An Intelligent System for diagnosis of Cardiovascular Disease empowered with Fuzzy Inference System

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Abstract: Today cardiovascular disease is a public health problem worldwide because the number of affected is increasing, that diseases compromise the quality of life, many incur chronicity, and can lead to death. Cardiovascular diseases are the main source of human life loss, taking an expected 17.9 million lives consistently. It's an alarming threat to global health. Recognizing those at the utmost possibility of cardiovascular diseases and ensuring they obtain suitable medication can avoid impulsive losses. Lack of medical facilities, inaccurate diagnosis, medication errors, and inappropriate or unnecessary treatment are other causes to increase in the mortality rate. Artificial Intelligence innovations in the medical sector can provide better, faster, more comprehensive diagnoses and it can increase the survival rate of patients. Therefore, we developed an intelligent system based on fuzzy logic to diagnose the disease at an early stage. Our proposed system is an extension of the Mamdani standard fuzzy logic controller. This system is based on several input variables such as blood pressure, cholesterol, sugar level, ECG, Obesity and heart rate. All implementation of this system is done on MATLAB software.

Keywords: Artificial intelligence, diagnosing, cardiovascular disease, Machine learning, Classification

1 Introduction:

Heart disease is a chain of diseases and conditions that cause cardiovascular problems. Cardiovascular disease (CVD) is a term for conditions that affect the coronary heart or veins. Most cardiovascular disease is an ongoing state that grows or persists for a long period. The unavailability or scarcity of radiologists and physicians is the main factor in high mortality rates all over the world (Ihnaini, 2021). It's frustrating when you can't get the doctor you need when you have an important health issue. If you're dealing with cardiovascular disease, this frustration can be even greater. While many excellent doctors specialize in treating this condition, they can be difficult to access (Ahmad, 2019). In many cases, patients have to wait months or even years for an appointment. This can be extremely frustrating, especially if your condition is serious (Cavaliere, 2020). If you're dealing with cardiovascular disease, don't give up hope. There are ways to get the treatment you need, even if it takes some time and effort. While there are many different types of heart disease, there are some common symptoms that can help to identify the condition. One of the supreme common indications of heart infection is chest soreness. This can be anything from mild discomfort to a more severe pain that radiates through the chest and into the arms or neck. Other symptoms may include shortness of breath, dizziness, lightheadedness, and fatigue (Sagheer Abbas, 2020).

If you experience any of these symptoms, it is important to see a doctor as soon as possible. While some of these symptoms may be caused by other conditions, they could also be signs of something more serious. Only a medical professional can properly diagnose and treat heart disease.

In this day and age, we are fortunate enough to have access to a wide variety of medical technologies that can help us diagnose and treat various diseases specially heart disease (Siddiqui, 2020). One such technology is the smart intelligent system, which is specifically designed for the diagnosis of cardiovascular disease. This article will introduce you to this system and explain how it works. A new smart system that can diagnose cardiovascular disease has been developed in this paper. The system, which is based on machine learning, can accurately identify patients who are at risk of developing the disease. The system was trained using data from more than 10,000 patients, and it was able to correctly identify those at risk with an accuracy of 82%. The system could be used to screen patients who are at risk of developing cardiovascular disease, and it could also be used to monitor patients who have already been diagnosed with the disease (Iqbal, 2018). The system is still in the early stages of development, but researchers believe that it has the potential to revolutionize the way we diagnose and treat cardiovascular disease. Our proposed system is an extension of the standard Mamdani fuzzy logic controller. This system is based on several input variables such as blood pressure, cholesterol, sugar level, ECG, and heart rate.

2 Literature review:

The proposed model is used to detect and classify brain tumors at an early stage for patients. This intelligent system is very important for specialists and doctors. The system classifies brain tumors into the fastest growing tumors in humans such as glioma, meningioma, and pituitary using deep learning. A convolutional neural network (CNN) is used to train data and is classified into different types. The proposed intelligent system classifies brain tumors into four main types such as non-tumor, glioma, meningioma, and pituitary, and achieves an accuracy rate of 92.12% (Khan A. A., 2022).

Kidney infections create a high impact on health worldwide and clinical professionals recommend that findings at an earlier stage are one of the main ways to treat kidney disease. Therefore, the proposed research discusses various techniques to treat this type of disease. For this purpose, the proposed model uses a fuzzy logic decision-based system with seven different parameters and an artificial neural network (ANN) with 25 different attributes of the kidney data set. This intelligent system successfully analyzes kidney disease at an early stage precisely with an accuracy rate of 94.16% (Khan A. K., 2021).

This article writes on the utilization of Artificial Intelligence for malignant growth determination and forecast and condenses its benefits. They discussed how Artificial Intelligence helps disease finding and guessing, explicitly concerning its phenomenal precision, which is much higher than the general measurable solicitations in oncology. We additionally exhibit manners by which these strategies are propelling the field. At last, prospects and difficulties in the medical execution of Artificial Intelligence are also conferred (Huang, 2020).

The proposed model targets recognizing likely utilizations of AI in the arena of irresistible illnesses. They intentionally emphasis on significant parts of contamination: finding, transmission, reaction to treatment, and obstruction. They are propositioning the utilization of outrageous qualities as a road of attention for upcoming advancements in the arena of irresistible illnesses. This paper covers a progression of utilizations specifically decided to grandstand how AI is affecting the arena of irresistible illness (Agrebi, 2020).

The primary use of AI in upper GI lots is endoscopy; Nonetheless, the need to examine the growing pool of mathematical and absolute information over a short period has prompted scholars to explore the use of AI frameworks in other upper GI settings, including gastro esophageal reflux disease, eosinophilia esophagitis, and motility problems. For non-access holders, the functioning standards and capability of AI might be as intriguing as dark (Visaggi, 2022).

The record difficult undertaking for AI in such medical services areas is to support its reception in day-to-day medical practice, whether or not the projects are adequately versatile to be valuable. Because of the abridged information, it has been presumed that AI can help medical services staff in growing their insight, permitting them to invest more energy in giving direct understanding consideration and diminishing exhaustion. By and large, we could reason that the upcoming of "regular medication" is nearer than we understand, with patients seeing a PC first and subsequently a specialist (Wani, 2022).

3 Proposed Methodology:

A Mamdani fuzzy logic controller (FLC) is a type of fuzzy logic controller that uses a Mamdani-type inference system to map inputs to outputs (AsadUllah, 2018). The advantage of using a Mamdani FLC over other types of FLCs is that it can handle more complex input/output relationships. Mamdani FLCs use a simple rule-based approach to mapping inputs to outputs (Singh, 2021). Each rule consists of an antecedent (input) and a consequent (output). The antecedent is typically conjunction of one or more fuzzy sets, while the consequent is typically a singleton value (Hussain, 2021).

For example, consider a simple two-input, one-output Mamdani FLC with the following rules:

IF x1 is A1 AND x2 is A2 THEN y is B

IF x1 is A3 AND x2 is A4 THEN y is C

The antecedents in these rules are conjunctions of two fuzzy sets, while the consequents are singleton values. To map an input vector (x1, x2) to an output value, the FLC must first determine which rule(s) are (Wroge, 2018). In our proposed model we use different input variables such as blood pressure, cholesterol, sugar level; ECG, and heart rate to diagnose cardiovascular disease. Using these variables we trained our system to predict the early medical health of a patient. The proposed system will show the prediction rate in percentage which indicates whether the patient medical condition is critical or not. **Fig 1** shows the fuzzy rule-based system.

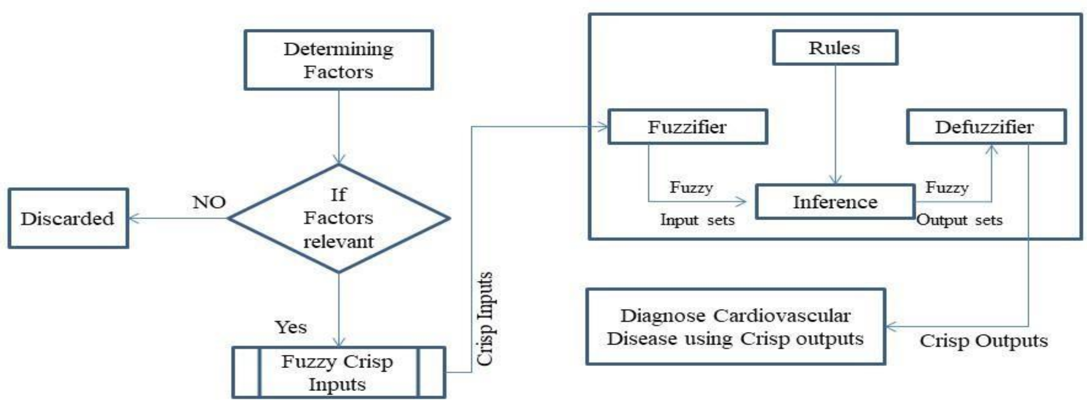

Fig 1: Fuzzy Rule Base System

Set rules as desired the diagnosing of cardiovascular diseases are shown below:

Sugar Level: Low, Normal, Pre-Diabetes, High Diabetes

Cholesterol Level: Desirable, Borderline High, Very High

Blood Pressure: Ideal Blood Pressure, Lower Blood Pressure, High Blood Pressure

ECG Level: Normal, ST-T abnormality, Hypertrophy

Obesity: Healthy, Pre-Obesity, Obesity

Heart Rate: Low, Normal, High

The proposed system has a single output variable indicating whether the patient has heart disease or not. The value of the output variable ranges from o to 4, this value means that the patient's health is normal, sick 1, sick 2. Sick 3 and sick 4, increasing the value of the given output indicated a higher risk of heart disease in the patient. **Table 1** shows the list of input variables. We categorize the input variable into three sub-groups shown in table 1. The minimum and maximum range and units for measurement of our given input variables also is mentioned.

Input Parameters	Unit	Fuzzy Variables	Min	Max
Heart Rate	bpm	Low, Normal, High	0bpm	150bpm
Sugar Level	mg/dL	Low, Normal, Pre-Diabetes, High Diabetes	0mg/dL	300mg/dL
cholesterol	mg/dL	Desirable, Borderline High, Very High	0 mg/dL	400 mg/dL
Blood Pressure	mmHg	Ideal, Lower, High Blood Pressure	0mmHg	200mmHg
ECG	mm	Normal, ST-T abnormality, Hypertrophy	0	2.5
Obesity	kg/m²	Healthy, Pre-Obesity, Obesity	0kg/m²	50kg/m²

Table 1: List of Input Variables

Be aware that we developed a smart intelligent system using four different input variables such as Sugar Level, Blood Pressure, ECG and Cholesterol.

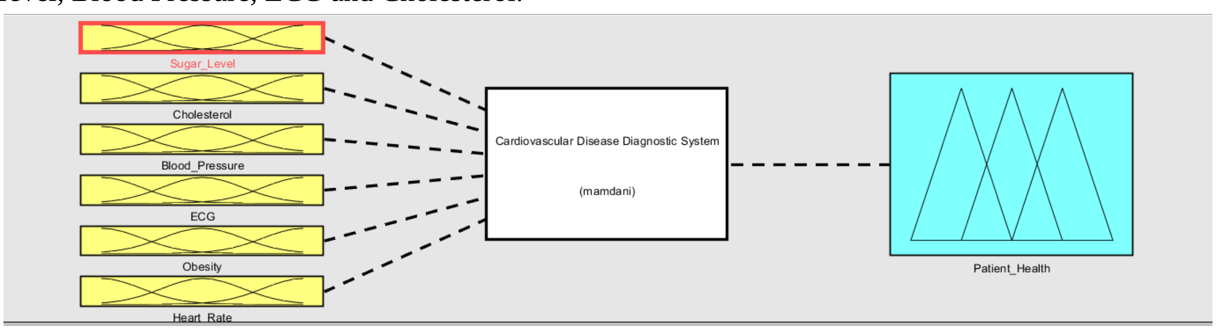

Fig 2: FIS editor diagnosing the cardiovascular diseases

3.1 Input Variable:

Using this four variable system predicts the patient's health is normal or abnormal, whether the patient consults a doctor or not. The proposed intelligent system consist four different input parameters and one output variable. **Fig 3:** shows the membership function of input variable Sugar Level.

Membership Function of Input Variable Sugar Level:

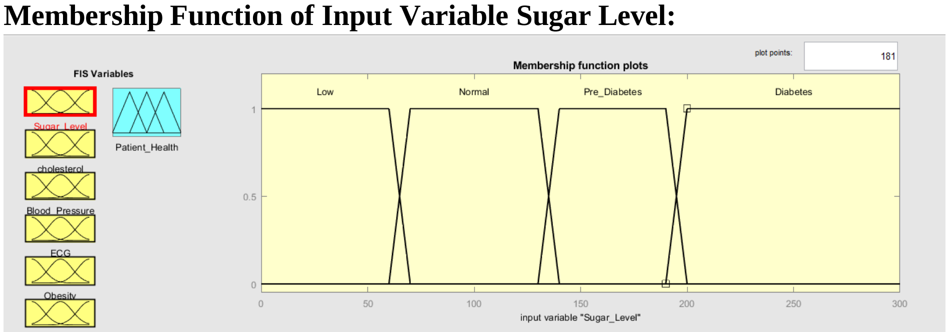

Fig 3: Membership Function of Input Variable Sugar Level

Sugar Level: Low, Normal, Pre-Diabetes, and Diabetes:

$$\mu_L(S) = \begin{cases} \dfrac{70-S}{70-60} (60 \le S \le 70 \end{cases}$$

$$\mu_N(S) = \begin{cases} \dfrac{S-60}{70-60} & (60 \le S \le 70 \\ \dfrac{140-S}{140-130} & (130 \le S \le 140 \end{cases}$$

$$\mu_{PD}(S) = \begin{cases} \dfrac{S-130}{140-130} & (130 \le S \le 140 \\ \dfrac{200-S}{200-190} & (190 \le S \le 200 \end{cases}$$

$$\mu_D(S) = \begin{cases} \dfrac{S-190}{200-190} (190 \le S \le 200 \end{cases}$$

Membership Function of Input Variable Cholesterol Level:

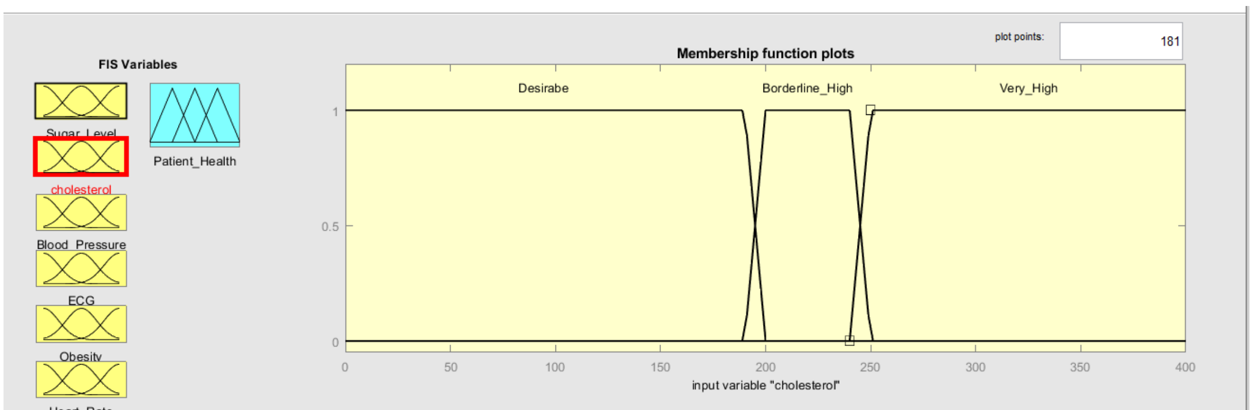

Fig 4: Membership Function of Input Variable Cholesterol Level

Cholesterol Level: Desirable, Borderline High, and Very High:

$$\mu_D(C) = \begin{cases} \dfrac{200-C}{200-190} (190 \le C \le 200 \end{cases}$$

$$\mu_{BH}(C) = \begin{cases} \dfrac{C-190}{200-190} & (190 \le C \le 200 \\ \dfrac{250-C}{250-240} & (240 \le C \le 250 \end{cases}$$

$$\mu_{VH}(C) = \begin{cases} \dfrac{C-240}{250-240} (240 \le C \le 250 \end{cases}$$

Membership Function of Input Variable Blood Pressure:

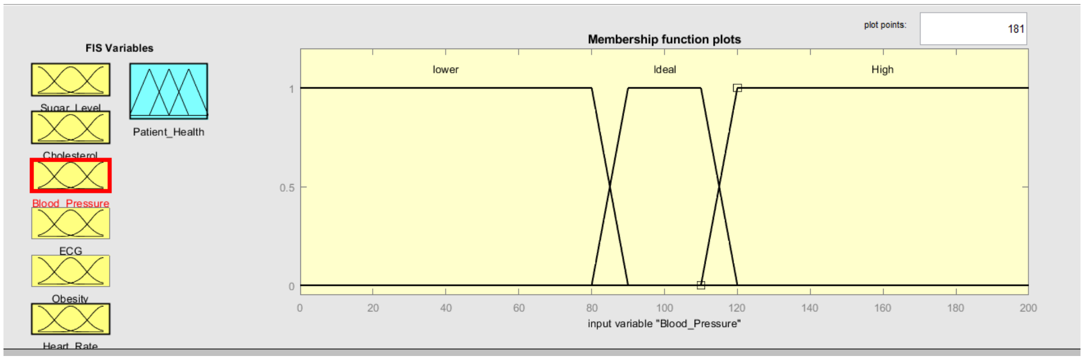

Fig 5: Membership Function of Input Variable Blood Pressure

Blood Pressure: Lower, Ideal, and High:

$$\mu_L(B) = \begin{cases} \dfrac{90-B}{90-80} (80 \le B \le 90 \end{cases}$$

$$\mu_I(B) = \begin{cases} \dfrac{B-80}{90-80} & (80 \le B \le 90 \\ \dfrac{120-B}{120-110} & (110 \le B \le 120 \end{cases}$$

$$\mu_H(B) = \begin{cases} \dfrac{B-110}{120-110} (110 \le B \le 120 \end{cases}$$

Membership Function of Input Variable ECG:

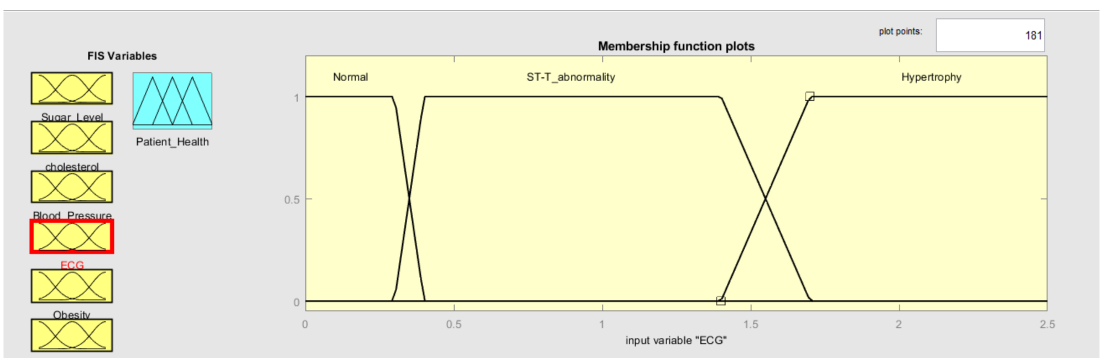

Fig 6: Membership Function of Input Variable ECG

ECG: Normal, ST-T abnormality, and Hypertrophy:

$$\mu_N(E) = \begin{cases} \dfrac{0.4-E}{0.4-0.3} (0.3 \le E \le 0.4 \end{cases}$$

$$\mu_{ST}(E) = \begin{cases} \dfrac{E-0.3}{0.4-0.3} & (0.3 \le E \le 0.4 \\ \dfrac{1.7-E}{1.7-1.4} & (1.4 \le E \le 1.7 \end{cases}$$

$$\mu_H(E) = \begin{cases} \dfrac{E-1.4}{1.7-1.4} (1.4 \le E \le 1.7 \end{cases}$$

Membership Function of Input Variable Obesity:

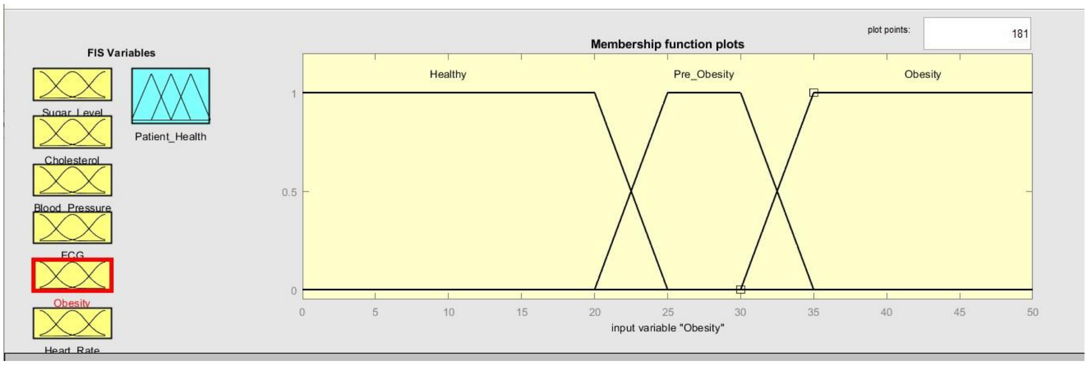

Fig7: Membership Function of Input Variable Obesity

Obesity: Healthy, Pre-Obesity, and Obesity:

$$\mu_H(O) = \begin{cases} \frac{25-O}{25-20} (20 \le O \le 25 \end{cases}$$

$$\mu_{PO}(O) = \begin{cases} \frac{O-20}{25-20} & (20 \le O \le 25 \\ \frac{35-O}{35-30} & (30 \le O \le 35 \end{cases}$$

$$\mu_O(O) = \begin{cases} \frac{O-30}{35-30} (30 \le O \le 35 \end{cases}$$

Membership Function of Input Variable Heart Rate:

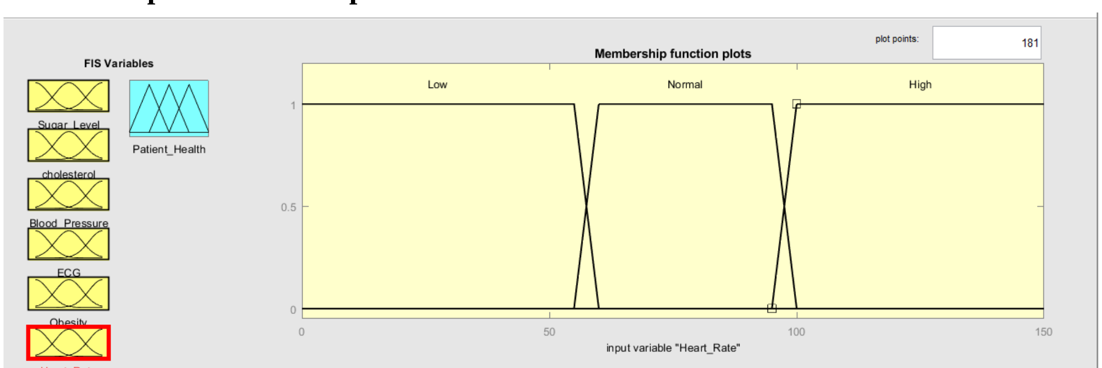

Fig 8: Membership Function of Input Variable Heart Rate

Heart Rate: Low, Normal, and High:

$$\mu_L(H) = \begin{cases} \frac{70-H}{70-60} (60 \le H \le 70 \end{cases}$$

$$\mu_N(H) = \begin{cases} \frac{H-60}{70-60} & (60 \le H \le 70 \\ \frac{100-H}{100-90} & (90 \le H \le 100 \end{cases}$$

$$\mu_H(H) = \begin{cases} \frac{H-90}{100-90} (90 \le H \le 100 \end{cases}$$

3.2 Output:

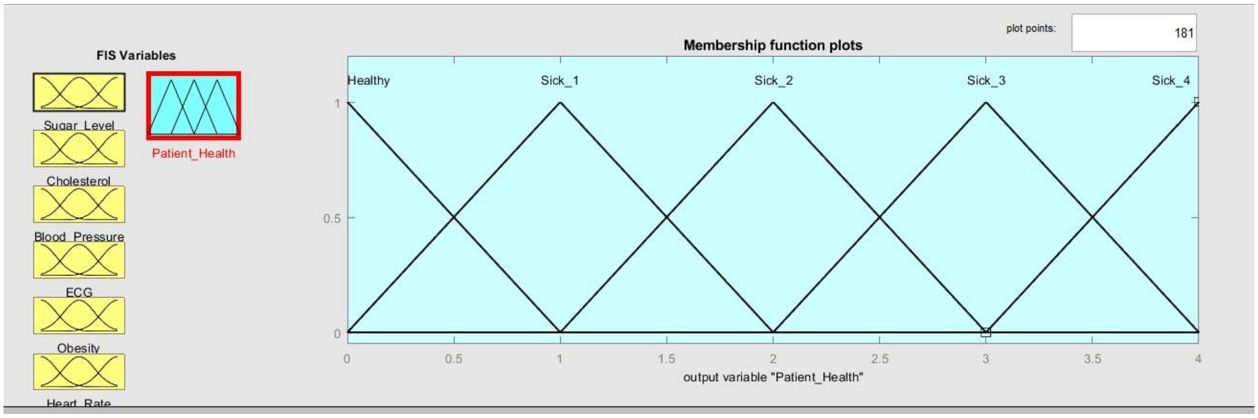

Fig 9: Membership function of output variable patient health

The range of the output variable is from 0 to 4. An increase in the number of integers indicates a high incidence of heart disease in the patient. This means that the patient should consult a medical specialist or doctor as soon as possible.

Membership Function of output Variable:

Healthy:

$$\mu_H(H) = \begin{cases} \frac{1-H}{1-0} & (0 \le H \le 1 \end{cases}$$

Sick Level 1:

$$\mu_{S1}(H) = \begin{cases} \frac{H-0}{1-0} & (0 \le H \le 1 \\ \frac{2-H}{2-1} & (1 \le H \le 2 \end{cases}$$

Sick Level 2:

$$\mu_{S2}(H) = \begin{cases} \frac{H-1}{2-1} & (1 \le H \le 2 \\ \frac{3-H}{3-2} & (2 \le H \le 3 \end{cases}$$

Sick Level 3:

$$\mu_{S3}(H) = \begin{cases} \frac{H-2}{3-2} & (2 \le H \le 3 \\ \frac{4-H}{4-3} & (3 \le H \le 4 \end{cases}$$

Sick Level 4:

$$\mu_{S4}(H) = \begin{cases} \frac{H-3}{4-3} & (3 \le H \le 4 \end{cases}$$

3.3 Inferences:

As per the observational examination of the relationship between the fuzzy input and fuzzy output planning and the conglomeration cycle of the result, 42 inference rules are created. A portion of the surmising rules as displayed in **Table 2**.

	Sugar Level	Cholesterol Level	Blood Pressure	Obesity	Heart Rate	ECG	Patient Health
Rule 1	Normal	Desirable	Ideal	Healthy	Normal	Normal	Healthy
Rule 5	Pre-Diabetes	Desirable	Low	Pre-Obesity	Normal	Normal	Healthy
Rule 7	Pre-Diabetes	Borderline High	Ideal	Healthy	Low	ST-T abnormality	Sick Level 1
Rule 11	Diabetes	Desirable	Low	Pre-Obesity	High	ST-T abnormality	Sick Level 1
Rule 15	Diabetes	High	High	Pre-Obesity	Low	Normal	Sick Level 2
Rule 17	Normal	Borderline High	Low	Obesity	Normal	Normal	Sick Level 2
Rule 20	Pre-Diabetes	Borderline High	ideal	Obesity	High	St-T abnormality	Sick Level 3
Rule 22	Pre-Diabetes	High	ideal	Healthy	High	Hypertrophy	Sick Level 3
Rule 25	Diabetes	Desirable	High	Pre-Obesity	Normal	St-T abnormality	Sick Level 4
Rule 28	Diabetes	High	Low	Obesity	Low	Hypertrophy	Sick Level 4

Table 2: Some of the inference rules

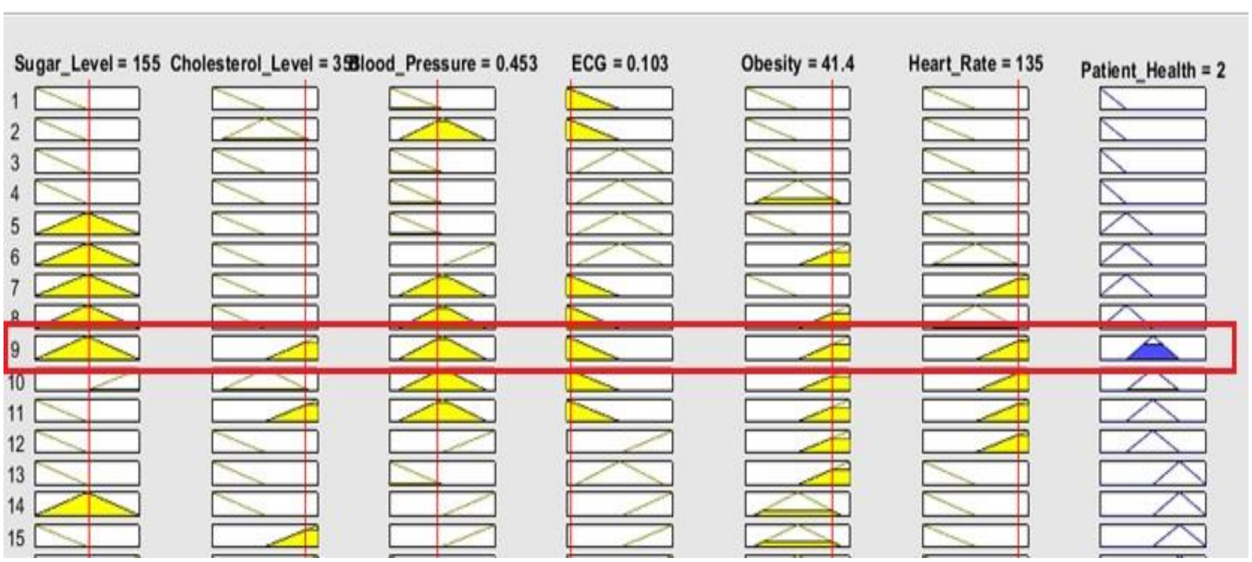

Fig 10: Rule Base

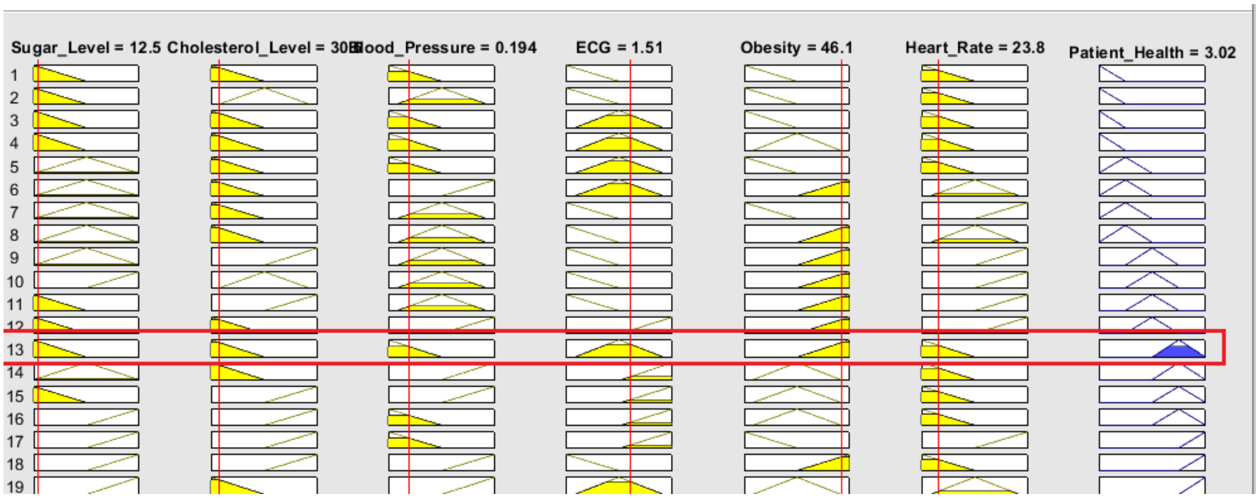

Fig 10: Rule Base

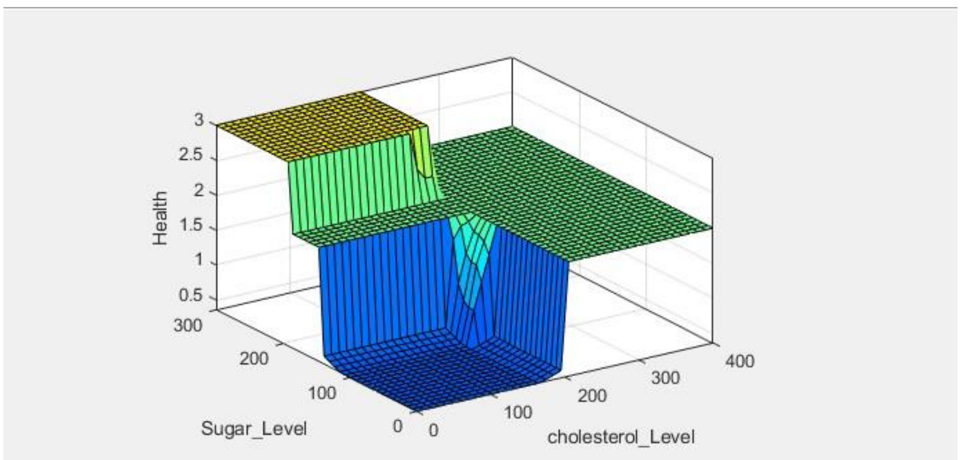

Fig 11: Surface Graph

Fig 11 shows the surface graph of the proposed system based on Sugar Level and Cholesterol, **Fig 12** shows the surface graph based on Blood Pressure and Cholesterol.

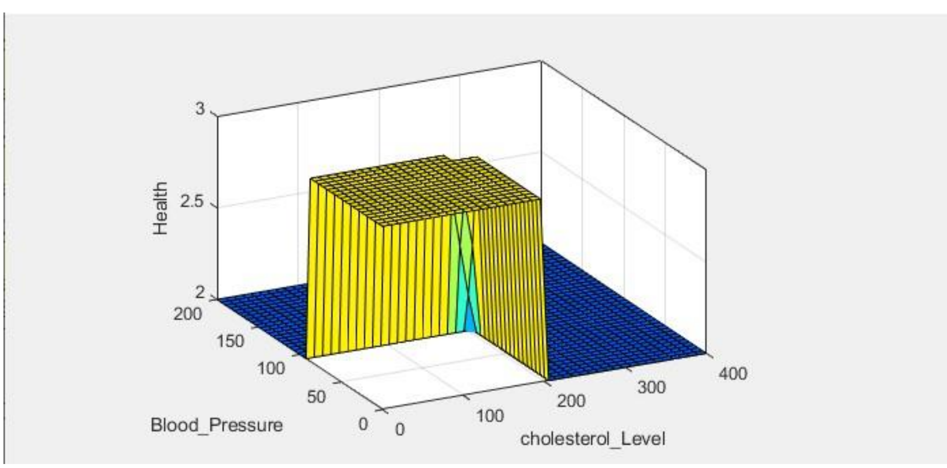

Fig 12: Surface Graph

For the FIS systems with at least two or more than two input variables, you can view the output interface for any grouping of two input variables. By default, the surface plot is restructured spontaneously when you transform the input or output variable selection or the number of grid points (Saleem, 2019). Fig 11 shows the surface plot based on Sugar Level and Cholesterol input variable and fig 12 shows the surface plot based on the Blood Pressure and Cholesterol input variable.

4 Results and Discussion:

There are four different input variables as Sugar Level, Blood Pressure, Cholesterol, and ECG used by this system, each input variable has three different linguistic values. The unit of measurement for these input variables is shown in **Table 1**. The single output generated by the proposed system represents the medical health of the patient. Graphical representation for blood pressure (x-axis), Cholesterol (y-axis), and generated output variable are shown in **Fig 12**. The output variable range is from 0 to 4. An increase in the number of integers indicates the patient is at high risk of developing heart disease, and he immediately consults any medical specialist. If the system shows less than 1 value so it indicates the patient health is normal and under control but if the system shows greater than 1 value so it indicates the patient health is critical.

5 Conclusion:

Artificial intelligence is transforming the way healthcare is delivered to the world. Artificial intelligence is used to help with different tasks in healthcare especially for diagnosing the disease at an early stage. Artificial intelligence -based software can help detect disease patterns and risk factors, or it can mine data to help doctors make better diagnoses. Recent advances in artificial intelligence have also been able to improve clinical decision support. We, therefore, developed an intelligent expert system based on a fuzzy logic decision-making system to diagnose possible cardiovascular disease in patients at an early stage. The system is based on six different input variables such as blood pressure, cholesterol, sugar level, Obesity, Heart rate, and ECG. The proposed system has a single output showing the medical health of the patient. Appropriate diagnosis, management, and treatment of these patients can reduce the mortality rate and increase the survival rate.

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