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# Fog Enabled Intelligence Clinical Decision Support System (FICDSS) For Healthcare Applications Using Fuzzy Logic Inference System (FLIS)

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**Abstract**
In today's world, healthcare facilities are a major problem, particularly in underdeveloped nations where rural areas lack access to high-quality hospitals and medical specialists. Soft computing has improved health in the same way that it has benefited other sectors of life. Smart healthcare applications rely heavily on wearable technologies. The technique of detecting and analyzing physiological data from healthcare sensor devices is critical in smart healthcare. Fog computing is used to reduce the delay imposed by cloud computing by analyzing physiological data. However, in a fog environment, latency for emergency health status and overloading become major difficulties for smart healthcare. This study addresses these issues by proposing a unique Fog enabled Intelligence Clinical Decision Support System (FICDSS) health architecture for physiological parameter detection that enhances therapeutic and diagnostic efficiency in the health area. Sensor layer, edge layer, fog layer, and cloud layer are the four layers that make up the entire system. Data from patients' wearable or non-wearable devices is sent over an interface to an edge layer with a microcontroller system in the first layer. The edge layer's goal is to collect, process, and transfer data to the fog layer for intelligent computing. We introduced the Fuzzy Logic Inference System (FLIS), which determines the user's health condition using temporal changes in data gathered from devices deployed at the edge layer to forecast the user's health state in real time. The FLIS system takes context information from the sensor as input (in crisp form), and the fuzzification module turns the input into a fuzzy linguistic variable, which is then provided to the patient or doctor as an output. The fog layer detects the user's

health state based on health parameter attributes. Finally, response and real time data from sensors is observed at cloud layer. Both cloud and fog layers take rapid response based on the user's health state. A comprehensive simulation in the MATLAB tool is used to build and evaluate the suggested fuzzy logic inference system. In terms of latency, execution time, and detection accuracy, it performs better.

**Keywords**: Clinical decision support system (CDSS); Fuzzy Logic Inference System (FLIS); Healthcare, Fog Computing; Internet of Things.

## 1. Introduction

In recent years, smart healthcare has emerged as a new internet of things application (IoT). IoT introduces gadgets for monitoring health to the healthcare system, which is the most dependable and cost-effective option. Sensors may be used to get health data with the aid of IoT [1]. Healthcare is a system that aims to enhance people's health and aid in the treatment of ailments. Wearable sensors are employed in a smart healthcare system to monitor the users' or patients' unique health condition. Most importantly, wearable technology has become a key component of not only remote patient monitoring but also routine user health monitoring. The emergence of wearable technologies has reduced the need for doctors to be involved in health monitoring on a regular basis. It also helps with illness diagnosis, medication development, smart hospital development, and safety providing. To build a smart healthcare system, two key technologies must be explored. To begin, the user's health state is investigated using biological sensors such as temperature, mobility, and blood pressure, as well as how wearable devices are attached to the user's body. Second, the beneficial fog computing technology that allows for real-time and delayed health services should be investigated. The data received from wearable or non-wearable devices is processed by the fog layer as a result of the fog-enabled healthcare system, further reducing latency for healthcare services [2-4].

Due to population growth and changing lifestyles throughout the world, the number of people visiting hospitals has increased in recent decades. As a result, the Medicare health system is under a lot of strain. On the other side, visiting the hospital is extremely difficult for the elderly, crippled, impoverished, or those who live far away. As a result, their medical condition may deteriorate to the point of death. As a result, remote health care solutions were created to address the above-mentioned complex difficulties with the Medicare health system. In which the patient's vital signs are read by electronic sensors and relayed via the internet to the hospital server so that the doctor can observe, diagnose, and prescribe the necessary medicine to heal the patient without the patient having to visit the hospital. The fact that certain diseases are well-known yet their origins and symptoms are unknown is a major issue with some diseases. As a result, predicting those diseases is difficult and ineffective unless highly qualified physicians or medical specialists are involved. With increased research and constant development of medical knowledge, physicians are finding it increasingly

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challenging to stay current on medical treatments outside of their specialty. Another crucial component is the ability to organise data, execute mathematical computations, and obtain results quickly. It's simple to get outcomes if you have the right facts and knowledge. Medical practitioners find it difficult to establish an accurate medical diagnosis due to the imprecise and unpredictable nature of medical data. Medical practises are becoming more complicated. It is critical to have access to personal medical specialists or to receive their advice in a timely manner [3] [5].

Computational techniques are gaining popularity in illness monitoring and treatment operations. As a result, computational intelligence and soft computing are assisting in the current era in a big way by creating new approaches to enhance therapy and diagnosis of difficult and challenging situations. Soft computing is a research project aimed at emulating human intelligence in computer technology, and several researchers have expressed interest in its medical applications [6]. One of the most effective qualitative computational approaches is fuzzy logic, which is one of the soft computing techniques. In the realm of medicine, fuzzy logic has been proved to be one of the most effective techniques for bringing clarity [7]. Fuzzy logic works with a large number of truth values. These values are frequently ambiguous, imprecise, and unclear. Flexible options for modifying the model without affecting the underlying logic of detection are available with fuzzy logic-based intelligent systems. The reason for this is that, unlike other machine learning algorithm languages, fuzzy logic is flexible and has less coupling in the system since the knowledge base is distinct from the code. If the knowledge base changes, the code also changes, and the code must be modified. Productivity and production have increased. Reduced decision-making time, as well as the requirement for costly expertise [8] [9].

A unique and intelligent healthcare system is presented in this paper, which is based on contemporary technologies such as the Internet of Things (IoT) and Soft Computing. This system is capable of sensing and processing patient data using a clinical decision support system that employs a fuzzy logic inference engine. This device is a low-cost option for people living in distant regions; they may use it to determine if they have a significant health problem and seek treatment by calling nearby hospitals. To arrive at a conclusion, the suggested system considers physiological characteristics or vital signs such as temperature, blood pressure (BP), heart rate, respiration rate, oxygen saturation, and blood sugar. The following is how the rest of the article is structured. The section "related work" gives a high-level overview of the current system architecture. We address suggested work in section "proposed work," "results and discussion" in part "results and discussion," and "conclusion" in section "conclusion," which describes the system's conclusion.

## 2. Related work

In this section some related approaches have been discussed. Authors discussed [1] a descriptive study of FL and its applications in healthcare-related domains. The goal of this paper [2] is to illustrate how fuzzy set theory, fuzzy decision-

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making, and hybrid fuzzy solutions may be employed in various models for supplier assessment and selection over a years. The use of fuzzy logic with a decision-making technique [3] offers a lot of research potential. It can aid academics in identifying the fuzzy logic's frontiers in the realm of decision making. A framework for enabling IoT applications to adaptively learn from other IoT applications is provided [4], and we give a case study of how the framework may be applied to real-world studies in the literature with important characteristics that influence future intelligent IoT applications. A fuzzy-logic-based context model and accompanying context-aware reasoning middleware [5] is given, which provides a customized, adaptable, and extendable reasoning framework for CARA, as well as findings indicating the system's viability for successful at-home monitoring. A brief overview of the broad usage of IoT solutions in health care is addressed [6] regarding the current developments in fog/edge computing for smart health, beginning with early health monitoring solutions from wearable sensors. [7] A five-layered heterogeneous mist, fog, and cloud-based IoHT architecture capable of effectively processing and routing real-time as well as offline/batch mode data is given. The system also provides optimum resource allocation and effective resource usage by using software defined networking and link adaption based load balancing. [8] A software architecture based on Fog Computing and aimed to simplify the maintenance of medical data was shown, in which Blockchain principles were used to offer the essential privacy characteristics and to allow Fog Nodes to carry out the authorisation procedure in a distributed manner.

According to the authors [9], this necessitates a shift from clinic-centric treatment to patient-centric healthcare, in which each agent, such as the hospital, the patient, and the services, are seamlessly connected to one another, necessitating a multi-layer architecture: (1) device, (2) fog computing, and (3) cloud to enable the handling of complex data in terms of its variety, speed, and latency. An implementation of the Intuitionistic Fuzzy Logic Decision Support System (IFLDSS) based on the Modified Early Warning Score (MEWS) standard in the Tunisian Sfax city-based ESSALEMA polyclinic also achieved results that appear to reveal that the IFLDSS demonstrates a commanding capacity in detecting uncertainty related to ICU patients' deteriorating cases [10]. The Anti-Diabetes Centre (CAD) of the Local Health Authority ASL Naples 1 (Naples, Italy) used fuzzy inference machines [11] to improve the quality of day-to-day clinical care of type-2 diabetic patients. It also allows remote monitoring of patients' clinical conditions, which can help to reduce hospitalizations [12]. A solution [13] that uses fuzzy rules to categorize the health statuses of monitored individuals was studied, as well as the computational cost of rule assessment in the Cloud and on Edge devices. A novel and intelligent healthcare system [14] has been introduced that is based on modern technologies such as the Internet of Things (IoT) and machine learning, and is intelligent enough to sense and process a patient's data through a medical decision support system with a low-cost solution for people living in remote areas. The authors utilized [15]

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Blood Pressure and human Body Temperature measurements as inputs and employed a fuzzy logic method to get more Pragmatic findings than any linear model. The design and implementation of an equivalent warning system [16] that employs fuzzy logic techniques to categorize patients' status also demonstrated that the implemented system produces reliable results that are comparable to the current Modified Early Warning Score system, with the added benefit of a scoring scheme that provides a better insight into the status or medical condition.

A fuzzy logic system based home healthcare system [17] is discussed for the chronic heart disease patients (in stable conditions) for out-of-hospital follow-up and monitoring which provided an innovative, timely resource and a supplement for the existing healthcare systems helping practioners's to treat efficiently to cardiac patients who lived alone at their homes. The goal of the work given [18] is to forecast or categorize the critically conditioned ICU patients for taking prompt steps to minimize the death rate with a comprehensive medical decision for the physicians. Authors compiled [19] of a complete research and analysis of contemporary IoT based patient monitoring systems with their design and security problems in ICU. A unique method created [20] where the caregivers may obtain the information about the temperature and the heart rate of the persons being watched at home. This work was tested [21] on a collection of data in order to show its efficacy furthermore simulation offers good results in identifying the activities of the individual generating an efficient system for health monitoring as comparison with conventional system. An analysis to monitor the fitness hazard which is related [22] to Blood Pressure, Pulse rate and Kidney function is proposed. The suggested approach employs [23] sophisticated methods and services like as embedded data mining, distributed storage, and notification services at the edge of the network.

The proposed system is built [24] based on three medical indicators as blood pressure, heart rate, and body temperature with Fuzzy Inference System (FIS) in order to get the infer result information to make decision which can help the doctors in determining the initial medical state of patients and make the right decision[25]. An intelligent fuzzy inference method is built [26] for the main diagnosis of COVID-19 which aid physicians in recognizing the condition and allow patients to undertake self-diagnostic on their own cases. A hybrid OFBAT-RBFL heart disease detection system is created [27] utilizing opposition based learning (OBL) which is hybrid to the firefly with BAT algorithm to increase the efficiency of the FAT algorithm while improving the rules of the fuzzy logic system. Resulting better performed than the previous strategy. A Fuzzy controller-based system [28] is suggested for assessing pedestrian flows and computing the shortest evacuation distance in panic circumstances. A ubiquitous system is described [29] to monitor the COVID'19 patient's circumstances within the hospital and outside by monitoring their medical and psychological status which allows improved healthcare support, especially for COVID'19 patients and quarantined persons. Also their results suggested that

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the utility of monitoring the COVID'19 patients depending on the present situation. The study thus evaluates [30] the privacy protection of healthcare data of the smart healthcare management system using the Fuzzy Analytical Hierarchy Process Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy AHP-TOPSIS) that the proposed fuzzy model can give the highest risk evaluation performance compared to existing models.

The goal of the research [31] is to develop a realistic solution for enhancing care for older individuals, while considerably decreasing the healthcare cost with robust and high accuracy identification rate.

## 3. Proposed work

Our proposed architecture implementation includes four layers: Things, Edge, Fog and Cloud layers which as shown below in figure 1.

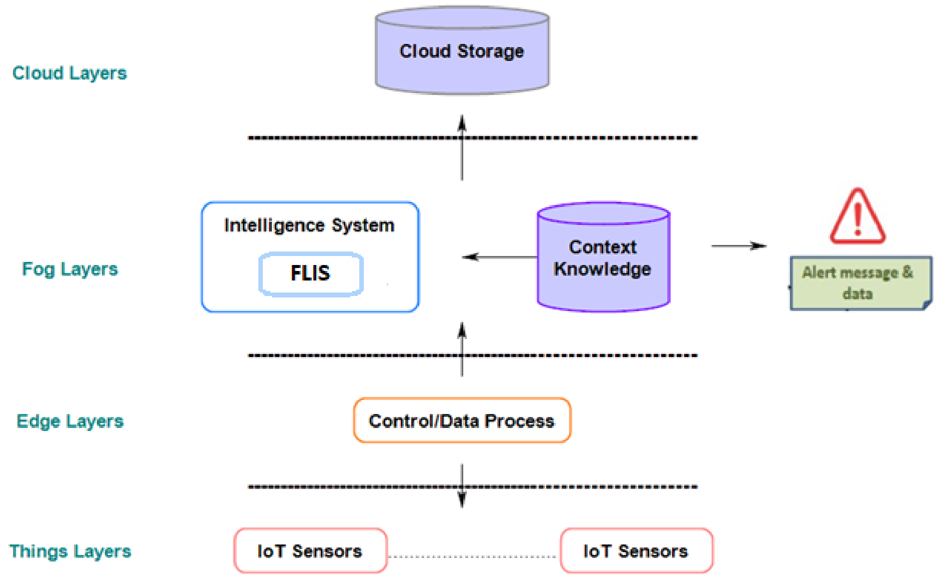


**Fig.1. Proposed framework of FCDSS**

***3.1 Things layer:*** This layer is made up of a variety of sensors that are used in healthcare applications. Temperature, spo2 oxygen concentration, heart rate, blood pressure rate, pulse rate, respiratory rate, and accelerometer for body position are all sensors linked to wearable body sensors in various disease diagnosis.

***3.2 Edge Layer:*** This layer comprises of a microcontroller-based system for data collecting from sensors attached to patients or people, which is then processed at the fog/cloud layer for data processing and monitoring.

***3.3 Fog Layer:*** This layer is made up of intelligence systems that are based on diverse context scenarios, such as fever, hypertensive patients, heart patients, Diabetic Patients, elderly patients and covid-19 impacted Patients. An intelligent system is a clinical decision support system that sends warnings to whomever is in charge if any adverse events occur while the patient is using it. For intelligence, the Fuzzy Logic Inference System is employed. Further processed data is sent to a cloud layer for real-time monitoring of patient health records.

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***3.4 Cloud Layer:*** This layer will hold all of the context information as well as other specified data. Also on this layer will be a UI application for monitoring for physicians, caregivers, personal usage, or anyone else it belongs to.

An intelligent monitoring system is one that can be a reason about acquired data and provide a context-aware interpretation of its meaning, as well as enhance comprehension and decision making. We used a rule-based method based on fuzzy logic inference system (FLIS) for context reasoning in the context management and reasoning (CMRS) system to accomplish this task. We chose FLIS because it is a straightforward approach to get a certain result based on confusing, noisy, imprecise or missing input data. It's a problem-solving strategy that works similarly to how people make judgments, but at a considerably quicker pace.

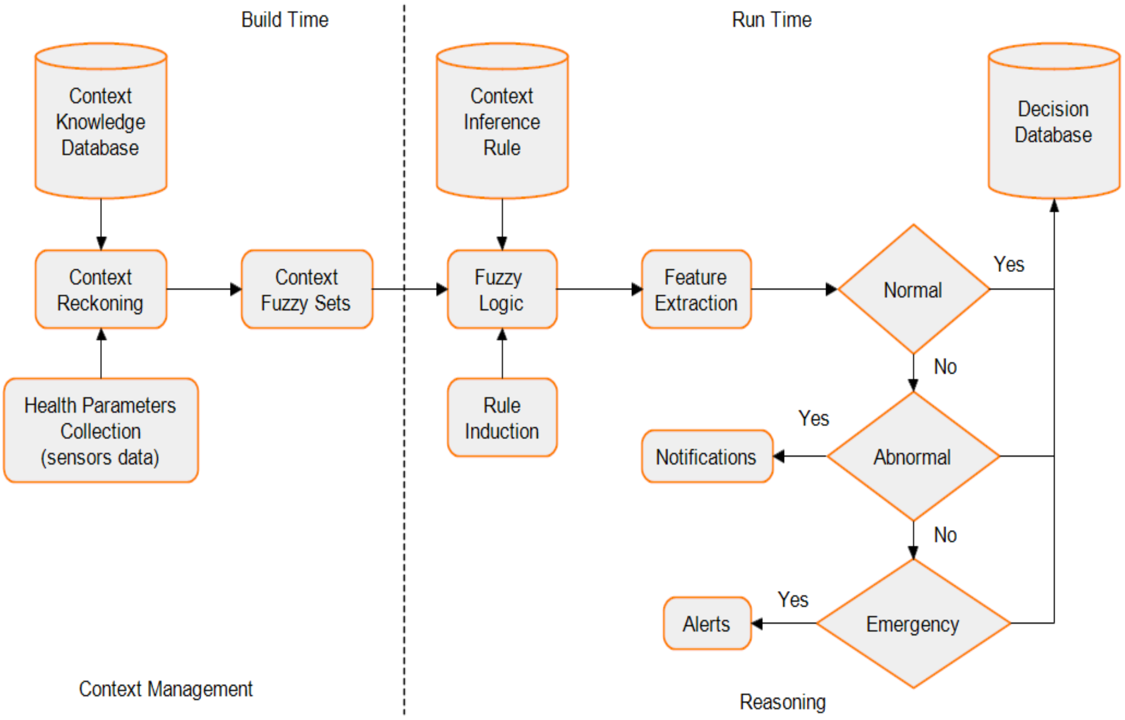


**Fig.2: Context Management and Reasoning System workflow of FCDSS**

Figure 2 depicts the interactions inside the CMRS. Context management services analyses raw data from sensors and combine it with context knowledge to create Context Fuzzy Sets. Then, to construct higher level context, Fuzzy Rules imported from the inference rule database are employed. Finally, depending on a combination of high-level context, the rule engine determines the present condition of the patient or health score. This may be accomplished in two steps: first, the common criteria are applied; second, the resulting output is further verified using the personal profile. Only if the final output is abnormal or urgent is a message or alarm sent to the remote monitoring server issued, and an emergency service contact can be made. The raw data collected is saved to aid in further decision-making and further analysis.

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As illustrated in fig 3, the key to creating a fuzzy-based reasoning engine is to create appropriate member functions, often known as fuzzy sets. A membership function represents the magnitude of each input's involvement. It assigns a weighting to each of the processed inputs, finds functional overlap between inputs, and, finally, calculates the output response.

*Fuzzifier, Rules, Inference Engine, and Defuzzifier are the four essential components of a fuzzy logic system. Fuzzification is the process of turning a precise number into a fuzzier one. To regulate the output variable, a rule base is built. An IF-THEN rule containing a condition and a conclusion is known as a fuzzy rule. The phrase "Defuzzification" refers to the process of generating a quantitative conclusion in fuzzy logic given fuzzy sets and related membership degrees.*

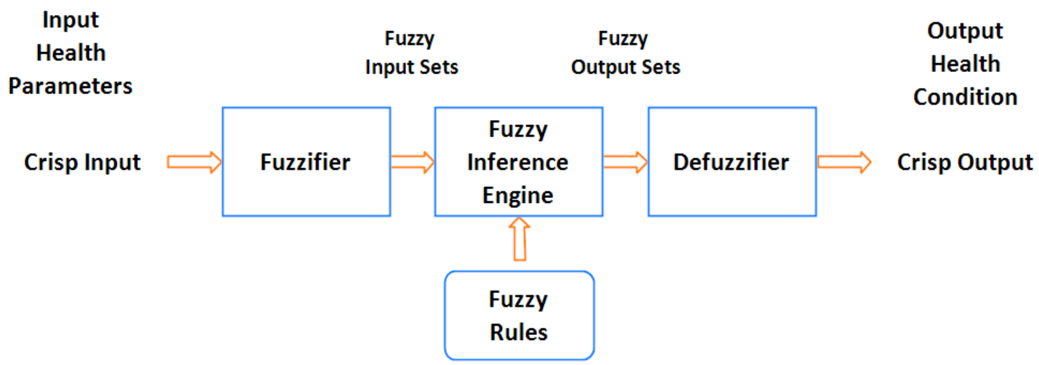



**Fig. 3: Block diagram of FLIS**

***Algorithm***

*Input:* Wearable or Non-wearable biomedical sensor value

*Output:* Predictive label or response

*Procedure:*

1 *Start:*Define linguistic variables and terms used to describe health metrics.

2 *Start:* Construct the membership function for it

3 *Start:* Construct the knowledge rule base

4 *Fuzzification:*Using the membership function, convert crisp facts to fuzzy values.

5 *Inference Engine:* Analyze the rules in the rule base.

6 *Inference Engine:* Combine the result of each rule

7 *Defuzzification:* Convert output data to values that aren't fuzzy.

## 4. Implementation

We recognized the competence knowledge supplied by the World Health Organization (WHO) for several health indicators depending on the contexts [32-35] and described in table 1. The thresholds of these health parameters are transformed into Linguistic values of Safe and Unsafe, which help to indicate the severity of the patient. When the FLIS is applied to health parameters, Good, Fair, Serious, or Critical are the output label as the patient's health status.

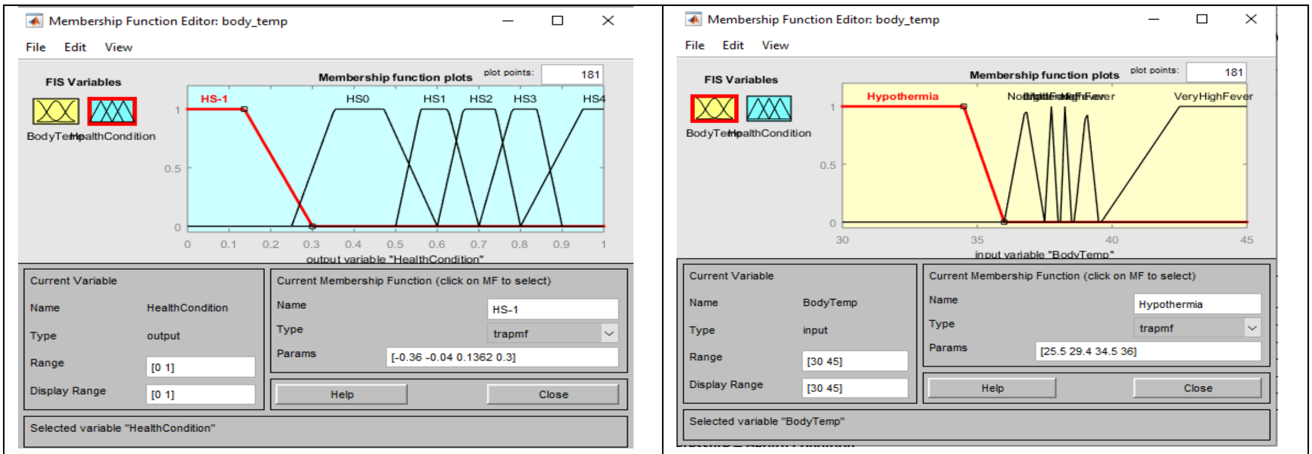
| Health Parameters | Facts (Safe) | Facts (Unsafe) |
|---|---|---|
| Body Temperature | 36.1-37.2 deg cel | Greater than 38deg cel = Fever |
| Blood Pressure | Less than 120 mmHg (sys bp), Less than 80 mmHg (dys bp) | Greater 120-80 mmHg |
| Heart Rate | 60-100 beats per minute | Below 60, greater 100 |
| Oxygen Level in Blood | 95% higher | Less than 95% |
| Breathing Rate | 12-20 breaths per min | Under 12 or over 25 |
| Sugar Level | 100-200 mg/Dl | More than 200 mg/dL |

**Table 1: Expertise Knowledge used for FLIS**

Temperature sensor, blood pressure sensor, heart rate sensor, spo2 sensor, breathing sensor, glucose sensor, and accelerometer sensor with Fuzzy Inference System are explained in table 2-7, and their corresponding membership function plot is given in fig 4-9. We've selected a number of health issues that will be taken into account while designing a Fuzzy Logic Inference System (FLIS) with linguistic values based on the Health Score (HS).

| Input Membership Function Variable | Ranges (Deg. Cel.) | Output Membership Function Variable |
|---|---|---|
| Hypothermia | < 36 | HS-1 (Health Score) |
| Normal | 36-37.5 | HS0 |
| Light Fever | 37.5-38 | HS+1 |
| Moderate Fever | 38.1-38.5 | HS+2 |
| High Fever | 38.6-39.5 | HS+3 |
| Very High Fever | 39.6-42.5 | HS+4 |

**Table 2: Fuzzy set information of body temperature**




a) b)

**Fig 4: Membership function plot a) input b) output for body temperature**

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| **Input Membership Function Variable** | **Systolic Ranges (mm Hg)** | **Diastolic Ranges (mm Hg)** | **Output Membership Function Variable** |
|---|---|---|---|
| Low | < 100 | < 60 | HS-1 |
| Normal | 100-120 | 60-80 | HS0 |
| Prehypertension | 120-139 | 80-90 | HS+1 |
| Hypertension stage1 | 140-159 | 90-99 | HS+2 |
| Hypertension stage2 | 160-180 | 100-110 | HS+3 |
| Hypertension crisis | 180-200 | 110-120 | HS+4 |

**Table 3: Fuzzy set information of blood pressure**

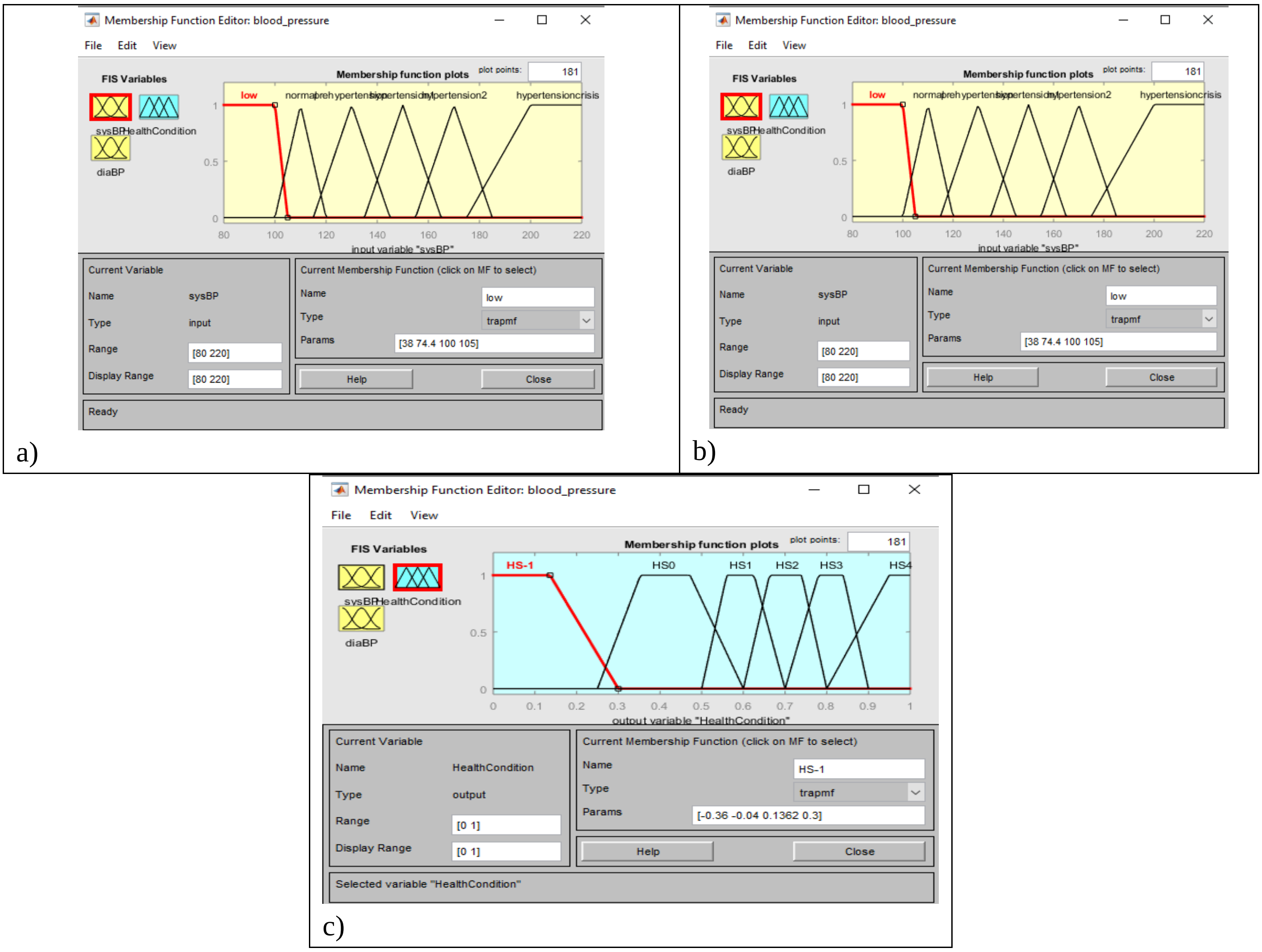


**Fig 5: Membership function plot a) b) input c) output for blood pressure**

| **Input Membership Function Variable** | **Ranges (beats per minute)** | **Output Membership Function Variable** |
|---|---|---|
| Bradycardia | < 60 | HS-1 |
| Normal | 60-100 | HS0 |

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| | | |
|---|---|---|
| Tachycardia | >100 | HS+1 |

**Table 4: Fuzzy set information of heart rate**

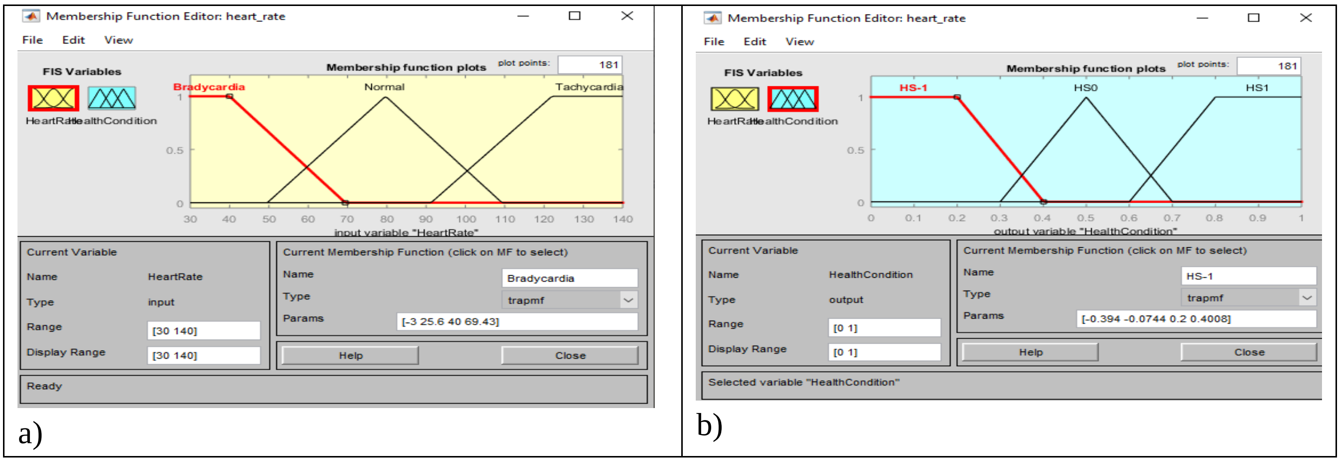


**Fig 6: Membership function plot a) input b) output for heart rate**

| **Input Membership Function Variable** | **Ranges (%)** | **Output Membership Function Variable** |
|---|---|---|
| Normal | 95-100 | HS0 |
| Mild Hypoxemia | 91-94 | HS+1 |
| Moderate Hypoxemia | 86-90 | HS+2 |
| Severely Hypoxemia | <85 | HS+3 |

**Table 5: Fuzzy set information of oxygen level**

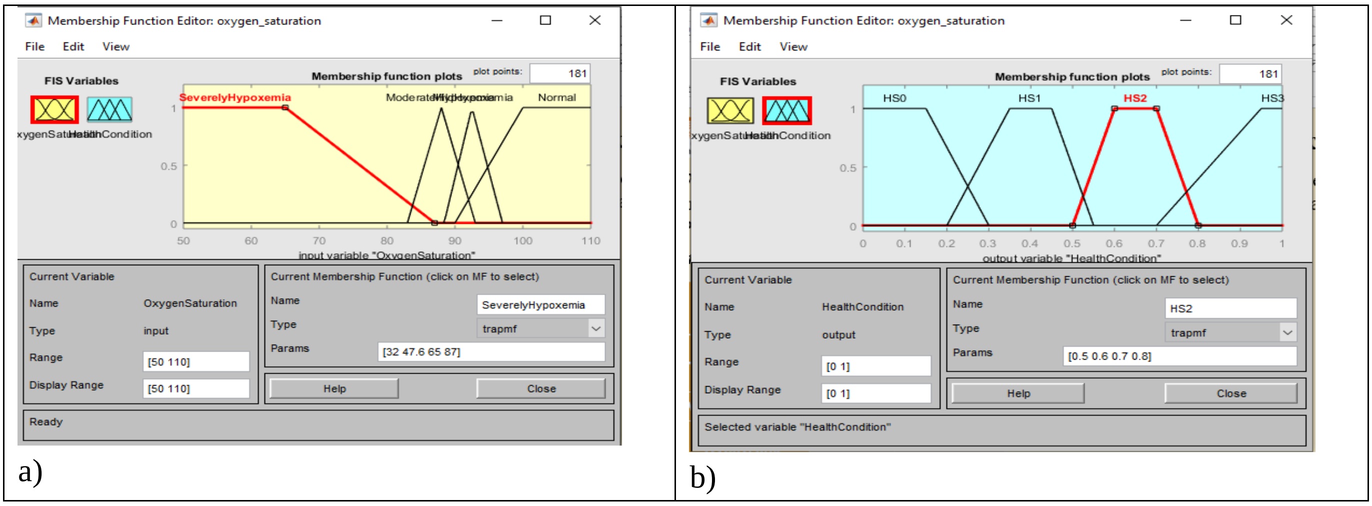


**Fig 7: Membership function plot a) input b) output for oxygen level**

| **Input Membership Function Variable** | **Ranges (breaths per minute)** | **Output Membership Function Variable** |
|---|---|---|
| Bradypnoea | <12 | HS-1 |
| Normal | 12-20 | HS0 |
| Tachypnoea | >20 | HS+1 |

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**Table 6: Fuzzy set information of breathing rate**

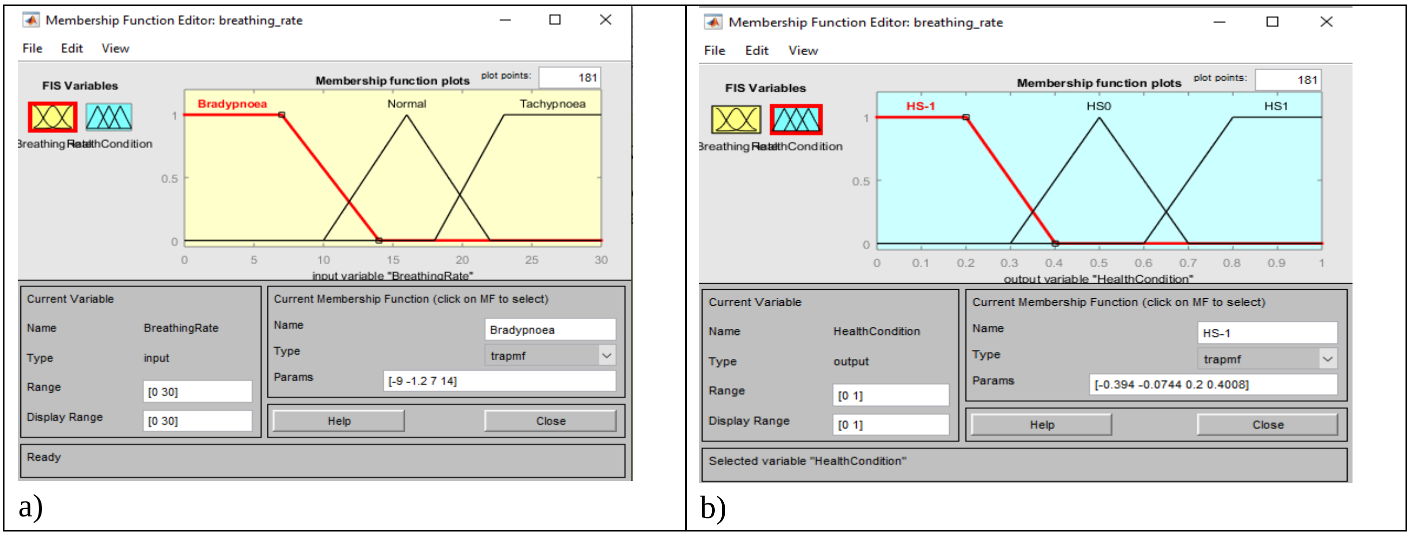


**Fig 8: Membership function plot a) input b) output for breathing rate**

| Input Membership Function Variable | Ranges (mg/dL) | Output Membership Function Variable |
|---|---|---|
| Poor | < 100 | HS-1 |
| Normal | 100-140 | HS0 |
| Prediabetes | 140-200 | HS+1 |
| Diabetes | >200 | HS+2 |

**Table 7: Fuzzy set information of sugar level**

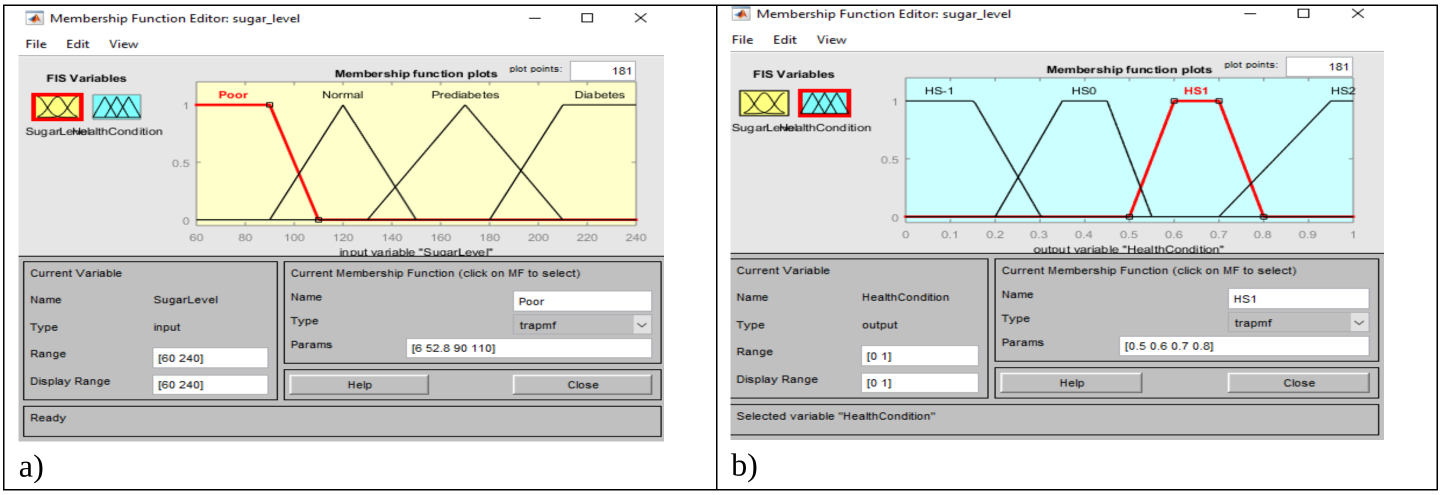


**Fig 9: Membership function plot a) input b) output for sugar level**

## 5. Results and Discussion

In this part, we discuss the suggested smart healthcare system's experimental setup and performance evaluation parameter analysis.

### *5.1 Experimental Setup*

The experimental model of the FICDSS system is shown in this section. The suggested system is modelled in

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MATLAB using the Fuzzy logic toolbox, and the code is written in the MATLAB programming language. On the PC, all of the essential programs and tools are installed in order to conduct tests on the proposed system. The hardware specifications were created using an Intel Core i5 CPU and 8 GB of RAM.

### *5.2 Experimental Dataset*

As a typical benchmark, we used the following standard benchmark sensor datasets. COVID 19 Dataset [36], Respiration Sensor, Heart Rate, Blood Oxygen SpO2 Sensor [37], Glucometer Sensor Dataset [38], and Blood Pressure Sensor Dataset [39] are utilized for rule-based analysis of different health indicators.

#### *5.2.1 Performance Evaluation*

The system's performance is assessed against a set of metrics in order to create a smart healthcare monitoring and management system. The Fuzzy Learning System (FLS) makes a judgement based on dataset benchmarking, and the decision's correctness is measured. The standard benchmark dataset readings from the sensors are then analyzed by a fuzzy logic inference system, which produces an output. Different sensor input values identified four to five types of health score measures (Good, Fair, Serious, Critical, or Very Critical). It demonstrates that the planned system is operating in accordance with the rules established for patient care and management decision-making. The formulas presented in measure the proposed system's accuracy.

$$\text{Accuracy} = \sum \frac{\mu(ai)}{n} \quad (1)$$

where, μ(ai) is the accuracy in the percentage for the data in Experiment and n is the number of experiments.

In this dataset, the average accuracy is 95.1 percent. The experimental findings demonstrate that sensor-based IoT systems are convenient and viable thanks to clever and smart decision making. The IoT approach helps to enhance the system's performance and throughput. The formula is used to determine the percent inaccuracy of the findings.

$$\text{percent\_error} = \frac{accepted\_value - experimental\_value}{total\_value} * 100 \quad (2)$$

where, accepted_value is required accuracy and experimental_value is achieved accuracy.

The statistics in table 8 demonstrate the correctness and consistency of the obtained results. Figure 10 depicts the results, which demonstrate that our method outperforms the conventional work systems. The suggested system's utility and accuracy are improved by the fuzzy logic system decision making. The findings also demonstrate that the proposed method is more accurate, time-saving, cost-effective, and simple to apply.

| **Parameters** | **Ref [13]** | **Our Approach** |
|---|---|---|
| Overall Accuracy | 93 % | 95.1 % |
| Overall Percentage of Error | 7 % | 4.9 % |
| Avg Testing Time (Latency) | - | 15.2 sec |

**Table 8: Comparative table**

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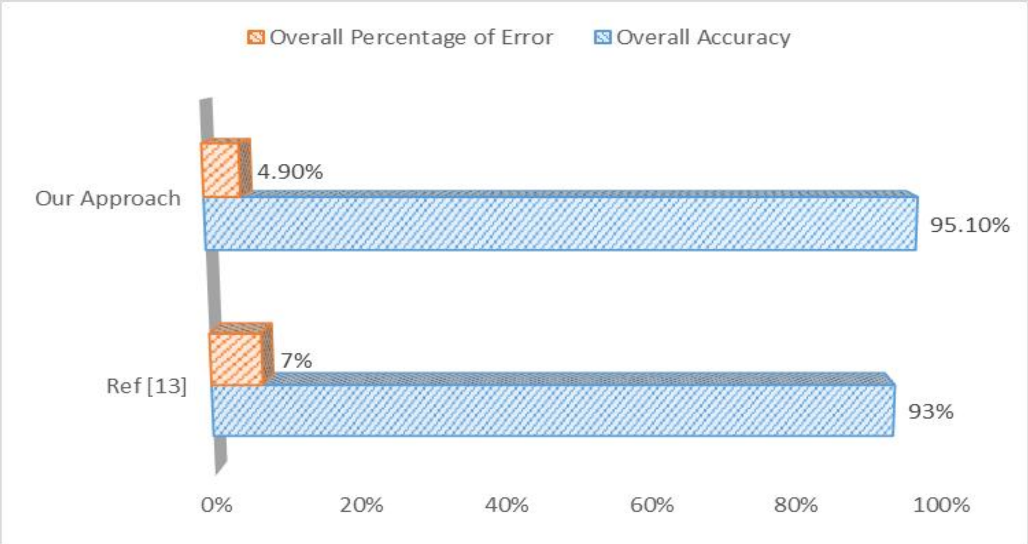


**Fig 10: Comparative analysis graph**

## 6. Conclusion

The experimental results demonstrate that intelligent and clever decision making makes the sensor-based IoT system convenient and practical to provide Clinical Decision Support System (CDSS) Using a Fuzzy logic inference system, the suggested model fulfils the high levels of quality characteristics in real-time health monitoring systems (FLIS) Sensors for body temperature, blood pressure, heart rate, spo2, breathing rate, sugar level, and body posture are used in the proposed technique to assess the state of the patient under surveillance. The system employed a knowledge base and fuzzy logic system for intelligent decision making for patient care, monitoring, and management to determine possible diagnoses and cures. The results of a comparative study suggest that using intelligent decision making for determining patient situations allows doctors to give better therapy to patients. Prior approaches to patient care and remote monitoring relied on simple decision-making, but the suggested solution relies on a fuzzy logic framework. The Fuzzy Logic Inference System (FLIS) was used to create models with health conditions that gave linguistic values based on Health Score (HS) or Health Position (HP). The created model has a high level of accuracy in determining the patient's severity. The model created will be beneficial in making decisions about whether or not to offer Medicare services to the patient. The findings also suggest that fuzzy logic systems are a solid alternative for intelligent decision-making systems, and that they provide a lightweight solution in terms of hardware and software components, making them more appropriate for IoT. We recommend that additional sensors be used in the future to collect more patient data for better and enhanced diagnosis.

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