunications and Signal Processing, 2019, pp. 601–604.
[33] U. Dampage, C. Balasuriya, S. Thilakarathna, D. Rathnayaka, L. Kalubowila, AI-based heart monitoring system, in: Proceeding 4th Conf Computing and Communication Technologies, 2021, pp. 1–6.
[34] M. Khan, S. Mehnaz, A. Shaha, M. Nayem, S. Bourouis, IoT-based smart health monitoring system for COVID-19 patients, Comput. Math. Methods Med. 2021 (2021) 591036.
[35] A.I. Taloba, R. Alanazi, O.R. Shahin, A. Elhadad, A. Abozeid, A. El-Aziz, M. Rasha, Machine algorithm for heartbeat monitoring and arrhythmia detection based on ECG systems, Comput. Intell. Neurosci. 2021 (2021) 7677568.
[36] V. Bhardwaj, R. Joshi, A.M. Gaur, IoT-based smart health monitoring system for COVID-19, SN Comput. Sci. 3 (2022) 137.
[37] M.Z.U. Rahman, A.H. Raza, A.A. Alsanad, M.A. Akbar, et al., Real-time artificial intelligence based health monitoring, diagnosing and environmental control system for COVID-19 patients, Math. Biosci. Eng. 19 (2022) 7586–7605.
[38] M. Bhushan, A. Pandit, A. Garg, Machine learning and deep learning techniques for the analysis of heart disease: a systematic literature review, open challenges and future directions, Artif. Intell. Rev. 56 (2023) 14035–14086.
[39] R. Ospina, A.G.O. Ferreira, H.M. de Oliveira, V. Leiva, C. Castro, On the use of machine learning techniques and non-invasive indicators for classifying and predicting cardiac disorders, Biomedicines 11 (2023) 2604.
[40] M.Z.U. Rahman, M.A. Akbar, V. Leiva, A. Tahir, M.T. Riaz, C. Martin-Barreiro, An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy logic for cardiac arrhythmia COVID-19 patients, Comput. Biol. Med. 154 (2023) 106583.
[41] W. Pedrycz, Why triangular membership functions?, Fuzzy Sets Syst. 64 (1994) 21–30.
[42] Y. Wang, A novel Chinese traditional medicine prescription recommendation system based on knowledge graph, J. Phys. Conf. Ser. 1487 (2020) 012019.
[43] D. Xue, MATLAB Programming: Mathematical Problem Solutions, de Gruyter, NY, US, 2020.
[44] H.M. de Oliveira, R. Ospina, V. Leiva, C. Martin-Barreiro, C. Chesneau, A new wavelet-based privatization mechanism for probability distributions, Sensors 22 (2022) 3743.
[45] E. Mahdi, V. Leiva, S. Mara'Beh, C. Martin-Barreiro, A new approach to predicting cryptocurrency returns based on the gold prices with support vector machines during the COVID-19 pandemic using sensor-related data, Sensors 21 (2021) 6319.
[46] F. Rojas, V. Leiva, M. Huerta, C. Martin-Barreiro, Lot-size models with uncertain demand considering its skewness/kurtosis and stochastic programming applied to hospital pharmacy with sensor-related COVID-19 data, Sensors 21 (2021) 5198.
[47] P. Sharma, A.K. Singh, V. Leiva, X. Cabezas, C. Martin-Barreiro, Modern multivariate statistical methods for evaluating the impact of WhatsApp on academic performance: methodology and case study in India, Appl. Sci. 12 (2022) 6141.
[48] A.S. Prasad, N. Kavanashree, ECG monitoring system using AD8232 sensor, in: Proceeding of the 2019 International Conference on Communication and Electronics Systems, 2019, pp. 976–980.
[49] P.E. Trahanias, An approach to QRS complex detection using mathematical morphology, IEEE Trans. Biomed. Eng. 40 (1993) 201–205.

[50] S.S. Gill, M. Xu, C. Ottaviani, et al., AI for next generation computing: emerging trends and future directions, Int. Things 19 (2022) 100514.
[51] A.K. Nor, S.R. Pedapati, M. Muhammad, V. Leiva, Abnormality detection and failure prediction using explainable Bayesian deep learning: methodology and case study with industrial data, Mathematics 10 (2022) 554.
[52] R.G. Aykroyd, V. Leiva, F. Ruggeri, Recent developments of control charts, identification of big data sources and future trends of current research, Technol. Forecast. Soc. Change 144 (2019) 221–232.
[53] P.B. Dhandapani, J. Thippan, C. Martin-Barreiro, V. Leiva, C. Chesneau, Numerical solutions of a differential system considering a pure hybrid fuzzy neutral delay theory, Electronics 11 (2022) 1478.
[54] O. Alshammari, M. Kchaou, H. Jerbi, S.B. Aoun, V. Leiva, A fuzzy design for a sliding mode observer-based control scheme of Takagi-Sugeno Markov jump systems under imperfect premise matching with bio-economic and industrial applications, Mathematics 10 (2022) 3309.
[55] H. Atlam, R. Walters, G. Wills, Fog computing and the internet of things: a review, Big Data Cogn. Comput. 2 (2018) 10.
[56] Y.T. Negash, L.S.C. Sarmiento, Smart product-service systems in the healthcare industry: intelligent connected products and stakeholder communication drive digital health service adoption, Heliyon 9 (2023) e13137.
[57] I. Shafi, M. Sajad, A. Fatima, D.G. Aray, V. Lipari, I.D.L.T. Diez, I. Ashraf, Teeth lesion detection using deep learning and the internet of things post-COVID-19, Sensors 23 (2023) 6837.
[58] S. Ahmed, J. Yong, A. Shrestha, The integral role of intelligent IoT system, cloud computing, artificial intelligence, and 5G in the user-level self-monitoring of COVID-19, Electronics 12 (2023) 1912.
[59] M. Chetoui, M.A. Akhloufi, Peer-to-peer federated learning for COVID-19 detection using transformers, Computers 12 (2023) 106.