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A Spectrum of Cardiac Health Risk Assessment Intelligent System

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Abstract. *Medical diagnosis, particularly for cardiac conditions, is complex due to clinical variability, subjectivity, and incomplete information, which can lead to delays or errors. This article presents the development of an intelligent system using ECG data to enhance clinical efficiency, reduce diagnostic errors, and support medical decision-making. The system smoothly integrates into clinical workflows, analyzes complex data, and enhances patient outcomes. The Python programming language has been used to develop the code for this model.*

Keywords: Linguistic strings, Utility sets, Fuzzy numbers, Linguistic variables, Degree of match, ECG graphs.

1. Introduction

The inherent complexity of medical diagnosis arises from the impreciseness and vague characteristics of symptoms and medical data. This challenge is particularly evident in the medical sciences, where certainty and complete information can hinder accurate diagnosis and treatment. In medicine, practitioners often face situations where clear-cut scientific models and strict diagnostic guidelines are insufficient to account for the variability in patient presentations. Consequently, medical experts frequently rely on their experience, clinical intuition, and judgment to make decisions, particularly in complex cases where the symptoms do not align perfectly with known medical conditions. Although medical professionals gain valuable knowledge through their experiences, utilizing this vast expertise effectively in every case is challenging, particularly during real-time clinical decision-making. The fast-paced nature of clinical settings often limits the ability to tap into their extensive knowledge base fully, making applying it comprehensively to each unique patient scenario challenging.

The concept of decision-making using fuzzy variables was first introduced by Jain, Ramesh [10]. Later, Bellman, R.E. and Zadeh, L.A. [3] extended this idea by proposing the application of fuzzy tools in medicine. Cho, Seongwon, Ersoy, Okan K., and Lehto, Mark [4] developed an algorithm to compute the degree of match (DM) between the antecedent part of a classification rule and an assertion.

In 1994, L.A. Zadeh [19] proposed the concept of Soft Computing for answers to this problem, with the goal of addressing partial truths, imprecision, and ambiguity in decision-making processes. Soft Computing is intended to be more flexible and adaptive to real-world settings where data is frequently ambiguous or missing, in contrast to traditional computing approaches that depend on accurate and complete data. Fuzzy logic is a crucial feature of Soft Computing and is especially important in medical applications. By combining intuition, approximation reasoning, and subjective evaluations—all of which are frequently crucial in medical practice—fuzzy tools mimic human thinking and decision-making.

Soft Computing techniques have become increasingly popular in recent years for the detection and management of cardiac conditions, especially fuzzy tools, which assist in controlling the degree of ambiguity involved in interpreting test findings, patient-reported data, and clinical symptoms. For example, electrocardiograms (ECGs), which employ skill and flexibility to interpret cardiac rhythms and spot abnormalities, are frequently used in the diagnosis of cardiac diseases. The electrocardiograph (ECG) was invented by Dutch scientist Willem Einthoven [2], who made important discoveries that allowed for accurate measurement of the electrical activity of the heart.

In summary, the development of the electrocardiograph was a cumulative process built on the foundations laid by earlier scientists who explored the relationship between electrical impulses and muscle movement. Einthoven's creation was pivotal in medical history, transforming cardiology and paving the way for the modern understanding of heart health.

In 1790, the Italian scientist Aloysio Luigi Galvani [5,8,9] caused a dead frog’s legs to move through electrical stimulation from a completed circuit connecting dissimilar metals. In 1820, the Danish scientist Hans Christian Oersted [11] observed that changes in electrical current could deflect a needle. This led to the creation of the electric rheoscope, later known as the galvanometer, in tribute to Galvani. In 1842, Matteucci [6] introduced and described the term “action potential” after demonstrating that the nerve of a suitably prepared frog limb, when placed over the muscle of a similarly prepared limb and stimulated, could contract the muscle below it.

Willem Einthoven [1,12] (1860–1927), known as the creator of the electrocardiograph, won a Nobel Prize in 1924 for his contributions to electrocardiography. Today, electrocardiography is essential for evaluating patients presenting with cardiac complaints. It is a crucial, non-invasive, cost-effective tool for assessing arrhythmias and ischemic heart disease.

Willem Einthoven built upon these earlier innovations. He realized that a more sensitive and precise instrument was needed to measure the heart's electrical activity accurately. In 1901, Einthoven introduced the string galvanometer, a susceptible device that allowed for the first accurate recordings of the heart's electrical signals. The results were dramatic: the device could produce clear, reproducible tracings of the heart's electrical activity. Einthoven's invention rapidly transformed cardiology. It provided a non-invasive method to diagnose heart conditions, allowing physicians to understand the electrical behavior of the heart in unprecedented detail. Over time, the electrocardiograph evolved, becoming more compact, reliable, and sophisticated, but the fundamental principles remain unchanged. Today, the ECG is a standard medical diagnostic tool used globally to monitor and diagnose heart conditions.

Several researchers have played critical roles in advancing Soft Computing, particularly in cardiac diagnostics. Among them, Srivastava Pankaj and his colleagues have made notable strides in applying Soft Computing techniques to medical applications. For instance, Srivastava Pankaj and Sharma Neeraja [13] developed a Spectrum of Soft Computing Model for Medical Diagnosis that leverages Soft Computing to identify and predict various cardiac conditions. This approach enhances the accuracy of classifying heart rhythm irregularities by blending clinical expertise with fuzzy algorithms.

In addition, Srivastava Pankaj and Srivastava Amit [14] created a comprehensive fuzzy expert system to assess the risk of coronary heart disease (CHD) in the Indian population. This system evaluates risk factors—such as cholesterol levels, blood pressure, lifestyle habits, and family history—to offer personalized recommendations, guiding patients on whether they can maintain their current lifestyle, need to adopt a modified diet, or require medical intervention through drug therapy. This fuzzy expert system has proven to be a valuable resource for healthcare professionals, allowing them to make more informed decisions by providing a detailed analysis of patient risk profiles.

Soft Computing has also demonstrated potential beyond cardiac diseases, showing promise in diagnosing and managing other critical health conditions. For instance, Srivastava Pankaj, Srivastava Amit, and Sirohi Ritu developed a Soft Computing-based classification system for hepatitis B [15]. This system simplifies the diagnostic process and helps determine the stage of the disease. Likewise, the classification of ECG beats, which signals different phases of cardiac conditions, has been further improved by Srivastava Pankaj and Sharma Neeraja [16,17], contributing to detecting and monitoring cardiac anomalies.

Another significant application of Soft Computing is in diabetes management. Srivastava Pankaj, together with Sharma Neeraja and Singh Richa [18], created a diagnostic system using fuzzy tools to assist in diagnosing diabetes and recommending suitable interventions to help patients regulate their blood sugar levels. Their work highlights the importance of developing intelligent systems that integrate with real-time data, offering personalized health recommendations for better diabetes management.

In collaboration with Rajkrishna Mondal, Pankaj Srivastava [7] developed a Diabetes Diagnostic Intelligent Information System, which enhances healthcare professionals' ability to manage diabetes by providing an intelligent system derived from patient data. This system significantly advances diabetes care, showing the decisive role of Soft Computing in medical diagnosis.

This article aims to design and develop an Intelligent system for assessing the current health status of patients. The proposed system utilizes Soft Computing techniques and ECG data from a standard 12-lead ECG machine.

2. Preliminaries

The following features of fuzzy have been considered for designing the model.

2.1 Definition

(i) *Fuzzy set*

Let U *be a non-empty set known as the universe of discourse or simply domain. A fuzzy set A on U is defined by a membership function* $\mu_A : U \to [0,1]$. *The function* μ_A *represents the membership grade of an element* x *in the fuzzy set* A.

$$\boldsymbol{A} = \{(\boldsymbol{x}, \boldsymbol{\mu_A}(\boldsymbol{x})) : \boldsymbol{x} \in \boldsymbol{U}\}$$

(ii) Intersection of two Fuzzy set

Let A and B be two fuzzy sets in the universe of discourse U, with their respective membership functions μ_A and μ_B. The fuzzy intersection of A and B, denoted as $A \cap B$ or the AND operation, is defined as a new fuzzy set. In this set, the membership grade of any element $x \in U$ is given by:

$$\mu_{A\cap B}(x) = \min\{\mu_A(x), \mu_B(x) : x \in U\}.$$

(iii) Fuzzy Rule

In a fuzzy inference system, a fuzzy rule captures uncertain and imprecise knowledge. It connects a condition, which is formed using AND/OR operations on relevant linguistic variables, to a corresponding conclusion.

(iv) Degree of Match

The degree of match (DM) measures how well the inputs and outputs align. It is calculated by using the membership grades of the input and output values in their respective fuzzy sets.

3. Methodology

a. Algorithm

(i) Initially, imprecise and uncertain facts are organized into r input fuzzy sets X_i where $i = 1, 2, \dots, r$ and n output fuzzy sets B_t (where $t = 1, 2, \dots, n$, based on their corresponding possibilities.

(ii) Partition each fuzzy set into k_i distinct linguistic terms, L_{ij}, where $i = 1, 2, \dots, r$ and $j = 1,2, \dots, k_i$.

(iii) Generate $m = k_1 k_2 \dots k_r$ linguistic strings J_K, where $K = 1, 2, \dots, m$, by applying appropriate AND/OR operations to the linguistic terms L_{ij} from each fuzzy set X_i, for $i = 1, 2, \dots, r$ and $j = 1,2, \dots, k_i$.

(iv) Construct an appropriate membership function for each linguistic term in every fuzzy set, based on the available data.

(v) Developed possible fuzzy rules with the help of medical experts.

(vi) Construct of utility matrix U of order $p \times q$. Where p is a number of outputs and q is a number of linguistic variables based on designed fuzzy rules.

(vii) Develop q utility sets, U_I, where $I = 1, 2, 3, \dots, q$, each corresponding to a different alternatives, by applying the operation $x \oplus y = x + y - xy$ for each pair of values $x, y \in U$.

(viii) Construct q maximizing sets U_{MI}, where $I = 1, 2, 3, \dots, q$, corresponding to each alternatives.

(ix) Let U_{OI}, where $I = 1, 2, 3, \dots, q$, represent the set of q optimal fuzzy utility sets. Each U_{OI} is obtained from fuzzy intersection ($\wedge$) of the fuzzy utility set U_I and the maximizing set U_{MI}. The membership function for U_{OI} is given by:

$$\mu_{U_{OI}}(x) = \min\{ \mu_{U_I}(x), \mu_{U_{MT}}(x)\}, \qquad \text{for all } x \in X,$$

(x) Select the highest membership value from each optimal utility fuzzy set.

(xi) The best alternative, denoted as B_O , is selected by finding the highest membership value among all available options. It is mathematically written as:

$$B_O = \{\max(\mu_{OI}(x), B_I) : \forall\, I \in U_{OI}\}, \quad where\ I = 1,2,3, \dots \dots ., n$$

(xii) To assess how closely the given inputs, outputs, and computed outputs align with the expected results, the degree of match method is applied to determine the level of satisfaction.

(xiii) The degree of match DM_i for each input $i = 1, 2, 3, \dots, r$ measures how well a precise input value (x_i) aligns with its corresponding fuzzy input set X_i . It is computed by this formula:

$$DM_i = 2\mu_{X_i}(x_i) - 1$$

(xiv) The total degree of match DM_I for the input is calculated by taking the minimum value among all individual degrees of match DM_i for $i = 1, 2, \dots, r$. This can be expressed as:

$$DM_I = \min\{ DM_1, DM_2, \dots, DM_r\}$$

and, the degree of match DM_O for the optimal alternatives.

(xv) To assess satisfaction, calculate the difference ($D = |DM_I - DM_O|$). If $0 \leq D < 1$ or D is close to zero, it means the output is satisfactorily aligned with the fuzzy inputs.

b. Flow chart

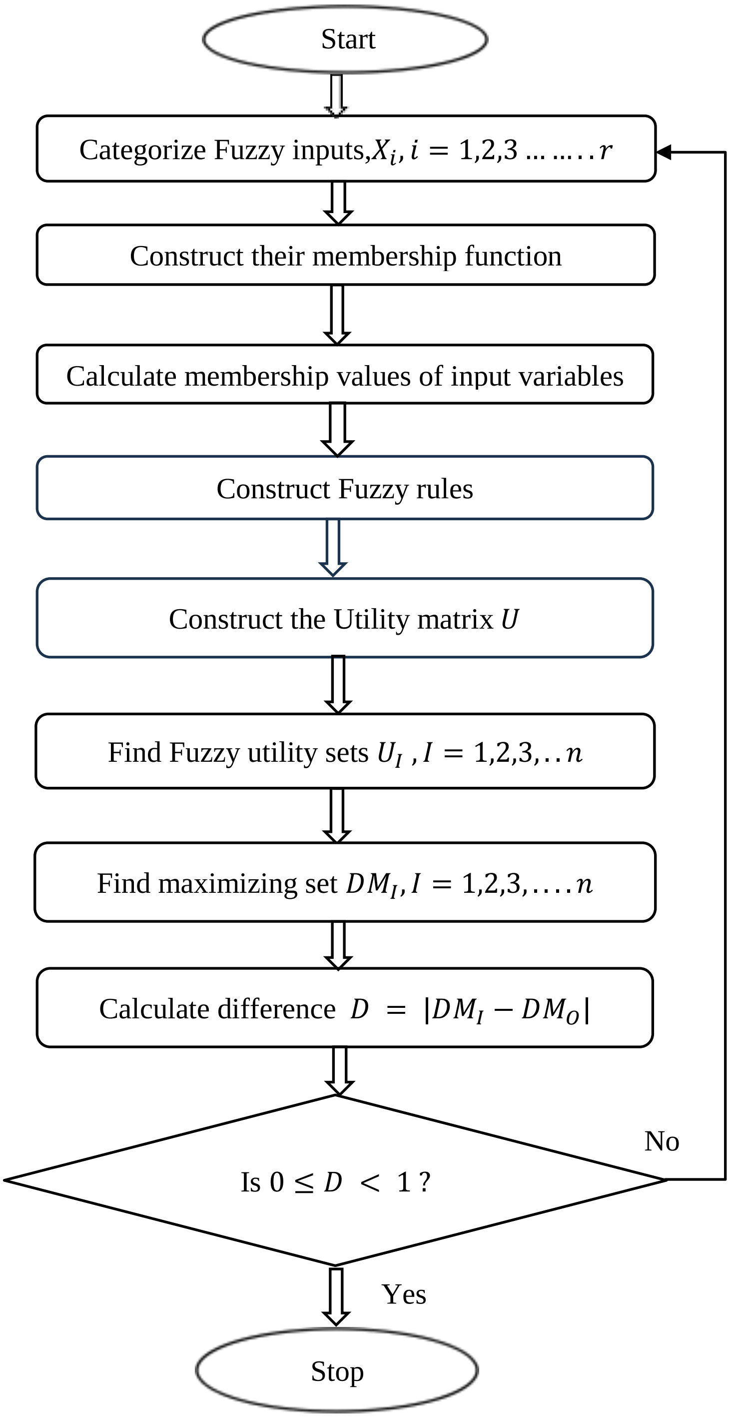


Fig. 1. Flow chart

4. Decision Making Methods

In order to design and develop Intelligent system, we have taken some basic features of ECG graphs as input variables, like Heart rate, QRS complex, RR and PR interval, and we have used trapezoidal and gaussian membership functions for their classification, which are as follows:

a. Heart rate

Heart rate is categorized into 7 linguistic variables, and their membership functions are given below:

Table 1. Heart rate classification

Linguistic variables	Heart rate (bpm)	Membership function
Very Slow	10-45	$\mu_{Very\ slow}(x) = max\left(min\left(\frac{x-10}{10}, 1, \frac{45-x}{15}\right), 0\right)$
Slow	35-60	$\mu_{Slow}(x) = max\left(min\left(\frac{x-35}{7}, 1, \frac{60-x}{10}\right), 0\right)$
Medium	55-70	$\mu_{Medium}(x) = max\left(min\left(\frac{x-55}{5}, 1, \frac{70-x}{5}\right), 0\right)$
Normal	65-100	$\mu_{Normal}(x) = max\left(min\left(\frac{x-65}{10}, 1, \frac{100-x}{15}\right), 0\right)$
Little bit High	90-132	$\mu_{Little\ bit\ high}(x) = max\left(min\left(\frac{x-90}{15}, 1, \frac{132-x}{12}\right), 0\right)$
High	125-150	$\mu_{High}(x) = max\left(min\left(\frac{x-125}{10}, 1, \frac{140-x}{18}\right), 0\right)$
Very High	130-175	$\mu_{Very\ high}(x) = max\left(min\left(\frac{x-130}{30}, 1\right), 0\right)$

b. QRS complex classification

QRS complex is categorized into 4 linguistic variables, and their membership functions are given below:

Table 2. QRS Classification

Linguistic Variables	QRS complex (degree)	Membership functions
Left axis deviation	-90 to -30	$\mu_{Left\ axis\ deviation}(x) = gaussmf(25, -60)$
Normal axis	-30 to 90	$\mu_{Normal\ axis}(x) = gaussmf(7,30)$
Right axis deviation	90 to 180	$\mu_{Right\ axis\ deviation}(x) = gaussmf(28,135)$
Extreme axis deviation	-90 to 180	$\mu_{Extreme\ axis\ deviation}(x) = gaussmf(8,45)$

c. RR interval

RR interval is categorized into 5 linguistic variables, and their membership functions are given below:

Table 3. RR interval classification

Linguistic variables	RR interval	Membership functions
Very short	200-500	$\mu_{Very\ short}(x) = max\left(min\left(\frac{x-200}{100}, 1, \frac{500-x}{100}\right), 0\right)$
Short	480-600	$\mu_{Short}(x) = max\left(min\left(\frac{x-480}{30}, 1, \frac{600-x}{60}\right), 0\right)$
Normal	580-1200	$\mu_{Normal}(x) = max\left(min\left(\frac{x-580}{120}, 1, \frac{1200-x}{300}\right), 0\right)$
Large	1180-1500	$\mu_{Large}(x) = max\left(min\left(\frac{x-1180}{100}, 1, \frac{1500-x}{110}\right), 0\right)$
Very large	1480-1580	$\mu_{Very\ large}(x) = max\left(min\left(\frac{x-1480}{200}, 1\right), 0\right)$

d. PR interval

PR interval is categorized into 5 linguistic variables, and their membership functions are given below:

Table 4. PR interval classification

Linguistic variables	PR interval	Membership function
Very short	20-100	$\mu_{Very\ short}(x) = max\left(min\left(\frac{x-20}{25}, 1, \frac{100-x}{30}\right), 0\right)$
Short	80-121	$\mu_{Short}(x) = max\left(min\left(\frac{x-80}{10}, 1, \frac{121-x}{5}\right), 0\right)$
Normal	100-200	$\mu_{Normal}(x) = max\left(min\left(\frac{x-100}{45}, 1, \frac{200-x}{30}\right), 0\right)$
Large	180-220	$\mu_{Large}(x) = max\left(min\left(\frac{x-180}{10}, 1, \frac{220-x}{15}\right), 0\right)$
Very large	200-320	$\mu_{Very\ large}(x) = max\left(min\left(\frac{x-200}{120}, 1\right), 0\right)$

5. Fuzzy Rule Base

We have developed 700 fuzzy rules based on the suggestions of cardiac experts. However, from the above rules, we have selected the most relevant ones, which are given below.

J_1= If heart rate is "Very Slow," QRS complex is "Left axis deviation," RR interval is "Very Short," and PR interval is "Very Short," then Risk is "Moderate."

J_2= If heart rate is "Very Slow," QRS complex is "Left axis deviation," RR interval is "Very Short," and PR interval is "Short," then Risk is "Moderate."

J_3 = If heart rate is "Very Slow," QRS complex is "Left axis deviation," RR interval is "Very Short," and PR interval is "Normal," then Risk is "High."

J_4= If heart rate is "Very Slow," QRS complex is "Left axis deviation," RR interval is "Very Short," and PR interval is "Large," then Risk is "Very High."

⋮

⋮

J_{313} = If heart rate is "Normal," QRS complex is "Left axis deviation," RR interval is "Normal," and PR interval is "Normal," then Risk is "Normal."

J_{314} = If heart rate is "Normal," QRS complex is "Left axis deviation," RR interval is "Normal," and PR interval is "Large," then Risk is "Moderate."

J_{413} = If heart rate is "Little bit high," QRS complex is "Left axis deviation," RR interval is "Normal," and PR interval is "Normal," then Risk is "Moderate."

J_{414}= If heart rate is "Little bit high," QRS complex is "Left axis deviation," RR interval is "Normal," and PR interval is "Large," then Risk is "High."

⋮

⋮

J_{452} = If heart rate is "Little bit high," QRS complex is "Right axis deviation," RR interval is "Very Short," and PR interval is "Short," then Risk is "High."

J_{453} = If heart rate is "Little bit high," QRS complex is "Right axis deviation," RR interval is "Very Short," and PR interval is "Normal," then Risk is "Very High."

J_{552} = If heart rate is "High," QRS complex is "Right axis deviation," RR interval is "Very Short," and PR interval is "Short," then Risk is "Very High."

J_{553} = If heart rate is "High," QRS complex is "Right axis deviation," RR interval is "Very Short," and PR interval is "Normal," then Risk is "Very High."

⋮

⋮

J_{695} = If Heart rate is "Very High", QRS complex is "Extreme axis deviation," RR interval is "Large," and PR interval is "Large," then Risk is "High."

J_{696} = If heart rate is "Very High," QRS complex is "Extreme axis deviation," RR interval is "Very Large," and PR interval is "Very Short," then Risk is "Very High."

J_{697} = If heart rate is "Very High," QRS complex is "Extreme axis deviation," RR interval is "Very Large," and PR interval is "Short," then Risk is "Very High."

J_{698} = heart rate is "Very High," QRS complex is "Extreme axis deviation," RR interval is "Very Large," and PR interval is "Normal," then Risk is "Moderate."

J_{699} = If heart rate is "Very High," QRS complex is "Extreme axis deviation," RR interval is "Very Large," and PR interval is "Large," then Risk is "High."

J_{700} = If Heart rate is "Very High," QRS complex is "Extreme axis deviation," RR interval is "Very Large," and PR interval is "Large," then Risk is "Very High."

e. Linguistic strings

In accordance with the respective input variables Heart Rate, QRS Complex, RR Interval, and PR Interval there are 700 linguistic strings were generated based on the number of layers for each variable. These strings are as follows:

$$J_1 = \mu_{Heart\ rate(Very\ slow)} \times \mu_{QRS\ complex(Left\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\ interval(Very\ short)}$$

$$J_2 = \mu_{Heart\ rate(Very\ slow)} \times \mu_{QRS\ complex(Left\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\ interval(Short)}$$

$\vdots$

$\vdots$

$$J_{313} = \mu_{Heart\ rate(Normal)} \times \mu_{QRS\ complex(Left\ axis\ deviation)} \times \mu_{RR\ interval(Normal)} \times \mu_{PR\ interval(Normal)}$$

$$\mathrm{J}_{314} = \mu_{\mathrm{Heart\ rate(Normal)}} \times \mu_{\mathrm{QRS\ complex(Left\ axis\ deviation)}} \times \mu_{RR\ interval(Normal)} \times \mu_{PR\ interval(Large)}$$

$$J_{413} = \mu_{Heart\ rate(Little\ bit\ high)} \times \mu_{QRS\ complex(Left\ axis\ deviation)} \times \mu_{RR\ interval(Normal)} \times \mu_{PR\ interval(Normal)}$$

$$J_{414} = \mu_{Heart\ rate(Little\ bit\ high)} \times \mu_{QRS\ complex(Left\ axis\ deviation)} \times \mu_{RR\ interval(Normal)} \times \mu_{PR\ interval(Large)}$$

$\vdots$

$\vdots$

$$J_{452} = \mu_{Heart\ rate(Little\ bit\ high)} \times \mu_{QRS\ complex(Right\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\ interval(Short)}$$

$$J_{453} = \mu_{Heart\ rate(Little\ bit\ high)} \times \mu_{QRS\ complex(Right\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\sim interval(normal)}$$

$$J_{552} = \mu_{Heartrate(High)} \times \mu_{QRS\ complex(Right\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\ interval(Short)}$$

$$J_{553} = \mu_{Heart\ rate(High)} \times \mu_{QRS\ complex(Right\ axis\ deviation)} \times \mu_{RR\ interval(Very\ short)} \times \mu_{PR\ interval(normal)}$$

$\vdots$

$\vdots$

$$J_{698} = \mu_{Heart\ rate(Very\ high)} \times \mu_{QRS\ complex(Extreme\ axis\ deviation)} \times \mu_{RR\ interval(Very\ large)} \times \mu_{PR\ interval(Normal)}$$

$$J_{699} = \mu_{Heart\ rate(Very\ high)} \times \mu_{QRS\ complex(Extreme\ axis\ deviation)} \times \mu_{RR\ interval(Very\ large)} \times \mu_{PR\ interval(Large)}$$

$$J_{700} = \mu_{Heart\ rate(Very\ high)} \times \mu_{QRS\ complex(Extreme\ axis\ deviation)} \times \mu_{RR\ interval(Very\ large)} \times \mu_{PR\ interval(Large)}$$

f. Output classification

The status of heart health is categorized into 5 outputs:

O_1= Low, O_2=Normal, O_3=Moderate, O_4=High, O_5= Very high.

6. Computation

The utility matrix U designed of order 5×700 as per fuzzy rule base:

$$U = \begin{pmatrix} 40 & 12 & \dots & 18 & 10 & \dots & 15 & 12 \\ 50 & 50 & \dots & 42 & 20 & \dots & 45 & 25 \\ 35 & 35 & \dots & 60 & 65 & \dots & 75 & 60 \\ 45 & 45 & \dots & 33 & 50 & \dots & 65 & 55 \\ 55 & 55 & \dots & 71 & 35 & \dots & 55 & 40 \end{pmatrix}$$

Case-I

Heart rate=131 bpm, QRS complex=90°, RR interval= 458 ms, PR interval=112 ms

The given fuzzy set which represents the state of concerned patients:

Heart rate={(Very slow,0),(Slow,0),(Medium,0),(Normal,0.46666667),(Little bit high,0.2),(High,0), (Very high,0)}

QRS complex={(Left axis deviation,0.910909),(Normal axis,0),(Right axis deviation,0), (Extreme axis deviation, 0)}

RR interval={(Very short,0),(Short,0),(Normal,0.5416667),(Large,0),(very large,0)}

PR interval={(Very short,0),(Short,0),(Normal,0.433333),(Large,0.7),(very large,0)}

The state of the system of concerned patients is as follows:

$A = (0.09977811, J_{313}), (0.16118015, J_{314}), (0.04276211, J_{413}), (0.06907730, J_{414})$

The fuzzy utilities with each alternatives sets are as follows:

$U_1 = \{(0.00962048,20), (0.00256546,10), (0.08081202,15), (0.02154987,12)\}$

$U_2 = \{(0.00962048,35), (0.00256546,20), (0.08081202,45), (0.02154987,25)\}$

$U_3 = \{(0.00962048,80), (0.00256546,65), (0.08081202,75), (0.02154987,60)\}$

$U_4 = \{(0.08965505,65), (0.00256546,50), (0.02154987,55)\}$

$U_5 = \{(0.00962048,50), (0.00256546,35), (0.08081202,55), (0.02154987,40)\}$

The maximizing sets corresponding to each alternatives are as follows:

$U_{M1} = \{(0.00024414,20), (0.00000381,10), (0.00004345,15), (0.00001139,12)\}$

$U_{M2} = \{(0.00701243,35), (0.0024414,20), (0.03167635,45), (0.00093132,25)\}$

$U_{M3} = \{(1.0000000,80), (0.28770024,65), (0.67893416,75), (0.17797852,60)\}$

$U_{M4} = \{(0.28770024,65), (0.05960464,50), (0.10559326,55)\}$

$U_{M5} = \{(0.05960464,50), (0.00701243,35), (0.10559326,55), (0.01562500,40)\}$

The optimal fuzzy utilities sets are as follows:

$U_{01} = \{(0.00024414,20), (0.00000381,10), (0.00004345,15), (0.00001139,12)\}$

$U_{02} = \{(0.00701243,35), (0.00024414,20), (0.03167635,45), (0.00093132,12)\}$

$U_{03} = \{(0.00962048,80), (0.00256546,20), (0.08081202,45), (0.02154987,60)\}$

$U_{04} = \{(0.08965505,65), (0.00256546,50), (0.02154987,55)\}$

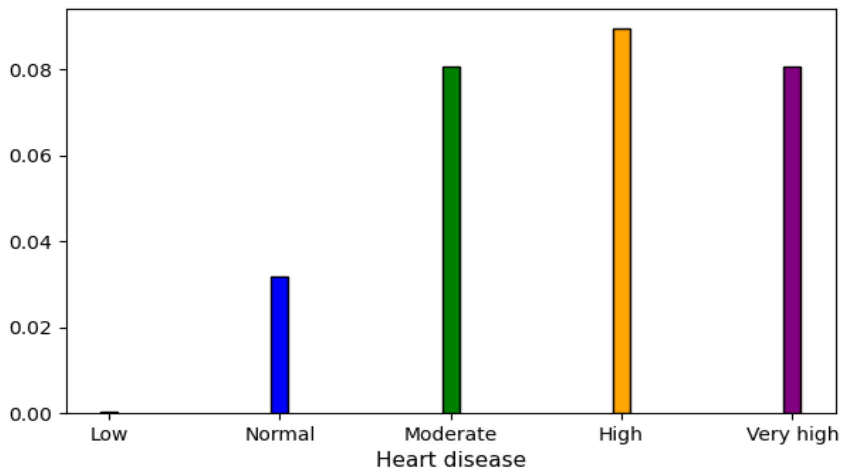
$U_{05} = \{(0.00962048,50), (0.00256546,35), (0.08081202,55), (0.02154987,40)\}$

The set of optimal alternatives are as follows:

B_0={ (0.00024414, Low), (0.03167635, Normal), (0.08081202, Moderate), (0.08965505, High), (0.08081202, Very high)}

The sets having the greatest grade of membership value, hence the best alternative, is High.

Fig. 2. Output for case-I



The above graphical sketches clearly indicate that the patients are in the high-risk category.
Degree of match for inputs as given below:

$DM_{I1'} = 2\mu_{Heart\ rate_{Little\ bit\ high}}(131) = 2(0.08333333) - 1 = -0.83333334$

$DM_{I1''} = 2\mu_{Heart\ rate_{High}}(131) = 2(0.7) - 1 = 0.40000000$

$DM_{I2} = 2\mu_{QRS\ complex_{Right\ axis\ deviation}}(90°) = 2(0.2748708) - 1 = -0.4502584$

$DM_{I3} = 2\mu_{RR\ interval_{Very\ short}}(458) = 2(0.42) - 1 = -0.16$

$DM_{I4'} = 2\mu_{PR\ interval_{Short}}(112) = 2(1) - 1 = 1.00000000$

$DM_{I4''} = 2\mu_{PR\ interval_{Normal}}(112) = 2(0.26666667) - 1 = -0.4666666$

To verify the consistency between input and output observations, the degree of match for the input (DM_I) is determined the minimum value among the given inputs:

$$DM_I = \min\{-0.83333334, 0.4, -0.4502584, -0.16, 1, -0.4666666\} = -0.83333334.$$

The degree of match for the optimal alternative (DM_0) is calculated using the given formula:

$$DM_0 = 2(0.08965505) - 1 = -0.8206899.$$

The absolute difference between the two degrees of match is computed as:

$$D = |DM_I - DM_0| = |-0.83333334 - (-0.8206899)| = 0.01264344.$$

This difference within the range ([0,1]) and is very close to zero, indicating that the noise between the input and output observations are close to each other. This minimal difference confirms a high level of satisfaction.

Case-II

Heart rate = 93 bpm; QRS complex= $-49.2°$; RR interval = 645 ms; PR interval=187 ms

The fuzzy sets represents the state of concerned patient:

Heart rate = {(Very short,0),(Short,0),(Medium,0),(Normal,0.46666667),(Little bit high,0.2),(High,0),(Very high,0)}

QRS complex={(Left axis deviation,0.910909),(Normal axis,0),(Right axis deviation,0),(Extreme axis deviation,0)}

RR interval={(Very short,0),(Short,0),(Normal,0.5416667),(Large,0),(Very large,0)}

PR interval={(Very short,0),(Short,0),(Normal,0.43333333),(Large,0.7),(Very large,0)}

The state of the system of concerned patients is as follows:

$A = \{(0.09977811, J_{313}), (0.16118015, J_{314}), (0.04276211, J_{413}), (0.06907730, J_{414})\}$

The fuzzy utility values associated with each set of alternatives are as follows:

$U_1 = \{(0.09977811,40), (0.16118015,12), (0.0427621,18), (0.06907730,24)\}$

$U_2 = \{(0.09977811,50), (0.16118015,38), (0.0427621,42), (0.06907730,29)\}$

$U_3 = \{(0.09977811,35), (0.16118015,55), (0.0427621,60), (0.06907730,34)\}$

$U_4 = \{(0.09977811,45), (0.16118015,48), (0.0427621,33), (0.06907730,28)\}$

$U_5 = \{(0.09977811,55), (0.16118015,25), (0.0427621,71), (0.06907730,24)\}$

The maximizing sets corresponding to each alternative are presented as follows:

$U_{1M} = \{(0.0567553,40), (0.00013792,12), (0.00104730,18), (0.00441331,24)\}$

$U_{2M} = \{(0.17320414,50), (0.02169092,38), (0.07243604,42), (0.01136837,29)\}$

$U_{3M} = \{(0.02911042,35), (0.27894699,55), (0.07243604,60), (0.01136837,34)\}$

$U_{4M} = \{(0.10227531,45), (0.14122592,48), (0.02169092,33), (0.00953890,28)\}$

$U_{5M} = \{(0.27898300,55), (0.14121548,25), (0.02169092,71), (0.00953890,24)\}$

The optimal fuzzy utility sets are given as follows:

$U_{01} = \{(0.05675553,40), (0.0013792,12), (0.00104730,18), (0.00441331,24)\}$

$U_{02} = \{(0.09977811,40), (0.02169092,38), (0.0427621,42), (0.01136837,29)\}$

$U_{03} = \{(0.02911042,35), (0.16118015,55), (0.0427621,60), (0.01136837,34)\}$

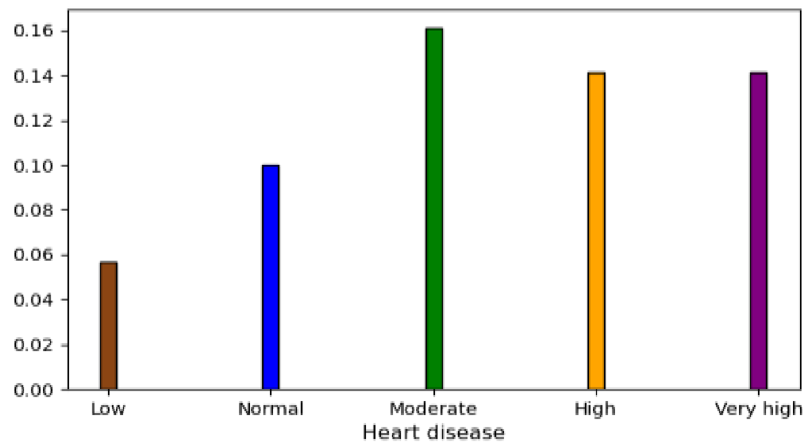
$U_{04} = \{(0.09977811,45), (0.14122592,48), (0.021690927,71), (0.00953890,24)\}$

The set of optimal alternative are as follows:

B_o={(0.05675553, Low), (0.09977811, Normal), (0.16118015, Moderate), (0.14122592, High), (0.14121548, Very high)}

The sets having the greatest grade of membership value, hence the best alternative, is Moderate.

Fig.3. Output for case-II



The above graphical sketches clearly indicate that the patients are in the moderate-risk category.

Degree of match for input variables are as follows:

$DM_{I1'} = 2\mu_{Heart\ rate_{Little\ bit\ high}}(93) = 2(0.46666666) - 1 = -0.06666668$

$DM_{I1''} = 2\mu_{Heart\ rate_{High}}(93) = 2(0.2) - 1 = -0.600$

$DM_{I2} = 2\mu_{QRS\ complex_{Left\ axis\ deviation}}(-49.2°) = 2(0.910909) - 1 = 0.8218185$

$DM_{I3} = 2\mu_{RR\ interval_{Normal}}(645) = 2(0.5416666) - 1 = 0.0833332$

$DM_{I4'} = 2\mu_{PR\ interval_{Normal}}(187) = 2(0.43333333) - 1 = -0.13333334$

$DM_{I4''} = 2\mu_{PR\ interval_{Large}}(187) = 2(0.7) - 1 = 0.4$

The degree of match for the input (DM_I) is calculated the minimum value among the given inputs:

$DM_I = \min\{-0.06666668, -0.6, 0.8218185, 0.08333332, -0.13333334, 0.4, -0.13333334, -0.13333334\} = -0.6.$

The degree of match for the optimal alternative (DM_0) is determined using the formula:

$$DM_0 = 2(0.16118015) - 1 = -0.6776397.$$

The difference between (D_{MI}) and (D_{M0}) is computed as:

$$D = |DM_I - DM_0| = |-0.6 - (-0.6776397)| = 0.0776397.$$

This difference lies within the range ($[0,1]$) and is close to zero. This indicates that the noise between the input and output observations is close to each other, verifying a high level of satisfaction. Similarly, we have computed the remaining patient's data.

7. Conclusion

This research paper shows that a Soft Computing diagnostic system can effectively replicate expert thinking, making it useful for handling complex cases. The proposed method will help in designing and developing a Soft Computing-based risk assessment system to support medical experts in classifying the severity of cardiac issues.

Conflict of Interest Declaration

The authors affirm that they have no financial interests, personal relationships, or other affiliations that could have influenced the research and findings presented in this paper.

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