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Predictive Modeling of Health Insurance Premiums for Cardiac Patients Using Fuzzy Inference Techniques

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Abstract- In the contemporary landscape, both insurance companies and customers (insurers) are increasingly motivated to secure the most advantageous deals, particularly in the realm of health insurance where the need for coverage is of paramount concern. Customers, in particular, exhibit a heightened sense of caution when evaluating health insurance options. Fuzzy logic is a computational approach that deals with uncertainty and imprecision, has emerged as a versatile solution across various real-world domains such as electronics, computer science, finance and medical science. This study offers a comprehensive exploration of the application of fuzzy sets methodologies within the field of actuarial science, focusing on health insurance risk assessment. It delves into the foundational mathematics underpinning fuzzy sets, providing a quick overview of their development and utilization. Moreover, the study demonstrates how fuzzy logic models can be effectively constructed and refined to adapt to changing rules and incorporate supplementary data, thus enhancing their predictive accuracy and practical utility. Here a model is presented, which is based on fuzzy expert system that will help the insurance companies to find out predictive modeling of health insurance premiums for cardiac patients using Fuzzy Inference Techniques. Through the application of fuzzy logic techniques, the study aims to derive actionable insights that can inform more informed decision-making processes in the realm of health insurance.

Keywords: Health insurance, Decision-making, Risk assessment, Predictive modeling, Policy evaluation.

1. Introduction: The policyholder pays the health insurance company a certain amount for a set period of time, known as the premium. This sum is due when the policy expires or, depending on factors such as the coverage limit, may differ from one insurance provider to another. Before settling on a health insurance plan, it's a good idea to shop around and compare prices from several providers to see what services and coverage are available.

In the past, an insurance agent would figure up the client's health insurance premium based on their needs. Many websites now include a premium comparison chart that details the costs of various insurance policies for the convenience of their customers. A premium calculator is available on several insurance websites, allowing clients to determine their own price. However, the health of the client, the chosen plan, the client's age, and the coverage limit are the factors that determine the health insurance price.

Fuzzy inference is a way of thinking that uses vague notions and generalized deduction procedures to get impressive conclusions from less-than-perfect inputs.

A fuzzy inferences system is one that uses a certain mapping to get an output y from an input space x. The four components that make up the x-y map are membership function assignment, fuzzy logical connective, aggregation, and defuzzification. These four components constitute what is known as a fuzzy inference methodology since they define the input-output map.

The whole thing is highly debatable. People could have vastly different preferences when it comes to the defuzzification techniques they use, the fuzzy connectives they use, and the membership functions they specify. Fuzzy set theory shines when used to formal decision-making models because of its flexibility in accommodating both objective and subjective data, as well as non-objective data.

The likelihood of developing cardiovascular disease (CD) can be predicted by examining certain variables called risk factors. These risk factors can be changed or eliminated altogether. Your risk of contracting some diseases may go down if you alter it. Tobacco usage, hypertension, sedentary lifestyle, high cholesterol, diabetes, obesity, smoking, excess alcohol intake, and unhealthy eating are all modifiable risk factors. Factors such as age and family history cannot be changed.

Heart disease is more likely to occur in people who have more risk factors. Another risk factor, hypertension, is the leading cause of stroke. The risk of cardiovascular illnesses is greatly increased in people with diabetes. The risk of death from coronary heart disease is two to four times higher and the risk of death from stroke is twice higher for people with diabetes compared to those without the disease, and these rates vary by gender.

Lifestyle factors such as inactivity, poor nutrition, smoking, etc., contribute to cardiovascular disease (CVD) and its associated complications, such as high blood pressure, diabetes, and high cholesterol. The risk of CVD-related complications can be reduced by lowering the prevalence of modifiable risk factors.

An effective risk assessment should focus on diseases rather than isolated variables. Cardiovascular illness is responsible for about 45% of all fatalities, according to recent medical study. It is well-established that cardiovascular disease is associated with an increased risk of death. Although the ethnology of cardiovascular disease risk assessment is very complicated, this does not make it any easier to summarize. Obesity, high cholesterol, and elevated systolic blood pressure are among the most dependable indicators.

A complex system with various and interacting variables is formed by these three variables. Since the number of rating classes grows in direct proportion to the degree of differentiation, this is the fundamental issue with conventional risk classification. Thus, just a tiny subset of applicants would be required to meet the specific requirements for a particular combination of the predictors-systolic blood pressure, cholesterol, and obesity in order to incur a higher risk per insured.

We present a novel theoretical framework for how insurance companies might categorize policyholders according to the prevalence of cardiovascular disease and diabetes, utilizing fuzzy inferences.

Using a two-part statistical model consisting of logistic and ordinary least squares regressions, Liu and Chen (2002) conducted an investigation into the factors that influence the chance of purchasing private health insurance as well as the amount of insurance they purchased. Abdullah et al. (2012) developed a decision model that made use of a fuzzy inference system in order to determine the likelihoods of obtaining health insurance depending on the risk factors that were chosen. In order to construct the likelihoods, input data was gathered from one hundred twenty-eight people working for five different organizations that fall under the jurisdiction of Kota Star Municipality Malaysia. Samani and Shahbodaghlou (2012) underscored the significance of a fuzzy deliberate primary way to deal with the gamble evaluation of development projects. They likewise presented the cycles that are important to frame a progressive precise design that depends on fuzzy logic by using the Fuzzy Decision Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) technique. Kumar and Singh (2013) proposed fuzzy logic is giving the arrangement of genuine issue viz gadgets, software engineering, finance, clinical science and so forth. consequently a fuzzy model is viewed as here for the estimation of expense of medical coverage of an individual having cardiovascular illness in this works gives a fuzzy based modular to compute the health care coverage charge of an individual having cardiovascular sickness and here it saw that the utilization of fuzzy master framework would give the best rest as contrast with the customary way to deal with ascertain the health care coverage charge. With the assistance of the traditional AHP process, Jagdale et al. (2014) have ranked insurance businesses, particularly in the sector of money-back insurance plans.Murugesan and Vetriv el. (2016) introduced an experimental relationship of boundaries administering the issues in financing the health care coverage plot for the rustic regions in Tamil Nadu. The philosophy depends on the information looking over in view of the boundaries recognized. To comprehend the necessities and inclusion of the medical coverage conspire among inhabitants of provincial India the proposed examination is directed. This study tends to the examination question that whether the public authority gave medical coverage plot give monetary wellbeing to alcove and corner of the general public. An experimental examination is directed utilizing fuzzy logic technique to improve the better foundation boundary in addressing the issues looked on the achievement of the health care coverage conspire and the review features the need to upgrade general wellbeing spending on medical services. Considering that the focal point of government spending on medical care has been towards protection, the public authority, to augment monetary security, necessities to improve mindfulness particularly among minimized segments of the general public and to energize the common society area to attempt to take part in this cooperative exertion in upgrading information among individuals in regards to plans started for their advantage. Sahoo and Ratha (2018) suggested that concentrate on how recommender frameworks can propose the strategies with the assistance of multi- criteria decision making (MCDM). This sort of utilization would be exceptionally useful to any individual for picking the right strategy with right assumptions. Since various organizations offer a wide assortment of strategies, a recommender framework which deals with multi-standards is formulated to rank the extra security approaches and rank them. The clients can be suggested the protection in view of the positions. An endeavor was made by Torbati (2018) to give a fuzzy logic framework to the motivation of exploring the presentation of the protection business in Iran. Sallam and Hashmi (2019) suggested that not entirely set in stone for an assortment of wellbeing pointers, similar to cholesterol, glucose, pulse, and resting pulse. These equivalent fuzzy classes can be connected to a specific wellbeing proposal which can work on understanding wellbeing. Thus is a definitive reason for the exploration and the qualities of fuzzy logic are particularly inclined toward the clinical area, and fuzzy conclusion programs essentially benefit all interested parties. As per the discoveries of Kalra et al. (2022), 8% of laborers demonstrated that they were probably going to buy medical care at a 'Low' level, while 34% of laborers showed that they introduced their conceivable outcomes at a 'significant' level. Their examination advocates that FIS would offer imminent legitimizations to set another technique in distinctive arranged medical care purchasers and may use for identifying the gamble factors in different organizations. This end was arrived at after thorough examination of their review. KalraBoadh et al. (2022) they said that study get the resend capable well outcomes as looked at the past review. It has likewise found that FCS used in this assessment has backing to take dependable decision at a definitive endeavor for proposing treatment to the patients in a split second and supporter furthermore hazard to change the way of life, food affinities, have checked from the treatment in future. The current FCS might be correspondingly thusly used to expect various types of wellbeing risk including scholarly and genuine contamination conditions and generally the current review advocates that FCS utilized in this study has supportive to take authentic decision at the ideal chance for offering treatment to the patients immediately and advocate additionally such kind of endanger to significantly impact the lifestyle, food penchants, have checking from the treatment in future.

2. Membership function plot of input and output variables: It is common practice to first establish the range of values for each variable in fuzzy inference systems before plotting the membership function curves that show how each value belongs to various linguistic words.

This is done in order to plot membership functions for input and output variables. In context of cardiac patients such as their factors systolic blood pressure, cholesterol, weight, diabetes and cigarette smoking show in figure 1 to 5 and risk of cardiac illness show in figure 6.

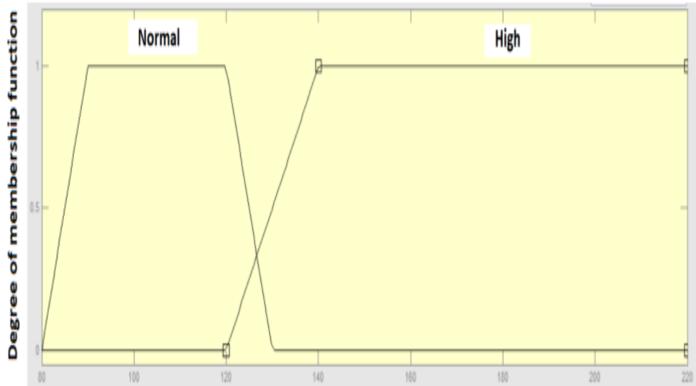

Figure 1: Membership function for systolic blood pressure (input variable)

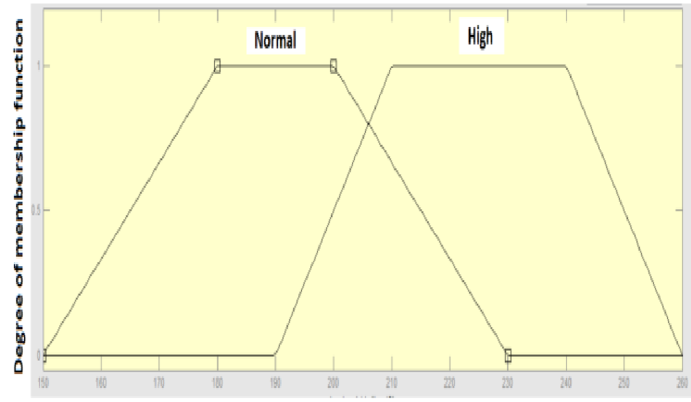

Figure 2: Membership function for cholesterol (input variable)

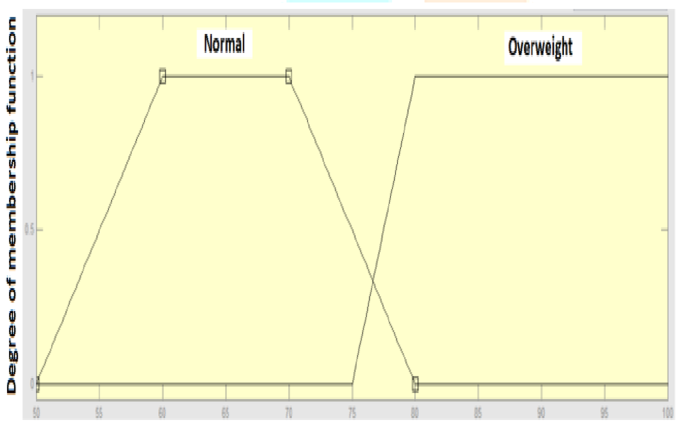

Figure 3: Membership function for weight (input variable)

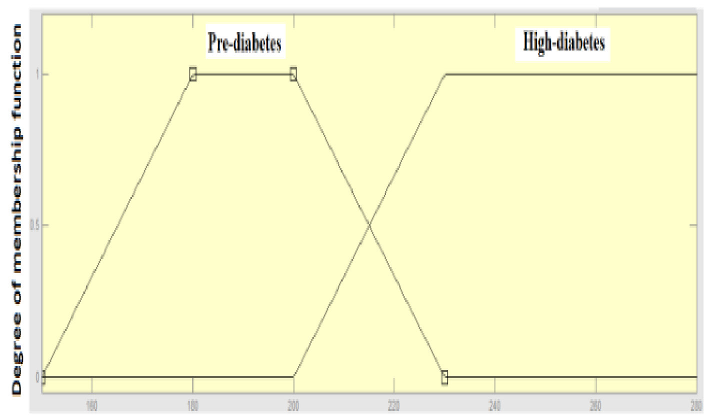

Figure 4: Membership function for diabetes (input variable)

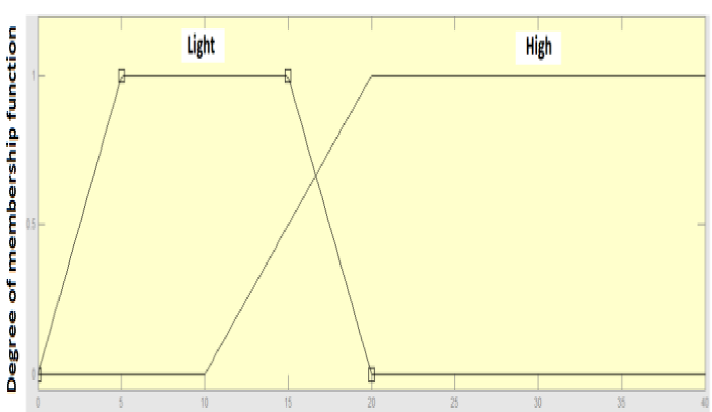

Figure 5: Membership function for cigarette smoking (input variable)

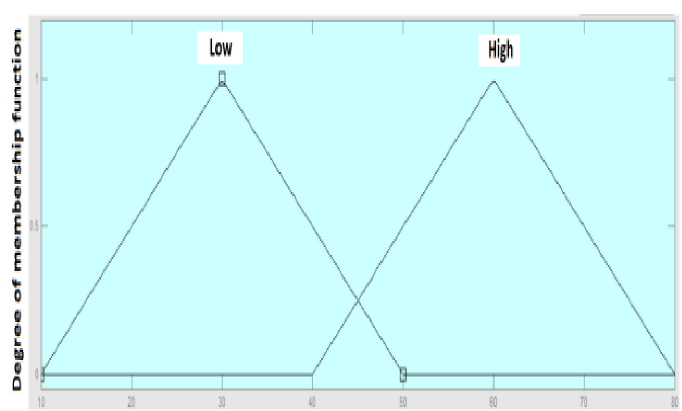

Figure 6: Membership function for risk of cardiac illness (output variable)

The corresponding membership functions are:

$$\mu_{Normal}^{SBP}(x_1) = \begin{cases} \frac{x_1-80}{10} & 80 \le x_1 \le 90 \\ 1 & 90 \le x_1 \le 120 \\ \frac{130-x_1}{10} & 120 \le x_1 \le 130 \end{cases} \qquad \mu_{High}^{SBP}(x_1) = \begin{cases} \frac{x_1-120}{20} & 120 \le x_1 \le 140 \\ 1 & x_1 \ge 140 \end{cases}$$

$$\mu_{Normal}^{C}(x_2) = \begin{cases} \frac{x_2-150}{30} & 150 \le x_2 \le 180 \\ 1 & 180 \le x_2 \le 200 \\ \frac{230-x_2}{30} & 200 \le x_2 \le 230 \end{cases} \qquad \mu_{High}^{C}(x_2) = \begin{cases} \frac{x_2-190}{20} & 190 \le x_2 \le 210 \\ 1 & 210 \le x_2 \le 240 \\ \frac{260-x_2}{20} & 240 \le x_2 \le 260 \end{cases}$$

$$\mu_{Normal}^{W}(x_3) = \begin{cases} \frac{x_3-50}{10} & 50 \le x_3 \le 60 \\ 1 & 60 \le x_3 \le 70 \\ \frac{80-x_3}{10} & 70 \le x_3 \le 80 \end{cases} \qquad \mu_{overweight}^{W}(x_3) = \begin{cases} \frac{x_3-75}{5} & 75 \le x_3 \le 80 \\ 1 & x_3 \ge 80 \end{cases}$$

$$\mu_{Pre}^{D}(x_4) = \begin{cases} \frac{x_4-150}{30} & 150 \le x_4 \le 180 \\ 1 & 180 \le x_4 \le 200 \\ \frac{230-x_4}{30} & 200 \le x_4 \le 230 \end{cases} \qquad \mu_{High}^{D}(x_4) = \begin{cases} \frac{x_4-200}{30} & 200 \le x_4 \le 230 \\ 1 & x_4 \ge 230 \end{cases}$$

$$\mu_{Light}^{CS}(x_5) = \begin{cases} \frac{x_5-0}{5} & 0 \le x_5 \le 5 \\ 1 & 5 \le x_5 \le 15 \\ \frac{20-x_5}{5} & 15 \le x_5 \le 20 \end{cases} \qquad \mu_{High}^{CS}(x_5) = \begin{cases} \frac{x_5-10}{10} & 10 \le x_5 \le 20 \\ 1 & x_5 \ge 20 \end{cases}$$

$$\mu_{Low}^{RCI}(x_6) = \begin{cases} \frac{x_6-10}{20} & 10 \le x_6 \le 30 \\ \frac{50-x_6}{20} & 30 \le x_6 \le 50 \end{cases} \qquad \mu_{High}^{RCI}(x_6) = \begin{cases} \frac{x_6-40}{20} & 40 \le x_6 \le 60 \\ \frac{80-x_6}{20} & 60 \le x_6 \le 80 \end{cases}$$

3. Rule Base: The rule base is an essential component in fuzzy inference techniques that are applied to predictive modelling of health insurance premiums for cardiac patients. It defines the manner in which inputs (such as patient characteristics, medical history, and so on) are translated into outputs (such as predicted risk levels, insurance premiums, and so on). In order to make inferences and apply reasoning, the rule base is made up of a collection of IF-THEN rules.

These rules provide a language description of the relationship that exists between the inputs and the outputs. Using fuzzy inference techniques, the following is a basic rule base that can be used to forecast health insurance premiums for diabetic patients.

Table: 1 Rule base of the system further from expert information thirty two rules are to be constructed.

Rules	Blood Pressure (Systolic)	Cholesterol	Weight	Diabetes	Cigarette Smoker	Risk
1	Normal	Normal	Normal	Pre-diabetes	Light Smoker	Low
2	Normal	High	Normal	Pre-diabetes	Light Smoker	Low
3	Normal	Normal	Overweight	Pre-diabetes	Light Smoker	High
4	Normal	High	Overweight	Pre-diabetes	Light Smoker	High
5	Normal	Normal	Normal	High-diabetes	Light Smoker	Low
6	Normal	High	Normal	High-diabetes	Light Smoker	High
7	Normal	Normal	Normal	Pre-diabetes	High Smoker	Low
8	Normal	High	Normal	Pre-diabetes	High Smoker	Low
9	Normal	Normal	Normal	High-diabetes	High Smoker	Low
10	Normal	High	Normal	High-diabetes	High Smoker	High
11	Normal	Normal	Overweight	Pre-diabetes	High Smoker	High
12	Normal	High	Overweight	Pre-diabetes	High Smoker	High
13	Normal	Normal	Overweight	High-diabetes	High Smoker	High
14	Normal	High	Overweight	High-diabetes	High Smoker	High
15	Normal	Normal	Overweight	High-diabetes	Light Smoker	High
16	Normal	High	Overweight	High-diabetes	Light Smoker	High
17	High	Normal	Normal	Pre-diabetes	Light Smoker	Low
18	High	High	Normal	Pre-diabetes	Light Smoker	High
19	High	Normal	Overweight	Pre-diabetes	Light Smoker	High
20	High	High	Overweight	Pre-diabetes	Light Smoker	High
21	High	Normal	Normal	High-diabetes	Light Smoker	High
22	High	High	Normal	High-diabetes	Light Smoker	High
23	High	Normal	Normal	Pre-diabetes	High Smoker	High
24	High	High	Normal	Pre-diabetes	High Smoker	High
25	High	Normal	Normal	High-diabetes	High Smoker	High
26	High	High	Normal	High-diabetes	High Smoker	High
27	High	Normal	Overweight	Pre-diabetes	High Smoker	High
28	High	High	Overweight	Pre-diabetes	High Smoker	High
29	High	Normal	Overweight	High-diabetes	High Smoker	High
30	High	High	Overweight	High-diabetes	High Smoker	High
31	High	Normal	Overweight	High-diabetes	Light Smoker	High
32	High	High	Overweight	High-diabetes	Light Smoker	High

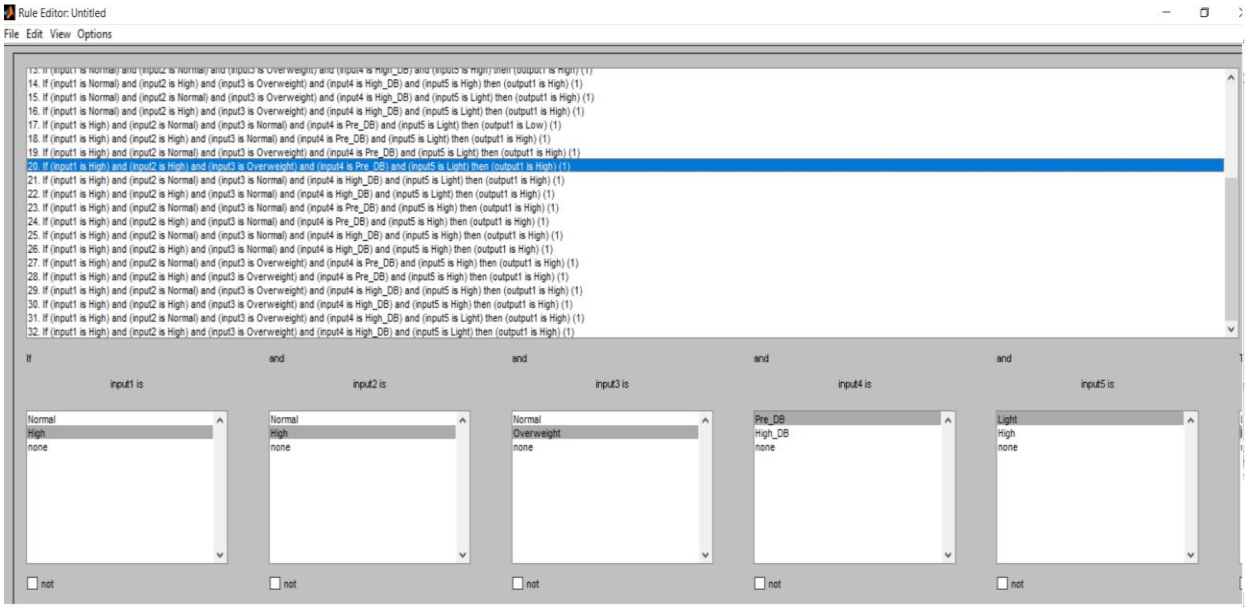

Figure 7: Rule base interface of FLS

4. Methodology: A rule base is used to store expert knowledge, a fuzzy inference system is built with linguistic terms and membership functions for each variable, and an inference engine is used to integrate rules for prediction. Fuzzification, rule evaluation, aggregation, and defuzzification are the steps used to train the fuzzy system with historical data. In order to help stakeholders understand and make informed decisions, the finalized model is then deployed for real-world predictions. It is continuously monitored and updated as needed. Finally, the entire process is documented and reported in detail. Health insurance rates for cardiac patients can be effectively predicted utilizing fuzzy inference techniques, according to the methodology's systematic approach.

4.1. Input variables: Now, let's think about the inputs for crisps for a policyholder.

$$x_1 = 125mmHg, x_2 = 205mg/dl, x_3 = 76kg/m^2, x_4 = 205mg/dl, x_5 = 18cigarette/day$$

4.2. Fuzzification: To get the fuzzy values that go with them, subsection (2) makes use of the membership function.

$$\mu_{Normal}^{SBP}(125) = \frac{130-125}{10} = \frac{1}{2} \qquad \mu_{High}^{SBP}(125) = \frac{125-120}{20} = \frac{1}{4}$$

$$\mu_{Normal}^{C}(205) = \frac{230-205}{30} = \frac{5}{6} \qquad \mu_{High}^{C}(205) = \frac{205-190}{20} = \frac{3}{4}$$

$$\mu_{Normal}^{W}(76) = \frac{80-76}{10} = \frac{2}{5} \qquad \mu_{overweight}^{W}(76) = \frac{76-75}{5} = \frac{1}{5}$$

$$\mu_{Pre}^{D}(205) = \frac{230-205}{30} = \frac{5}{6} \qquad \mu_{High}^{D}(205) = \frac{205-200}{30} = \frac{1}{6}$$

$$\mu_{Light}^{cs}(18) = \frac{20-18}{5} = \frac{2}{5} \qquad \mu_{High}^{cs}(x_5) = \frac{18-10}{10} = \frac{4}{5}$$

4.3. Rule Evaluation:

$\min\{\mu_{Normal}^{SBP}, \mu_{Normal}^{C}, \mu_{Normal}^{W}, \mu_{Pre}^{D}, \mu_{Light}^{cs}\} = \min\left\{\frac{1}{2},\frac{5}{6},\frac{2}{5},\frac{5}{6},\frac{2}{5}\right\} = \frac{2}{5}$(Strength of Rule 1)

$\min\{\mu_{Normal}^{SBP}, \mu_{Normal}^{C}, \mu_{Normal}^{W}, \mu_{Pre}^{D}, \mu_{High}^{cs}\} = \min\left\{\frac{1}{2},\frac{5}{6},\frac{2}{5},\frac{5}{6},\frac{4}{5}\right\} = \frac{2}{5}$(Strength of Rule 7)

$\min\{\mu_{Normal}^{SBP}, \mu_{Normal}^{C}, \mu_{Normal}^{W}, \mu_{High}^{D}, \mu_{High}^{cs}\} = \min\left\{\frac{1}{2},\frac{5}{6},\frac{2}{5},\frac{1}{6},\frac{4}{5}\right\} = \frac{1}{6}$(Strength of Rule 9)

$\min\{\mu_{Normal}^{SBP}, \mu_{Normal}^{C}, \mu_{overweight}^{W}, \mu_{High}^{D}, \mu_{High}^{cs}\} = \min\left\{\frac{1}{2},\frac{5}{6},\frac{1}{5},\frac{1}{6},\frac{4}{5}\right\} = \frac{1}{6}$(Strength of Rule 13)

$\min\{\mu_{Normal}^{SBP}, \mu_{High}^{C}, \mu_{overweight}^{W}, \mu_{High}^{D}, \mu_{High}^{cs}\} = \min\left\{\frac{1}{2},\frac{3}{4},\frac{1}{5},\frac{1}{6},\frac{4}{5}\right\} = \frac{1}{6}$(Strength of Rule 14)

$\min\{\mu_{High}^{SBP}, \mu_{Normal}^{C}, \mu_{Normal}^{W}, \mu_{Pre}^{D}, \mu_{Light}^{cs}\} = \min\left\{\frac{1}{4},\frac{5}{6},\frac{2}{5},\frac{5}{6},\frac{2}{5}\right\} = \frac{1}{4}$(Strength of Rule 17)

$\min\{\mu_{High}^{SBP}, \mu_{High}^{C}, \mu_{Normal}^{W}, \mu_{Pre}^{D}, \mu_{Light}^{cs}\} = \min\left\{\frac{1}{4},\frac{3}{4},\frac{2}{5},\frac{5}{6},\frac{2}{5}\right\} = \frac{1}{4}$(Strength of Rule 18)

$\min\{\mu_{High}^{SBP}, \mu_{High}^{C}, \mu_{overweight}^{W}, \mu_{Pre}^{D}, \mu_{Light}^{cs}\} = \min\left\{\frac{1}{4},\frac{3}{4},\frac{1}{5},\frac{5}{6},\frac{2}{5}\right\} = \frac{1}{5}$(Strength of Rule 20)

$\min\{\mu_{High}^{SBP}, \mu_{High}^{C}, \mu_{overweight}^{W}, \mu_{High}^{D}, \mu_{High}^{cs}\} = \min\left\{\frac{1}{4},\frac{3}{4},\frac{1}{5},\frac{1}{6},\frac{4}{5}\right\} = \frac{1}{6}$(Strength of Rule 30)

$\min\{\mu_{High}^{SBP}, \mu_{High}^{C}, \mu_{overweight}^{W}, \mu_{High}^{D}, \mu_{Light}^{cs}\} = \min\left\{\frac{1}{4},\frac{3}{4},\frac{1}{5},\frac{1}{6},\frac{2}{5}\right\} = \frac{1}{5}$(Strength of Rule 32)

4.4. Aggregation: $Maximum\ strength = max\left\{\frac{2}{5},\frac{2}{5},\frac{1}{6},\frac{1}{6},\frac{1}{6},\frac{1}{4},\frac{1}{4},\frac{1}{5},\frac{1}{6},\frac{1}{5}\right\} = \frac{2}{5}$

There is a minimal chance of cardiac illness while following rules (1) and (7), which have maximum strength output.

4.5. Defuzzification: According to Kumar et al. (2010), the gross premium is determined by adding the risk loading, which is proportionate to the class rate.

$$P\ (k/a_1, a_2, a_3) = \ C_{a_1a_2a_3} \ + \left[\frac{\nu(k)}{100}\right] C_{a_1a_2a_3}$$

$$\frac{x_6 - 10}{20} = \frac{2}{5} \Rightarrow x_6 = 18$$

$$\frac{50 - x_6}{20} = \frac{2}{5} \Rightarrow x_6 = 42$$

Using MOM (Mean of maxima)

$$x_6{}^* = \frac{42 + 18}{2} = 30\ \%$$

Our outputs are now clear, and we may modify the class rates by adding the risk loading to the insurance premium. At this point, our application would be responsible for paying.

$$P\ (k/a_1, a_2, a_3)\ = C_{a_1a_2a_3} \ + \left(\frac{30}{100}\right) C_{a_1a_2a_3} = C_{a_1a_2a_3} \ + 0.3C_{a_1a_2a_3} = 1.3C_{a_1a_2a_3}$$

Where $C_{a_1a_2a_3}$ is the class rate.

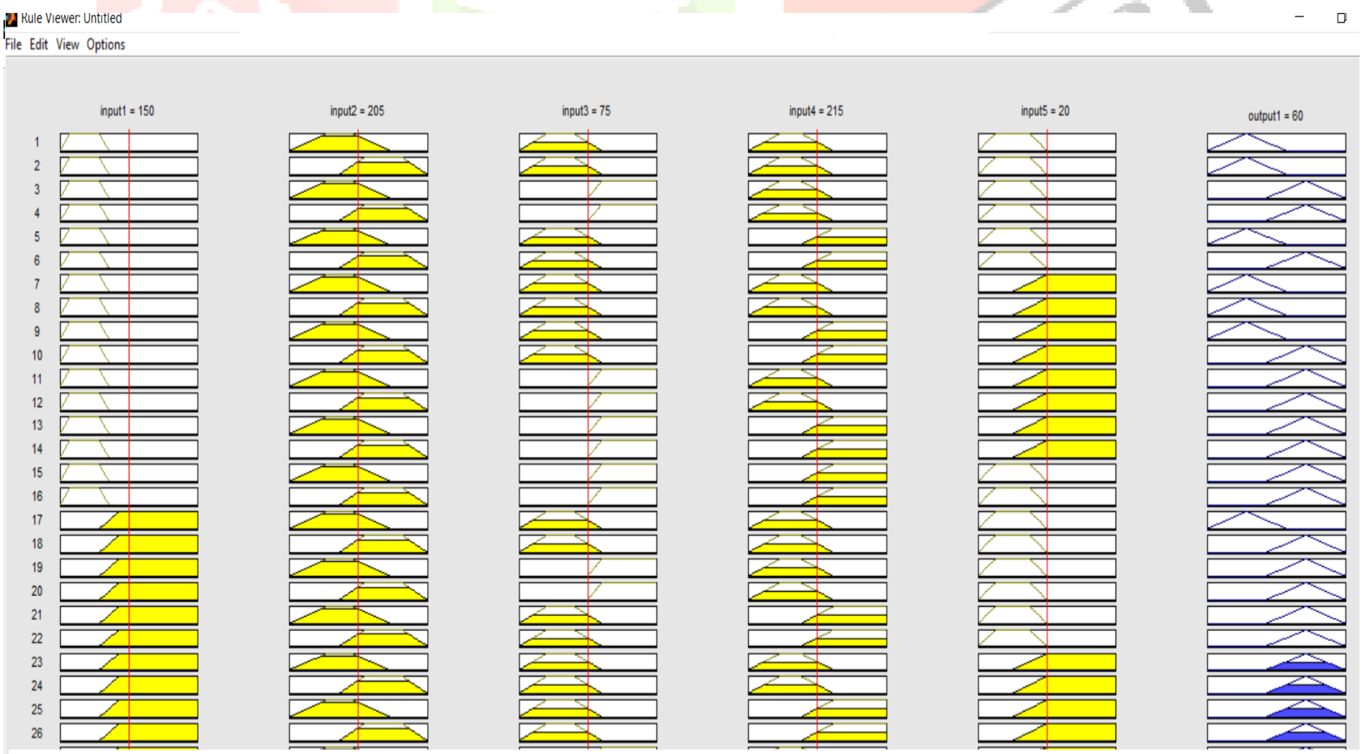

Figure 8: Inputs and output interface of FLS

Table 2: Estimated values of risk for cardiac patients using FLS

S.No.	Blood Pressure (Systolic)	Cholesterol	Weight	Diabetes	Cigarette Smoker	Risk
1	150	205	75	215	20	60
2	91.7	180	52.5	165	36.7	30
3	145	188	69.2	206	10.8	38.2
4	159	223	71.8	216	13.7	50.1
5	165	215	61.5	169	7.07	46.3
6	131	182	70.2	195	16.1	45
7	170	196	63.8	181	10.8	40.2
8	121	183	69.5	219	18.5	31.7
9	97.3	222	77.2	237	8.93	48.4
10	122	212	66.2	204	13.7	35.5
11	146	181	68.2	187	19.9	58.7
12	153	160	63.5	216	12.9	45
13	108	164	77.2	250	35.3	47.6
14	134	196	78.8	196	18.5	54.5
15	129	204	70.5	236	22	54

5.3D surface plots of output variable:

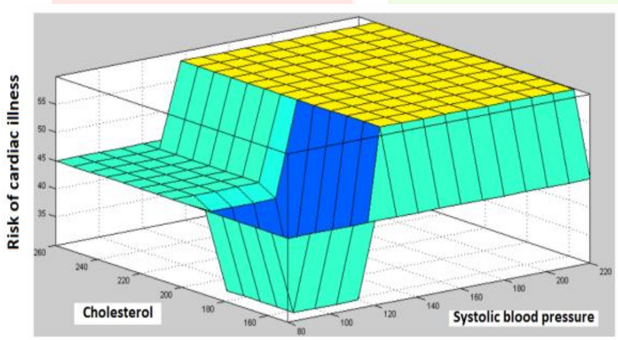

Figure 9: 3D surface plot of risk of cardiac illness for different values of systolic blood pressure and cholesterol

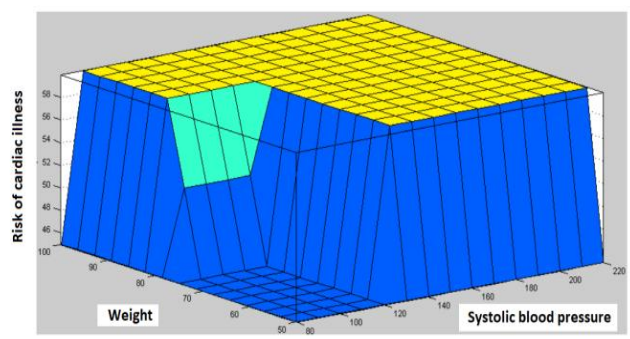

Figure 10: 3D surface plot of risk of cardiac illness for different values of systolic blood pressure and weight

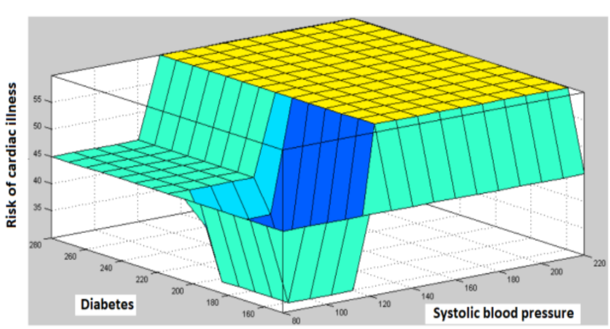

Figure 11: 3D surface plot of risk of cardiac illness for different values of systolic blood pressure and diabetes

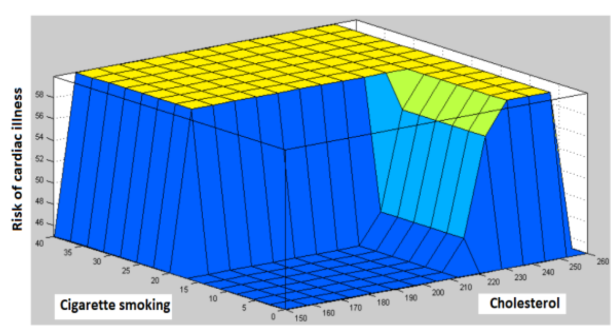

Figure 12: 3D surface plot of risk of cardiac illness for different values of cholesterol and cigarette smoking

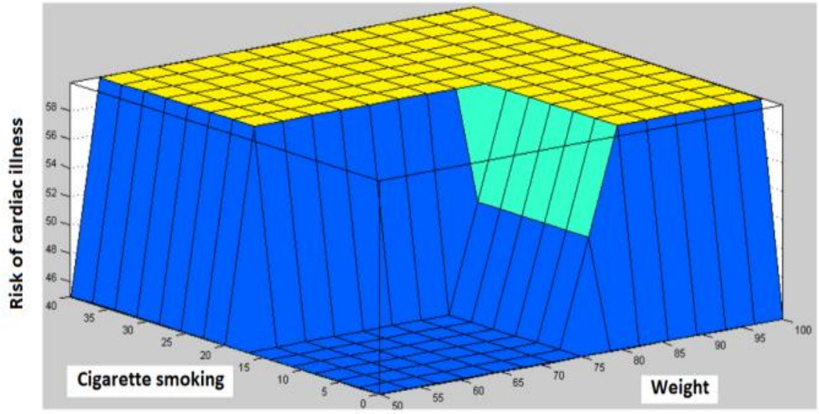

Figure 13: 3D surface plot of risk of cardiac illness for different values of weight and cigarette smoking

Figure 9 shows the estimated risk level as the height of the surface at each point, which is the combination of systolic blood pressure and cholesterol. The anticipated risk of heart sickness is higher for lower values and lower for higher values. Cholesterol, systolic blood pressure, and the likelihood of cardiac disease are depicted by the surface contour of the plot. Make better decisions, like how much insurance to charge or how to best help people who are at higher risk, with the help of this visualization that shows trends, thresholds, and danger zones.

Figure 10 surface form depicts the correlation between anticipated risk of cardiac disease, weight, and systolic blood pressure. Its manifestations are highly conditional on the degree of intricacy of the link that the fuzzy inference method attempts to capture. If, for instance, weight and systolic blood pressure have a synergistic effect on risk, the surface may exhibit uneven or steep gradients in some areas.

Figure 11 shows the anticipated risk level at each stage, which is a mix of diabetes status and systolic blood pressure. The surface colour or height represents this level. The anticipated risk of heart sickness is higher for lower values and lower for higher values. Surface features like steep gradients or uneven shapes could be indicative of a synergistic interaction between diabetes and high systolic blood pressure, which could increase risk.

At each stage (cholesterol level + smoking status), the surface colour or height in figure 12 represents the estimated risk level. The anticipated risk of heart sickness is higher for lower values and lower for higher values. The surface form of the plot shows the correlation between smoking status, cholesterol levels, and the likelihood of heart illness. Its manifestations are highly conditional on the degree of intricacy of the link that the fuzzy inference method attempts to capture. For instance, the surface may exhibit more pronounced gradients or uneven shapes in some areas if smoking intensifies the effect of high cholesterol on the risk of cardiac problems.

In figure 13, the plot shows the association between weight, smoking status, and the estimated risk of cardiac illness. The contour of the surface represents this relationship. Its manifestations are highly conditional on the degree of intricacy of the link that the fuzzy inference method attempts to capture. Experts in healthcare and data analysis can use the plot to deduce the relative importance of weight and smoking status in determining the likelihood of cardiac disease. Insights gained from this visualization can guide decision-making processes like insurance premium setting and the development of tailored interventions for high-risk individuals by revealing patterns of risk and possible thresholds.

6. Concluding Remarks: Although this model might be expanded by including more critical risk factors, it now only accounts for five of the most important ones in this field. The incorporation of more parameters would undoubtedly increase the size of the rule base. As a result, tweaking the base using data from real-life scenarios will be considered required to optimize the system's performance.

In this case, it is clear that, compared to the conventional method, using a fuzzy expert system to determine a health insurance premium would give the greatest results. Additionally, it is suggested that a neural network can generate an optimal surface that represents all possible combination points from a small number of experiments.

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