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Research Article

# Internet of Things Based COVID-19 Patient in Self-Isolation Monitoring System

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**Abstract:** Self-isolation has become a critical measure for managing symptomatic or asymptomatic COVID-19 patients, particularly when healthcare facilities are overwhelmed. This study explores a monitoring system based on commercially available Wear OS smartwatches designed to track patient vital signs, specifically oxygen saturation ($SpO_2$), heart rate, and location, and generate alerts during atypical events. The research has two primary objectives, first, to propose a method for remote patient monitoring using market-ready wearable devices; and second, to implement a fuzzy logic model in MATLAB that analyzes vital sign data, including heart rate, $SpO_2$, body temperature, systolic and diastolic blood pressure, and respiratory rate, for health assessment. The findings demonstrate that the system successfully acquires data from the wearable device and processes it through the fuzzy logic engine. This model can effectively categorize patient status as healthy, requiring warning, or in an emergency based on the integrated vital sign inputs.

**Keywords:** COVID-19, MATLAB, Fuzzy Logic, Internet of Things, Wearables

## Introduction

Infectious diseases have been encountered in human history from ages ago, from the black plague, yellow fever until the recently encountered Corona Virus Disease 2019 (COVID-19). We as humanity have been struggling to control the waves of the infections from across the world. According to the World Health Organization (WHO), the COVID-19 pandemic resulted in over 520 million confirmed cases and approximately 6 million deaths globally (World Health Organization, 2021). The high transmission rate of the virus is attributed to its droplet-based spread, which occurs when infected individuals talk, cough, sneeze, or exhale without a mask. Infection can result when another person inhales these droplets, stays in close proximity to an infected person, or touches contaminated surfaces and then their eyes, nose, or mouth (Kementerian Kesehatan Republik Indonesia, 2021). This is most common in infected individuals younger than 45 years old who have little to no symptoms and no comorbid diseases (Aqil, 2021). Indonesia employs a protocol known as "Isolasi Mandiri" (Self-Isolation) for managing COVID-19 cases. This protocol is mandatory for patients presenting with specific symptoms, which include fever (≥38°C), cough, shortness of breath, severe respiratory distress indicated by low blood oxygen saturation (<90%), and tachypnea (a respiratory rate exceeding 30 breaths per minute) (Tharakan *et al*., 2020).

This is where the Internet of Things (IoT) comes into play. IoT technology aims to make daily life easier, automating tasks like climate control and security, and it has significant applications in healthcare. For instance, wearable IoT devices are now used to transmit real-time patient data, enabling continuous fever monitoring (Ahmed *et al*., 2021), postoperative temperature tracking in pediatric care (Shin *et al*., 2020), and even the prediction of heart attacks (Chowdhury *et al*., 2019).

A system using IoT to transmit real-time data for diagnosing COVID-19 severity presents a viable solution for patient monitoring, particularly for those in self-isolation. This study proposes such a system, employing an IoT wearable to track changes in patient health status and facilitate remote monitoring.

This study provides the following contributions, developing a program to measure and track patient data via a wearable device; creating a model that uses Mamdani inference to analyze heart rate, $SpO_2$, body temperature, systolic and diastolic pressure, and respiratory rate; and presenting the tracked data to patients through an Android application.

### *Literature Review*

### *COVID-19*

COVID-19, caused by the SARS-CoV-2 virus, is an infectious disease transmitted primarily through respiratory droplets. It can cause severe damage to the respiratory system, particularly in the form of Acute Respiratory Distress Syndrome (ARDS), and affects individuals across all age groups and genders. While patient symptoms vary, key clinical indicators are reflected in vital sign abnormalities. These include hypoxemia (low blood oxygen saturation), tachycardia (elevated heart rate), fever, blood pressure instability, and tachypnea (elevated respiratory rate) (Ikram & Pillay, 2022). Given their direct correlation with disease severity, these vital signs form the central focus of this research, as monitoring them provides a critical means of assessing patient condition.

### *Sensors and Wearables*

Previous studies select sensors based on specific research requirements. For instance, Mukhtar *et al.* (2021) employed the MAX30100 for heart rate and oxygen saturation and the MAX30205 for body temperature. In contrast, this research utilizes sensors commonly available on the consumer market. These typically include Photoplethysmography (PPG) sensors for heart rate and $SpO_2$ and a dedicated sensor for body temperature. However, accurate measurement of blood pressure and respiration rate remains a significant challenge for current wearable devices.

Research into the public discourse on wearable technology, such as Wear OS, Fitbit, and Apple Watch, has been conducted by Lai *et al.* (2022). The study analyzed social media conversations to examine how online users discuss wearables for health tracking. It found that a significant portion of this population already uses such devices, primarily for monitoring fitness.

Another study by Skibińska *et al.* (2021) utilized wearables and machine learning to monitor COVID-19 patients. Their research demonstrated that market-ready wearables could distinguish between healthy and infected individuals with a 78% success rate. This finding aligns the present study with existing research on using consumer wearables to monitor the health of self-isolating COVID-19 patients.

### *Fuzzy Logic*

Fuzzy logic, developed by Lotfi A. Zadeh in 1965, provides a mathematical framework for handling imprecision by representing vague concepts with overlapping membership functions. Its capacity to process ambiguous information has led to widespread adoption in healthcare, particularly during the COVID-19 pandemic, for tasks such as decision-making and risk assessment. For example, Prasandy *et al.* (2023) applied a Mamdani-type fuzzy inference system with 20 rules to assess the likelihood of early-stage COVID-19 infection, using inputs including heart rate, oxygen saturation, body temperature, systolic pressure, and cough frequency.

The Mamdani method relies on the fuzzification of crisp inputs into membership functions, rule evaluation via the minimum operator, and aggregation using the maximum operator. The final crisp output is derived through defuzzification using the Center of Gravity (COG) method presented in Eq. (1):

$$y^* = \frac{\int_y \; y.\mu_{output}(y)\,dy}{\int_y \; \mu_{output}(y)\,dy}\,. \tag{1}$$

### *Related Work*

Previous research aimed at detecting early COVID-19 infection via wearable sensors was conducted by Al-Bassam *et al.* (2021). They monitored vital signs like heart rate, body temperature, and oxygen saturation ($SpO_2$) with a prototype device, focusing on identifying sudden data drops to alert doctors swiftly. A similar study by Mukhtar *et al.* (2021) used analogous variables to check for early infection stages. This study employed a rule-based decision-making algorithm, incorporating the same vital signs with the addition of cough frequency, measured by a similar prototype. Another prototype-based study by Singh *et al.* (2020) tracked absconding individuals during quarantine using the same vitals as Al-Bassam *et al.* (2021), supplemented by GPS location tracking.

While these studies successfully utilized wearables, their prototypes were often bulky and uncomfortable. Skibińska *et al.* (2021) proposed an alternative by using commercially available wearables with machine learning to identify early COVID-19 signs, though this approach may consume significant battery life. In contrast, fuzzy logic systems are known to be more battery-friendly due to lower computational complexity and memory requirements (Chen and Yang, 2020), presenting a viable, efficient alternative.

Fuzzy logic has been employed in previous research to develop early detection systems for COVID-19. For instance, Prasandy *et al.* (2023) utilized a modeling technique to identify and evaluate the input parameters affecting system efficiency. Building upon this foundation, the present study seeks to extend prior research by modifying both the input variables and the application's objective. Specifically, it incorporates diastole and respiration rate as additional vital sign inputs and adapts the system's purpose from early disease detection to monitoring self-isolating patients.

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Furthermore, this research implements a key suggestion from Prasandy *et al*. (2023) by integrating a commercially available IoT wearable device to collect patient data directly.

Building on this foundation, this paper proposes an enhanced model to determine the severity of COVID-19 in self-isolated patients, categorizing them as being in a reasonably healthy condition, in an emergency, or requiring ICU care. The model incorporates six vital inputs: heart rate, oxygen saturation, body temperature, systolic pressure, diastolic pressure, and respiration rate, expanding on prior approaches to improve accuracy and clinical applicability.

## Materials

### *Software Tools*

The fuzzy logic model was developed using the MATLAB Fuzzy Logic Toolbox. The accompanying wearable interface and Android application were programmed in Android Studio.

### *Hardware Tools*

The experiment was conducted using a Samsung Galaxy Watch 5 as the primary wearable device and a Xiaomi Poco F5 smartphone for application deployment and data relay.

## Methods

### *System Design*

The proposed system integrates an Android wearable (Wear OS device), an Android smartphone, and Firebase Firestore. The wearable device collects patient data through its integrated sensors, measuring primary variables: oxygen saturation ($SpO_2$), body temperature, and heart rate. This data is transmitted via Bluetooth to a companion application on the smartphone. The application interface provides additional input fields for variables that cannot be measured by the wearable (e.g., diastolic/systolic blood pressure, respiration rate). All consolidated data is then sent to a cloud database (Firebase Firestore) for secure storage and management. The stored data is subsequently retrieved and processed by a fuzzy logic controller to assess infection severity. The result is finally displayed within the smartphone application for user feedback. The system architecture is illustrated in Figure 1, with the workflow detailed below:

1. Android Wearable: The Wear OS device serves as the primary data acquisition unit. It utilizes a photoplethysmography (PPG) sensor to measure heart rate and oxygen saturation ($SpO_2$), alongside a dedicated temperature sensor.
2. Android Smartphone with Companion App: The smartphone application acts as the user interface and data aggregator. It receives the wearable's sensor data via Bluetooth and allows manual entry of supplementary clinical parameters. This app facilitates initial data review and manages all communications with the cloud server
3. Firebase Firestore: This cloud-based NoSQL database functions as the central data repository. The smartphone application transmits the complete patient dataset to Firestore via Wi-Fi or mobile data, where it is automatically timestamped and stored with a unique document ID
4. Fuzzy Logic Inference Module: The core analysis engine resides within the application. The latest patient data from Firestore is fed into a Mamdani-type fuzzy rule-based system. This module processes all input variables through a defined set of rules to generate a final, crisp output classifying the patient's COVID-19 status (e.g., stable, warning, or critical)

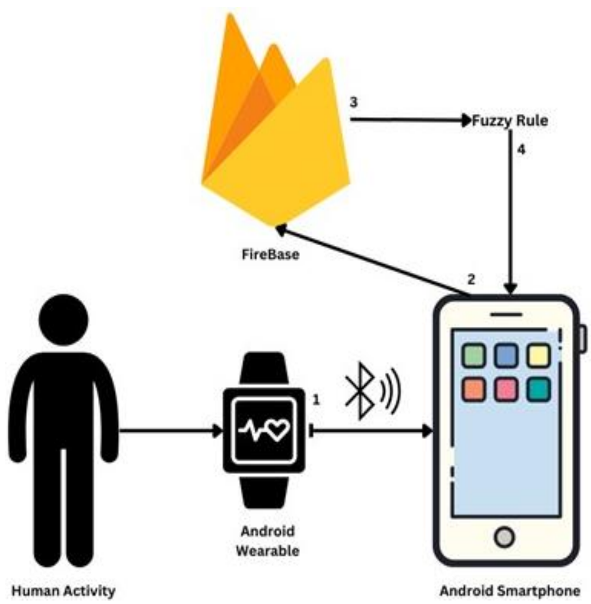


**Fig. 1:** System Schematics

The proposed system workflow, illustrated in Figure 2, begins with data retrieval from the wearable device. Three types of data are obtained: Two continuous trackers (body temperature and heart rate) and one on-demand measurement (oxygen saturation). If data retrieval fails, the process is reinitiated. The acquired data is first displayed on the wearable device itself.

When the user presses the "Send" button on the wearable, the vital sign data is transferred to the paired smartphone via Health Connect. Upon receipt, the phone's companion application displays this data and provides optional fields for manually entering additional vital

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signs, specifically, systolic and diastolic blood pressure and respiration rate.

Submitting the data from the mobile application triggers its transfer to the cloud via the Firebase API. Upon successful receipt, the cloud service indexes and stores the dataset in a Firestore document named "vital_sign_data." The application then requests the latest stored data to synchronize with the phone.

Finally, this synchronized data is fed into the fuzzy logic inference engine to classify the severity of the patient's COVID-19 infection. The prediction result is then displayed on the smartphone screen.

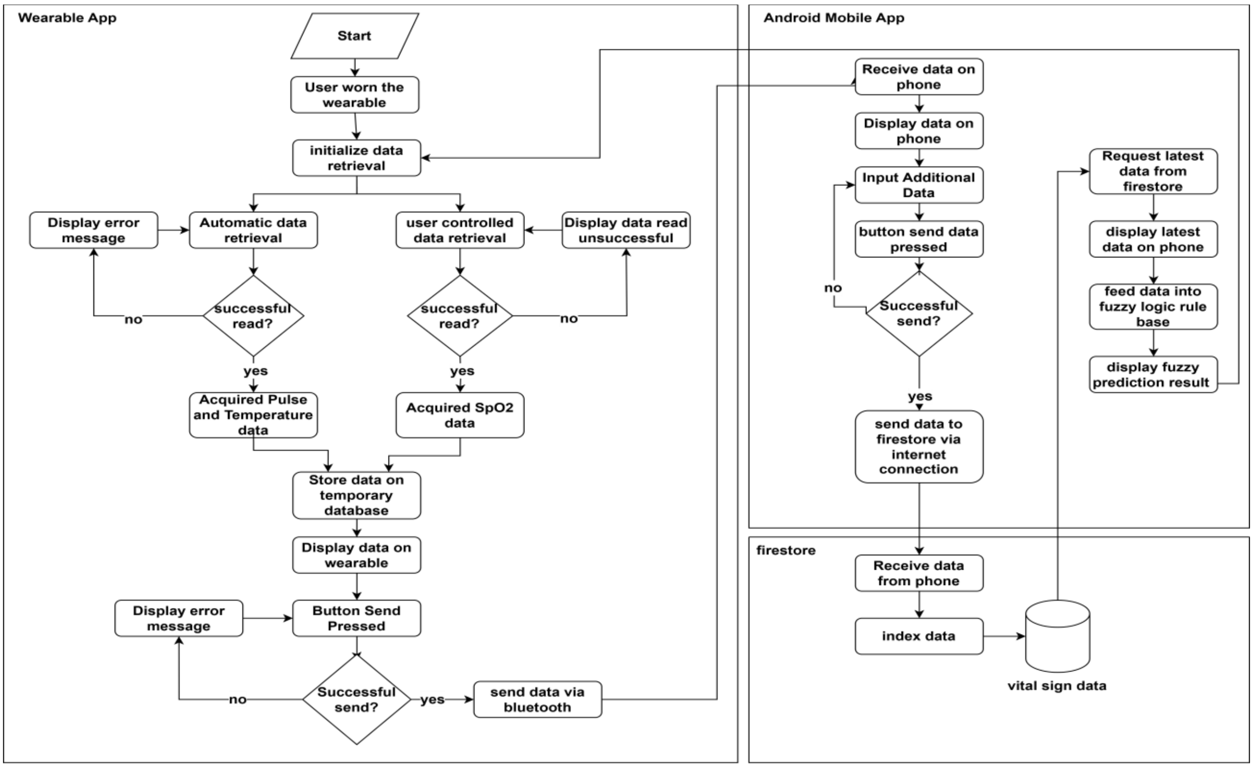


**Fig. 2:** System Flow

## *Data Acquisition*

Data gathering will be conducted to collect the necessary input data for developing and testing the fuzzy logic rule base. This process will commence after the full system implementation, enabling a seamless stream of data from the wearable device and smartphone application into the central database.

Data will be collected from a local volunteer sample to simulate real-world usage and populate the system with realistic vital sign readings. This sample consists of individuals within the author's household and immediate social circle.

The dataset will comprise the six variables designated as inputs for the fuzzy logic model:

- Heart Rate
- Oxygen Saturation ($SpO_2$)
- Body Temperature
- Systolic Pressure
- Diastolic Pressure
- Respiration Rate

All collected data will be recorded systematically, organized into a structured format, and transmitted to the cloud for persistent storage in the Firebase Firestore database.

## *Fuzzy Rule Base Modelling*

A fuzzy rule base is a set of expert-defined "if-then" rules designed to solve a specific problem by linking inputs to outputs. In this research, the rule base is designed to determine the emergency status of a COVID-19 patient. The rules applied are adapted from previous studies. For example, Mukhtar *et al*. (2021) defined severity rules as follows:

1. Class 0: Non-symptomatic
   - $SpO_2 \geq 95\%$
   - Heartbeat Rate $\leq 100$ bpm
   - Temperature $\leq 37.2$ °C
   - Cough Rate NIL
2. Class 1: Mild Symptoms
   - $93\% \leq SpO_2 \leq 94\%$
   - Heartbeat Rate $\leq 100$ bpm

- 36 °C ≤ Temperature ≤ 38 °C
- Cough Rate ≤ 5/min

3. Class 2: Moderate clinical symptoms
   - 93% ≤ SpO2 ≤ 94%
   - Heartbeat Rate > 100 bpm
   - Temperature ≥ 38 °C
   - 5/min ≤ Cough Rate ≤ 30/min
4. Class 3: Serious clinical symptoms
   - $SpO_2$ ≤ 94%
   - Heartbeat Rate > 120 bpm
   - Temperature > 38 °C
   - Cough Rate ≥ 30/min

## Results and Discussion

### *Android Wearable*

A companion wearable application for the Galaxy Watch 5 was developed in Java/Groovy using the Samsung Health SDK to initialize the device's sensors, including the Photoplethysmography (PPG) sensor for measuring $SpO_2$. The application establishes a data client to transfer the collected measurements via Bluetooth to the paired smartphone. The final application interface is shown in Figure 3.

The interface features two primary buttons. The first triggers an on-demand measurement of oxygen saturation ($SpO_2$), a function intentionally made manual to conserve battery life. The second is a "Send" button, which transmits the captured vital sign data to the connected Android application for subsequent processing.

### *Android Application*

A companion Android application was also developed in Java/Groovy. Its primary functions are to receive vital sign data from the wearable device, allow for the manual entry of additional clinical parameters, and transmit the complete dataset to Firebase for storage and processing. The application interface is shown in Figure 4.

The interface consists of two main sections: An input form for entering new patient data (including values sent from the wearable) and a display area showing the most recent vital sign submissions. The top section of the layout is dedicated to presenting the output classification generated by the fuzzy logic system.

**Fig. 3:** Application on wearable device


**Fig. 4:** Companion App

### *Data Acquisition*

To construct the fuzzy logic rule base, data were acquired from a sample of local volunteers using the implemented application, supplemented by a separate blood pressure monitor. The results of this data acquisition are presented in Table 1.

### *Fuzzy Modelling*

Based on the obtained data and WHO guidelines, the membership functions for each input and output variable were defined. Using the Mamdani method in MATLAB, membership functions were created for the following parameters: Heart rate, oxygen saturation, body temperature, systolic and diastolic pressure, and respiration rate. An example of a resulting input membership function is provided below:

Oxygen Saturation Membership Function $\mu$ (low) =
$1; x \leq 90$
$(92-x)/(92-90), 90 \leq x < 92$
$0; x \geq 92$
$\mu$ (medium) =
$0; x \leq 90 \text{ or } x \geq 96$
$((x-90))/((92-90)); 90 < x \leq 92$
$1; 92 < x \leq 94$
$((96-x))/((96-94)), 96 < x < 94$
$\mu$ (high) =
$0; x \leq 94$
$((x-94))/((96-94)); 94 < x \leq 96$
$1; x > 96$

These defined membership functions were then implemented as the input variables for the Mamdani method in the MATLAB simulation, as shown in Fig. 5.

**Table 1:** Data acquisition sample

| Heart rate | $SpO_2$ | Temperature | Systole | Diastole | Respiration Rate |
|---|---|---|---|---|---|
| 94 | 95 | 35 | 133 | 86 | 26 |
| 82 | 97 | 31.95 | 159 | 87 | 22 |
| 86 | 97 | 30.09 | 153 | 106 | 24 |
| 77 | 95 | 35.06 | 129 | 96 | 26 |
| 83 | 97 | 34.82 | 145 | 108 | 22 |

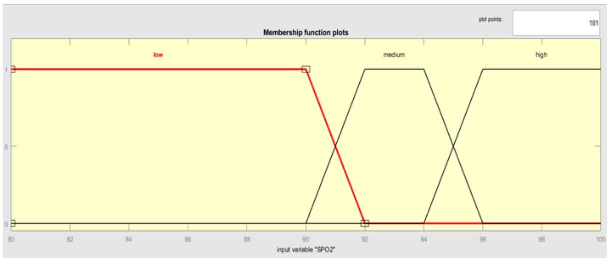


**Fig. 5:** Oxygen saturation membership function as input

Correspondingly, an output variable must be defined. For this model, the output is the emergency prediction level, with its membership function defined below:

$\mu$ (low) =
$1; x \leq 0.2$
$(0.3–x)/(0.3–0.2), 0.2 \leq x < 0.3$
$0; x \geq 0.3$
$\mu$ (medium) =
$0; x \leq 0.2 \text{ or } x \geq 0.7$
$((x-0.2))/((0.3-0.2)); 0.2 < x \leq 0.3$
$1; 0.3 < x \leq 0.6$
$((0.7–x))/((0.7-0.6)), 0.6 < x < 0.7$
$\mu$ (high) =
$0; x \leq 0.6$
$((x–0.6))/((0.6–0.7)); 0.6 < x \leq 0.7$
$1; x > 0.7$

This membership function is similarly configured as the output variable for emergency prediction in MATLAB, as shown in Figure 6.

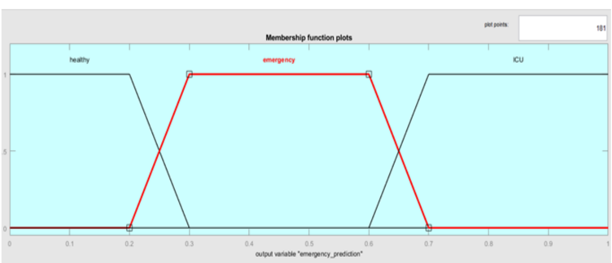


**Fig. 6:** Oxygen saturation membership function as input variable

Once all membership functions are defined, the rule base is established to map every possible interaction between inputs and output. A total of 64 rules were formulated to manage these relationships, for example:

1. IF oxygen saturation IS low AND heart rate IS high AND body temperature IS high AND systole IS low
2. And diastole IS low AND respiration rate IS high THEN emergency prediction IS icu
3. IF oxygen saturation IS high AND heart rate IS medium AND body temperature IS medium AND systole IS high AND diastole IS high AND respiration rate IS high THEN emergency prediction IS emergency
4. IF oxygen saturation IS medium AND heart rate IS medium AND body temperature IS medium AND systole IS low AND diastole IS low AND respiration rate IS medium THEN emergency prediction IS emergency
5. IF oxygen saturation IS high AND heart rate IS medium AND body temperature IS high AND systole IS medium AND diastole IS medium AND respiration rate IS low THEN emergency prediction IS emergency
6. IF oxygen saturation IS low AND heart rate IS medium AND body temperature IS high AND systole IS high AND diastole IS high AND respiration rate IS high THEN emergency prediction IS icu

This model can be evaluated using the MATLAB Rule Viewer, as shown in Figure 7. Following this validation, it was integrated into the Android application for implementation.

## *Findings*

After experimenting with the model through the application, the tests revealed that while the wearable successfully acquired the necessary sensor data, consistent readings often required multiple attempts. This was particularly true during hand movement, which disrupted the photoplethysmography (PPG) signal. Similar issues occurred during data acquisition, where the application occasionally failed to record reliably if the watch was worn loosely or during user motion.

Despite these limitations in data collection under certain conditions, the system demonstrated overall success. The core functionality, extracting vital signs and transmitting the data, was achieved reliably. Therefore, the wearable sensor component is deemed successful for the purposes of this evaluation.

The evaluation of the fuzzy rule base was conducted using five randomized test cases. For each scenario, including those representing potential emergencies, the system produced the expected severity classification.

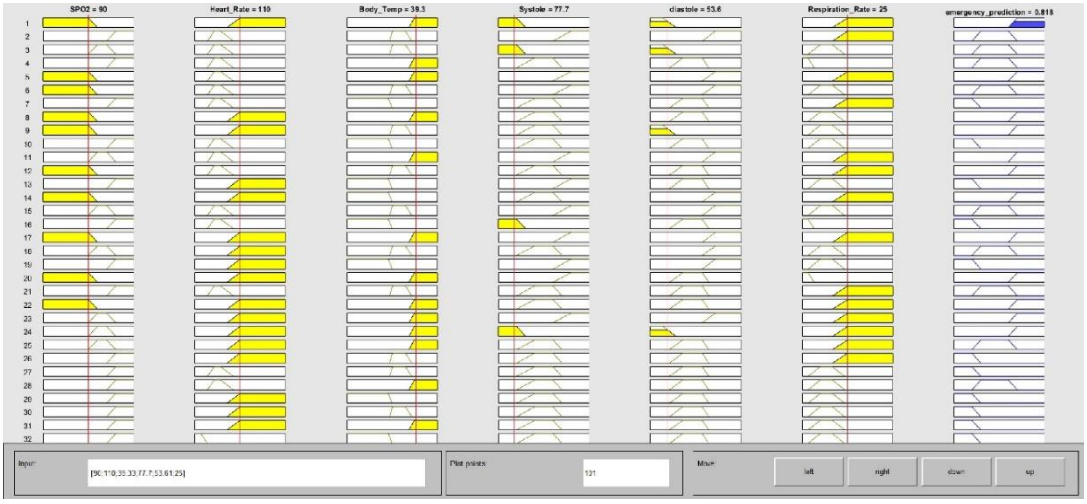

**Fig. 7:** Fuzzy model on rule viewer

In parallel, the application's functionality was assessed by verifying the numerical output against the clinical scenario and by evaluating the responsiveness of the user interface. The complete results of these tests are presented in Table 2.

**Table 2:** Model Evaluation

| Test No | Expected | Output | Status |
|---|---|---|---|
| Test 1 | Healthy | Healthy | Success |
| Test 2 | Emergency | Emergency | Success |
| Test 3 | ICU | ICU | Success |
| Test 4 | ICU | ICU | Success |
| Test 5 | Healthy | Healthy | Success |

## Conclusion

The COVID-19 pandemic, while devastating, has accelerated significant technological and social adaptations, including the rapid advancement of telemedicine. This study demonstrates that effective remote patient monitoring can be achieved using readily available consumer devices rather than custom-built hardware, provided the key health parameters are well-defined and accurately modeled. For COVID-19, these parameters are distinctly reflected in vital signs: Heart rate, oxygen saturation, body temperature, systolic and diastolic blood pressure, and respiration rate. This research successfully measured these variables and implemented a fuzzy logic model to assess patient status, enabling individuals in self-isolation to better understand their own condition.

The proposed system proved successful in identifying potential COVID-19 emergencies. However, its limitations suggest clear avenues for improvement. As this system utilized market-ready devices designed for fitness, future work could employ medical-grade wearables for more precise data acquisition. Subsequent studies could also incorporate additional diagnostic variables, such as patient comorbidities and recent laboratory results, to enhance severity assessment.

Ultimately, it is hoped that this model's framework can be extended to monitor other diseases, making healthcare more accessible to patients and providing clinicians with a powerful tool for remote care across various medical conditions.

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## Author's Contributions

**Bagaskara Akbar Fadhlillah**: Contributed to conceptualization, data curation, and methodology; developed software and visualizations; prepared the original draft of the manuscript.

**Ditdit Nugeraha Utama**: Conducted formal analysis; managed project administration and supervision; contributed to manuscript review and editing.

## Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

*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 study.

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