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Intelligent decision-making in healthcare telemonitoring via forward-backward chaining and IoT

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ABSTRACT

Healthcare telemonitoring has emerged as a promising approach to remotely monitor patients remotely, enabling timely intervention and personalized care. Internet of things (IoT) device-generated patient data necessitates innovative solutions for intelligent healthcare decision-making, as current methods struggle to provide timely, context-aware, and data-driven recommendations, resulting in suboptimal patient care. This study aims to develop an intelligent decision-making framework for healthcare telemonitoring by leveraging forward-backward chaining and IoT technology. The research focuses on a system using forward-backward chaining algorithms to analyze real-time patient data from IoT devices. It utilizes machine learning models to adapt to changing conditions and refine decision-making, demonstrating its ability to provide real-time context-aware recommendations. Temperature, blood pressure, oxygen level, and heart rate measurement errors are 2.01%, 1.74 to 2.13%, 0.61%, and 1.45%, respectively. The success rate of early disease diagnosis using an expert system is 81%, with an average application interface responsiveness time of 4.978 s. The integration of IoT data with intelligent decision-making algorithms in healthcare telemonitoring has the potential to revolutionize patient care. However, future work should focus on scalability and interoperability for diverse healthcare settings.

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1. INTRODUCTION

The convergence of cutting-edge technologies, such as the internet of things (IoT) and advanced data analytics with the healthcare industry [1], [2]. It has opened up new horizons in patient care and monitoring. Healthcare telemonitoring characterized by remote patient data tracking, presents an opportunity to address the evolving healthcare landscape and ensure timely, personalized, and efficient care [3]–[5]. However, the flood of real-time patient data generated by IoT devices presents a formidable challenge and need for intelligent decision-making to transform this data into actionable insights.

Healthcare telemonitoring has gained substantial traction in recent years due to its potential to enhance patient outcomes, reduce healthcare costs, and improve overall quality of care [6], [7]. IoT devices, ranging from wearable sensors to intelligent medical equipment, facilitate the continuous collection of vital patient data. While this technology shows great potential, it also introduces unparalleled difficulties to the healthcare industry, including translating substantial quantities of real-time patient data into well-informed decisions considering the context. Such decisions should enable healthcare providers to deliver optimal care.

The dynamic and heterogeneous nature of IoT-generated patient data, combined with the ever-evolving body of clinical knowledge and guidelines, makes it increasingly difficult for healthcare providers to make timely and well-informed decisions. Inaccurate or delayed decisions can significantly impact patient outcomes, resource allocation, and the efficiency of the healthcare system. The system aims to enhance healthcare decision-making by providing real-time, context-aware recommendations derived from IoT-generated data and improve healthcare telemonitoring quality by implementing forward-backward chaining algorithms [8].

The proposed solution is a system utilizing real-time patient data from IoT devices, historical records, clinical guidelines, and specialist knowledge. It refines decision-making and adapts to changing patient conditions using machine learning models. The system's objective is to augment the quality of patient care, optimize resource allocation, and decrease response times for healthcare providers. The design and implementation of a proposed system will be examined in this paper, with an emphasis on the integration of IoT-generated data and the utilization of forward-backward chaining algorithms.

The rest of this paper is structured as follows. Section 2 provides a detailed description of the proposed framework, including its components. Section 3 presents the system's testing and analyzes the implementation results. Finally, we conclude the paper in section 4 and discuss future work.

2. METHOD

2.1. Forward-backward chaining

Forward-backward chaining is an essential concept in the telemonitoring of healthcare patients in community settings. Forward chaining is a reasoning method that begins with the initial data and applies rules to reach conclusions which is shown in Algorithm 1 [9].

Algorithm 1 Forward chaining algorithm (Input: Γ, α) // α is a query, Γ is knowledge base

while True **do**
  new = {}
  for each sentence $s \in \Gamma$ **do**
    Convert s into the format $p_1 \wedge p_2 \wedge \cdots \wedge p_n \rightarrow q$
    for each substitution θ such that $(p_1^{'} \wedge p_2^{'} \wedge \cdots p_n^{'}) \leftarrow (p_1 \wedge p_2 \wedge \cdots \wedge p_n)\,\theta$ for some $p_i^{'}s \in \Gamma$ **do**
      $q^{'} \leftarrow q\theta$
      $new \leftarrow new \cup \{q^{'}\}$
      $\alpha \leftarrow unify(q^{'}, \alpha)$
      if λ is not null **then**
        return λ
      end if
    end for
    $\Gamma \leftarrow \Gamma \cup new$ ▷ add new inferences in knowledge base
  end for
end while
Return Fail

This approach integrates the benefits of forward and backward chaining methodologies to monitor and oversee remote patient health effectively. Healthcare providers can remotely monitor and address individuals' well-being by applying forward-backward chaining principles. Telemonitoring in community healthcare enables continuous monitoring of patient's vital signs, symptoms, and medication adherence. This proactive approach allows healthcare providers to identify potential health issues early and intervene promptly, improving patient outcomes and decreasing hospital readmissions. Expert systems utilize forward and backward chaining as reasoning techniques to emulate human intelligence. These techniques derive inferences and reach conclusions by utilizing the existing data.

On the other hand, backward chaining is a reasoning method that starts with the desired goal and works backward to identify the necessary data. Expert systems employ reasoning techniques to offer valuable insights and recommendations to healthcare providers, thereby enhancing their decision-making process [10]. Backward chaining is a problem-solving method that starts with the desired goal and works backward to determine the essential facts that need to be established in order to achieve the goal. Expert systems often employ this technique to address intricate problems and arrive at well-informed decisions. Backward chaining is a problem-solving approach that begins with the desired goal which is shown in Algorithm 2 [9]. This method eliminates unnecessary steps and focuses only on the information required to achieve the goal, resulting in a more focused and efficient process. Backward chaining is especially valuable in healthcare environments due to the urgency of time and the criticality of precise decision-making for patient care [11].

Algorithm 2 Backward chaining algorithm (Input: Γ, α, θ) // α is a query, Γ is knowledge base, θ current substitution(initially empty), λ represent substitution set for the query to be satisfied (initially empty)

$\theta = \{\}, \lambda = \{\}$
$q^{'} \leftarrow \alpha\theta$
for each sentence $s \in \Gamma$, where $s = p_1 \wedge p_2 \wedge \cdots \wedge p_n \rightarrow q$ and $\gamma \leftarrow unify(q, q^{'}) \neq null$ **do**
  $\alpha_{new} \leftarrow (p_1 \wedge p_2 \wedge \cdots \wedge p_n)$
  $\theta \leftarrow \theta\gamma$
  $\lambda \leftarrow$ backward-chaining $(\Gamma, \alpha_{new}, \theta) \cup \lambda$
end for
return λ

The data used in the forward-backward chaining system is shown in Tables 1–3. The responses to questionnaires distributed to several respondents and the outcomes of interviews with medical personnel provided the information for Tables 1–3. The community has five prevalent diseases: hypertension, diabetes, heart failure, bronchitis, and diarrhea [12]–[16]. These diseases have been extensively studied, and their symptoms, risk factors, and treatment options are well documented. The data in Table 1 provides a comprehensive overview of the prevalence and characteristics of these suspected diseases (SD) within the community.

Table 1. Suspected disease data

Code	Suspected disease
SD1	High blood pressure (hypertension)
SD2	Diabetes
SD3	Heart failure
SD4	Bronchitis
SD5	Diarrhea

Table 2 displays 32 prevalent disease symptoms (DS) for five predetermined diseases [17]–[19], it does not provide information on the risk factors or treatment options for these diseases. Therefore, additional research may be necessary to fully understand the implications of these symptoms and how they relate to the prevalent diseases in the community. Table 3 provides information on the 24 preventive and assistance actions required for the five diseases [20], [21]. By implementing these preventive and assistance actions, communities can take proactive steps towards reducing the burden of these prevalent diseases and promoting overall health and well-being.

Figure 1 shows the design of the expert system used in the health monitoring system in this study. Figure 1(a) depicts a disease inference engine using the forward chaining method. This figure explain the forward chaining technique for determining the disease from data on disease symptoms. The probability method will be used to determine the most significant percentage of the symptoms of the disease to determine the initial diagnosis of the user's disease. This inference engine can be a valuable tool in healthcare settings as it allows for early detection and prompt treatment of diseases. By accurately identifying the initial diagnosis, healthcare professionals can provide appropriate interventions and improve patient outcomes. This technology can also aid in disease surveillance and monitoring at the community level, enabling timely public health interventions to prevent disease outbreaks and promote overall well-being.

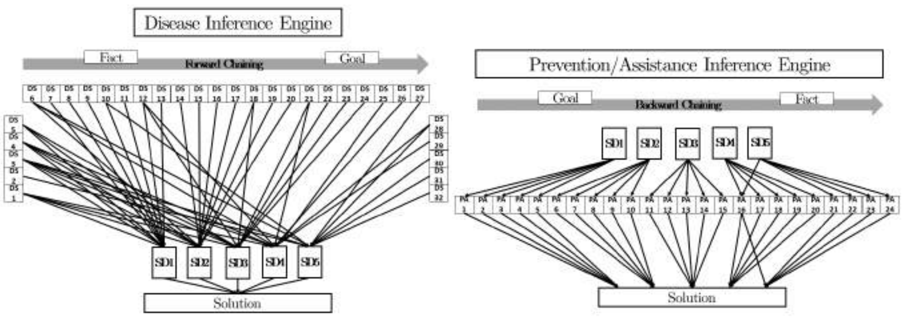
In addition, refer to Figure 1(b) to determine the necessary actions for the emerging diseases. This figure explains the preventive/assistance inference engine utilizing the backward chaining technique. After determining the disease that arises, several appropriate preventive and assistance actions will be performed. These actions may include providing vaccinations, implementing quarantine measures, conducting contact tracing, and distributing educational materials on disease prevention. By utilizing the backward chaining technique, public health officials can efficiently respond to emerging diseases and mitigate their impact on the community. This approach ensures a proactive and targeted approach to disease prevention and control.

Table 2. Disease symptom data

Code	Disease symptoms	Code	Disease symptoms	Code	Disease symptoms
DS1	High blood pressure	DS12	Chest pain	DS23	Coughing continuously
DS2	Low blood pressure	DS13	Feeling anxious	DS24	Excess fluid buildup (edema)
DS3	Rapid and irregular heartbeat	DS14	Frequent urination	DS25	Dry cough followed by cough with phlegm
DS4	Low oxygen levels	DS15	Feeling hungry	DS26	Sore throat
DS5	Unstable body temperature	DS16	Feeling thirsty	DS27	Low-grade fever
DS6	High body temperature	DS17	Weight management	DS28	Weakness
DS7	Headache, especially in the back of the head	DS18	Feeling tired	DS29	Dizziness
DS8	Vertigo	DS19	Dry skin	DS30	Liquid/loose stool
DS9	Buzzing or hissing in the ears	DS20	Wounds difficult to heal	DS31	Blood appears in the stool
DS10	Nausea/vomiting	DS21	Shortness of breath (dyspnea)	DS32	Flatulence and heartburn
DS11	Vision problems	DS22	Swelling of the legs		

Table 3. Preventive/assistance action data

Code	Preventive actions	Code	Preventive actions	Code	Preventive actions
PA1	Reduce salt intake	PA9	Control blood sugar levels	PA17	Take adequate rest
PA2	No smoking	PA10	Consult a doctor	PA18	Steam inhalation
PA3	Exercise regularly	PA11	Call the nearest hospital	PA19	Taking medication
PA4	Avoid stress	PA12	Take the patient to a safer place	PA20	Avoid triggering factors (cigarette smoke, air pollution and other chemicals)
PA5	Avoid alcohol consumption	PA13	Loosen the patient's clothes	PA21	Consume easily digestible foods
PA6	Give sugary drinks	PA14	Do not panic excessively	PA22	Take natural diarrhea medication such as chamonile tea
PA7	Take glucose tablets	PA15	Provide basic life support (CPR) if needed	PA23	Take oral rehydration solution (ORS)
PA8	Treat diabetic wounds	PA16	Drink enough water	PA24	Seek medical attention if diarrhea persists or is accompanied by other symptoms



(a) (b)

Figure 1. Expert system on health telemonitoring (a) diseases inference engine with forward chaining method and (b) preventive/assistance inference engine with backward chaining method

2.2. Development method

The research will explore the development of hardware and software platforms for health telemonitoring systems. It will begin with a literature review on materials for improving manufacturing and design processes, including sensors and signal conditioning. The platform will be conceptualized, focusing on mechanical and electrical aspects. The design process will involve a comprehensive arrangement and design of the system, aiming for ergonomic and efficient design. The assembly process will involve the sequential installation of mechanical components and the integration of electrical circuitry. Platform testing will assess the system's effectiveness and suitability for alternative measurement devices. The instrument's input block contains several sensors, including the MLX90614, MPX5500DP, ADS1115, and MAX30100 sensors, as shown in Figure 2.

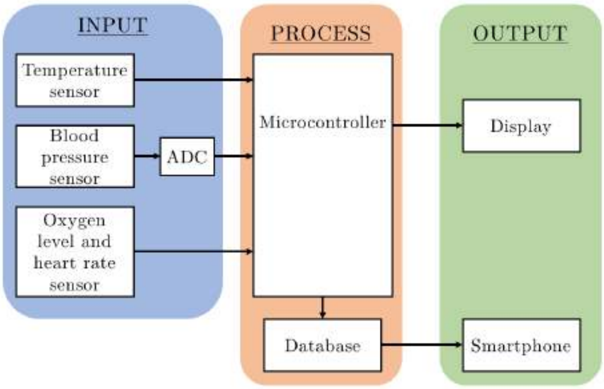


Figure 2. Block diagram of health telemonitoring system

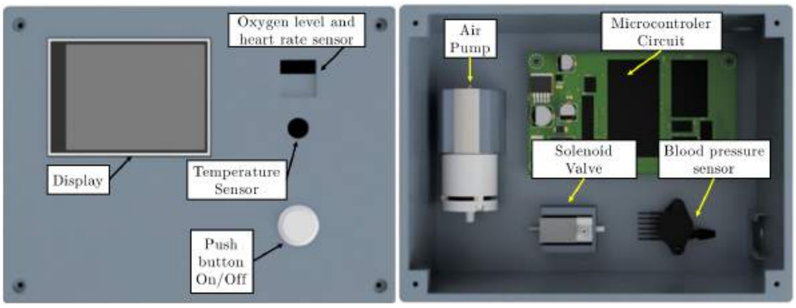
The health telemonitoring system uses various sensors to measure physiological parameters such as body temperature, blood pressure, oxygen levels, and heart rate. The MLX90614 sensor measures body temperature, while the MPX5500DP sensor measures blood pressure. The ADS1115 is an external analog to digital converter (ADC) that converts analog signals into digital ones. The MAX30100 sensor measures oxygen levels and heart rate. The ESP32 microcontroller processes the data and displays it on a thin-film-transistor (TFT) display. The data is then transmitted to a firebase database, which is stored for easy retrieval via the Kodular application. The output block features a 2.8-inch TFT display, and the smartphone allows access to the Kodular application, which retrieves the data stored in the database. The health telemonitoring system uses various sensors to evaluate physiological parameters.

2.3. Mechanical design system

The health telemonitoring system tool uses 3D printing technology, utilizing polylactic acid (PLA) material as the primary substrate. The device measures $16.8 \times 12.8 \times 8$ cm. Figure 3 shows the schematic representation of the mechanical design of the health telemonitoring system. Figure 3(a) shows the arrangement of components at the top of the apparatus, including a 2.8-inch TFT display screen, a MAX30100 sensor, an MLX90614 sensor, and a push button. Figure 3(b) illustrates the components involved in the system, including a printed circuit board (PCB), an air pump, a solenoid valve, and an MPX5500DP sensor.

2.4. Electrical design system

The device's electronic system comprises three components: input, processing, and output. The input system includes three sensors: the MLX90614 temperature sensor, the MAX30100 oxygen level and heart rate sensor, and the MPX5500DP pressure sensor. The output system uses a TFT 2.8-inch display. The MLX90614 sensor is a non-contact temperature sensor that uses thermopile and infrared technology to measure objects' temperature. The MAX30100 sensor uses infrared and red-light technology to measure vital physiological parameters like heart rate and blood oxygen saturation. The MPX5500DP sensor uses piezoresistive technology to measure pressure differences between two locations. The TFT display uses TFT technology to control pixels on the screen, enhancing visual acuity, precision, and fidelity compared to traditional display systems. The system uses the photoplethysmography (PPG) method to determine pulse rate and blood oxygen saturation levels.



(a) (b)

Figure 3. Mechanical design of health telemonitoring system from (a) upper view and (b) inside view

2.5. IoT device integration

The IoT is a wireless device network that collects, transmits, and stores data. It connects various physical devices and facilitates data gathering and sharing [22], [23]. In the medical domain, it is often called the internet of health things (IoHT) is shown in Figure 4.

IoHT can improve treatment effectiveness, mitigate risks, and support good health by monitoring individuals in real time and providing better access to high-quality healthcare [24], [25]. IoT devices facilitate the digital storage of personal health information for patients and establish connections with multiple databases. IoT also facilitates cost-effective and secure real-time communication between healthcare institutions. IoT has the potential to improve personalized medicine and remote health assessment. Advancements in other technological domains can contribute to significant progress in biotelemetry. Overall, IoT has the potential to enhance healthcare by providing efficient, secure, and cost-effective communication between healthcare institutions.

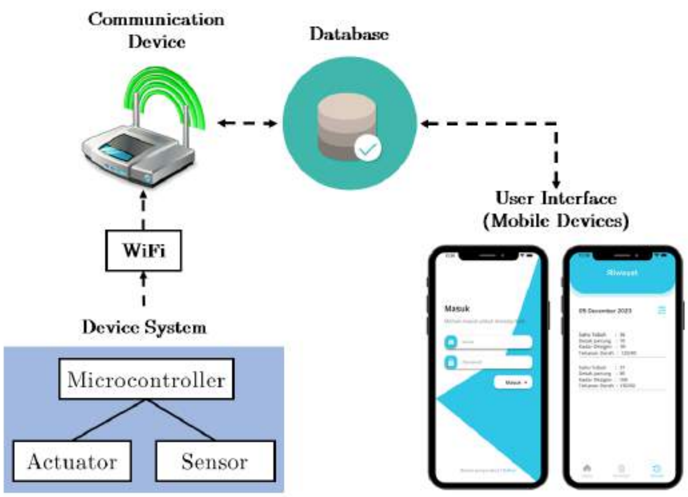


Figure 4. An overview of the internet of things system

2.6. User interface design of health telemonitoring system

This study aims to implement an IoT based telemonitoring system to remotely monitor essential health parameters such as oxygen levels, heart rate, blood pressure, and body temperature. The system effectively integrates with a specialized application, facilitating the seamless real-time transmission and analysis of data. This application is intended for Android and iOS smartphone users. The use of a database is necessary to store and provide data on sensor measurements, including their value, status, and historical records. The firebase database is recommended for this purpose. This program includes various functionalities such as displaying database-retrieved data, implementing a user account login and registration system, transmitting data to the database, and facilitating data exchange via Bluetooth. Figure 5 illustrates the android design of the telemonitoring system, displaying data on oxygen levels, heart rate, blood pressure, and body temperature using IoT technology. The graphical user interface (GUI) of the health monitoring system consists of a login page in Figure 5(a), a main page in Figure 5(b), a device configuration page in Figure 5(c), a history page in Figure 5(d), the backward analysis page in Figure 5(e), and the forward analysis page in Figure 5(f).

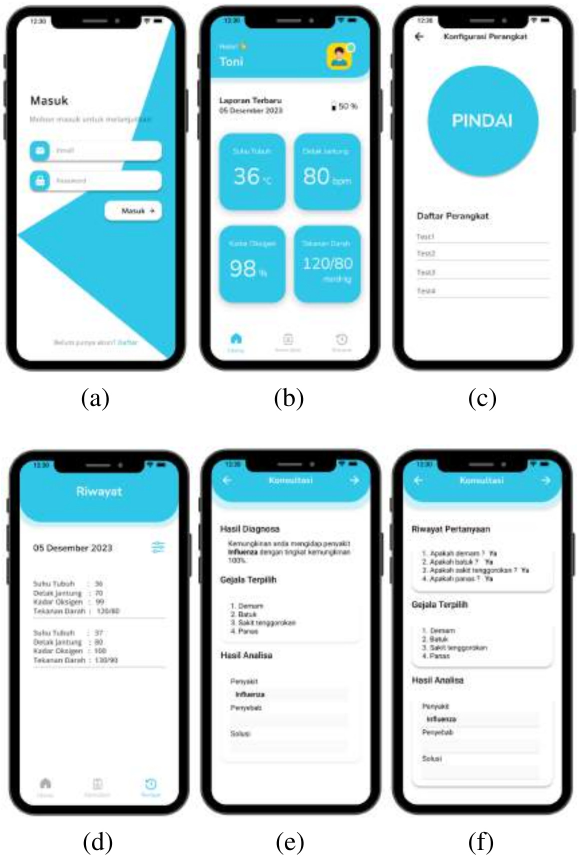


Figure 5. An illustrative GUI design for a health telemonitoring system: the application consists of: (a) a login page, (b) a main page, (c) a device configuration page, (d) the history page, (e) the backward analysis page, and (f) the forward analysis page

3. RESULTS AND DISCUSSION

3.1. Sensor testing for the measurement of four health vital signs

This section describes the results of sensor testing for four vital signs. The first test performed on the sensor was comparing the MLX90614 temperature sensor to a calibrated thermometer. The test results revealed a percentage inaccuracy of 2.014 and an average standard deviation of 0.127 is shown in Figure 6.

Based on these results, it appears that the sensitivity of the temperature sensor must be improved by experimenting with more sensitive temperature sensors to acquire more precise measurements. Improving the temperature sensor's sensitivity is essential for accurate measurements, particularly in healthcare contexts where precise monitoring is essential. By investigating alternative temperature sensors with greater sensitivity, healthcare professionals can acquire more reliable and accurate data for patient health monitoring.

The subsequent test will compare the MPX5500DP sensor's measurement results to those of a calibrated digital sphygmomanometer. The results of the three health vital signs measurements are shown in Figure 7. The average errors of systole and diastole were 2.13 and 1.74, respectively, with standard deviations of 3.090 and 2.164 for systole and diastole is shown in Figure 7(a). Compared to a calibrated digital sphygmomanometer, the MPX5500DP sensor provides relatively accurate measurements of systole and diastole.

Additional analysis and testing are required to ascertain the overall reliability and consistency of the sensor's readings in various patient scenarios.

Two further tests were performed to assess the oxygen level and heart rate. This study conducted a comparative analysis of the MAX30100 sensor and a calibrated oximeter is shown in Figure 7(b). The test findings indicate that the average error in measuring oxygen level and heart rate is 0.61 and 1.45, respectively. The standard deviation values for oxygen level and heart rate measurements were determined to be 1.023 and 1.515, respectively. The findings suggest that the measurements obtained from the MAX30100 sensor about oxygen saturation and heart rate exhibited a moderate degree of inaccuracy on average, accompanied by a reasonably slight standard deviation. Nevertheless, it is imperative to acknowledge that additional examination and experimentation are required to ascertain the comprehensive dependability and uniformity of the sensor's measurements across different patient scenarios.

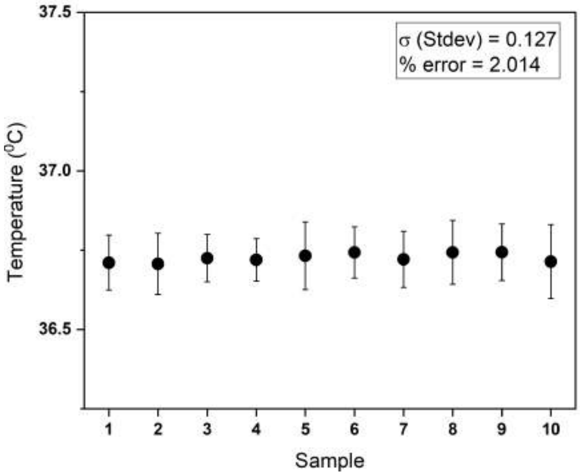


Figure 6. Test results for body temperature using the MLX90614 sensor

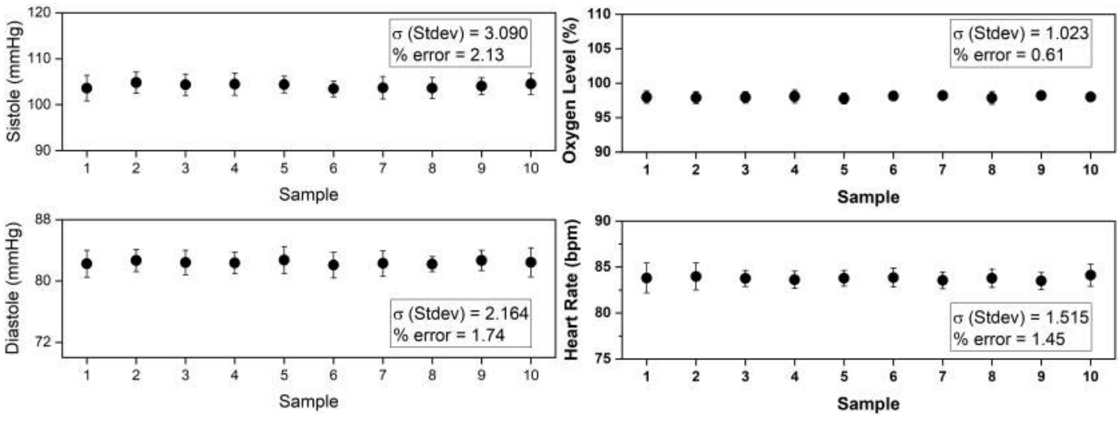


Figure 7. Measurement results of three health vital signs (a) blood pressure (systole and diastole) using MPX5500DP sensor and (b) oxygen levels and heart rate with MAX30100 sensor

3.2. Forward-backward chaining expert system testing

This section provides an overview of the testing process for the forward-backward chaining expert system in the context of the user health telemonitoring system. Table 4 presents the results of expert system testing, specifically employing forward-backward chaining, for early disease identification. A study was done on 100 participants, who were subsequently separated into five distinct groups based on their suspected disorders. The health data of each participant was obtained and entered into the expert system, which subsequently performed a sequence of commands to assess the data and ascertain potential disorders. The testing procedure encompassed the execution of diverse scenarios and the assessment of the system's diagnostic precision. The findings shown in Table 4 offer significant insights into the efficacy of forward-backward chaining for early disease detection in the user health telemonitoring system.

Test group 1 exhibits the highest propensity for hypertension, as evidenced by 17 accurate diagnoses. Test group 2 exhibits the highest chance of diabetes, achieving 15 accurate diagnoses. The third test group demonstrates 16 accurate diagnoses of heart failure condition. Test group 4 shows 15 accurate diagnoses, with the highest chance percentage observed in cases of bronchitis disease. In the fifth test group, 18 accurate diagnoses were observed, with the most significant likelihood being attributed to identifying the Diarrhea condition. Out of a sample size of 100 users, 81 accurate diagnoses were achieved, resulting in an 81% success rate for early disease diagnosis using the expert system. The demonstrated high success rate serves as evidence for the efficacy of the expert system in effectively diagnosing a range of ailments. The capacity to accurately detect and anticipate illnesses in their first stages can significantly enhance patient outcomes and optimize the efficiency of healthcare systems.

This healthcare telemonitoring system assists patients in self-care by: (i) enhancing behaviours that promote emotional and physical well-being (self-care). This system is especially beneficial for patients who rely on app-based education to ensure the ongoing delivery of educational programs that empower them to manage respiratory exacerbations and maintain their emotional and physical well-being [26], (ii) employ self-monitoring techniques to promptly identify signs and symptoms that signify a patient's health condition deterioration. Indeed, this review has demonstrated that implementing telemonitoring with operator support or patient reminders prevents acute stages, particularly in patients with decompensated diseases, and enables early detection of health status deterioration [27], and (iii) enables all patients to implement lifestyle modifications (self-management) expeditiously, mainly when app-based educational programs are utilized [28].

Table 4. Expert system testing (forward-backward chaining) on early diagnosis of diseases

Expert system diagnosis result		Conventional diagnosis result	Number of correct diagnoses /user	Expert system diagnosis result		Conventional diagnosis result	Number of correct diagnoses /user
Suspected disease (SD)	% Probability			Suspected disease (SD)	% Probability		
SD1	57.14	High blood pressure (hypertension)	17/20	SD1	60.14	Bronchitis	15/20
SD2	15.33			SD2	15.73		
SD3	12.5			SD3	12.5		
SD4	9.74			SD4	6.34		
SD5	5.29			SD5	5.29		
SD1	60.14	Diabetes	15/20	SD1	53.54	Diarrhea	18/20
SD2	12.33			SD2	17.33		
SD3	10.5			SD3	14.5		
SD4	9.74			SD4	9.34		
SD5	7.29			SD5	5.29		
SD1	70	Heart failure	16/20				
SD2	13.33						
SD3	9.3						
SD4	5.08						
SD5	2.29						
						Total	**81/100**

3.3. Application interface responsiveness test

Application Interface interface responsiveness measures the time required to control the device through the interface. The average time for the application interface responsiveness test is displayed in Table 5 as 4.978 seconds. The application is tested by issuing commands, such as tapping the on/off switch on each module setting and calculating the time required for the device to respond. The internet network and/or prior device commands affect the response time test results. It is essential to observe that the response time test results may vary based on the stability and speed of the Internet network. Additionally, any preceding commands executed on the device may affect the response time.

Table 5. Application interface responsiveness test result

Data delivery no.	Time (s)
1	6.32
2	4.23
3	6.36
4	3.98
5	7.19
6	5.46
7	2.16
8	6.75
9	5.8
10	1.53
Average time	**4.978**

4. CONCLUSION

The objective was to construct a sophisticated decision-making framework by integrating IoT data and forward-backward chaining to enhance patient care quality, optimize resource distribution, and furnish healthcare providers with the essential instruments to make well-informed and prompt judgments. According to the research, our intelligent decision-making system can provide real-time, context-aware recommendations in a simulated healthcare environment, thereby reducing response times, optimizing resource allocation, and augmenting the quality of patient care. The early disease diagnosis expert system has a success rate of 81% and an average application interface responsiveness time of 4.978 s. Potentially transforming patient care, this data-driven decision support can generate enhanced outcomes and more streamlined healthcare systems. In the future, additional supporting sensors and those with greater sensitivity can be added to this task. Additionally, other artificial intelligence can be used to improve the success rate of early disease diagnosis.

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