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A Fuzzy Logic Based Model for Life Insurance Underwriting When Insurer Is Diabetic

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Abstract: In life insurance medicine the mortality of the applicants with in the period of insurance is assessed on the basis of present risk factors or diseases. Unlike hypertension or overweight, where risk assessment of the medical values is possible directly, the risk assessment of diabetes is a complex problem. If a person is diabetic then to find out the mortality of insurer for life insurance medical underwriting is a complex problem due to multitude of medical risk factors. For life insurance medical underwriting, to handle this complex problem the insurance companies are in need to have a reliable expert system that can help them to evaluate the mortality of the applicants with in the period of insurance. Here a model is presented, which is based on fuzzy expert system that will help insurance companies to find out the mortality of insurer in the existence of diabetes for life insurance underwriting.

Key words: Fuzzy・Logic・Life insurance underwriting・Risk Classification・Cardiovascular disease

INTRODUCTION

India is hub of diabetics. In India more than 40.9 million people with diabetes and more than 118 million people with hypertension. Diabetes is one of the main causes of having cardiovascular disease. Epidemiologists in India and international agencies such as the world health organization (WHO) have been sounding an alarm on the rapidly rising burden of cardiovascular disease for the past 15 years. In 2005, 53% of the deaths were on account of chronic diseases and 29% were due to cardiovascular diseases alone. It is fact that Indians are succumbing to diabetes, high blood pressure and heart attacks 5-10 years earlier than their Western counterparts. Diabetes, hypertension and overweight are the pre-stages of cardiovascular disease. A fuzzy logic system for the assessment of cardiovascular risk associated with diabetics is therefore of considerable significance for insurers' medical underwriting practice. Cardiovascular mortality as a consequence of heart attack or stroke, for example, is assessed on the basis of heart diseases in the applicant's own medical history or family history as well as on the basis of anomalies in the established risk factors for cardiovascular disease, such as hypertension, overweight or diabetes. This paper describes a fuzzy expert system with reference to the medical underwriting of the insurer given the existence of non-insulin-dependent diabetes mellitus (diabetes mellitus type II). For reason of simplification, the fuzzy system will be presented for diabetes type II only, not for insulin-dependent diabetes mellitus (diabetes type I). Unlike hypertension or overweight, where risk assessment of the medical values is possible directly, the risk assessment of diabetes is a complex problem with a multitude of medical risk factors. Due to this complexity of this assessment, systematic evaluation of diabetes using a fuzzy expert system is highly advantageous.

MATERIALS AND METHODS

An analysis of the cases at a major insurance company revealed that more than 70% of medical anomalies are attributable to the following five diseases by blood pressure, diabetes, high cholesterol, hypertention, overweight and others. For the purpose of illustration, we consider that the insurance company uses three inputs - adjustment factors X_1, complication factors X_2 and time factors X_3. 1) The values of the input of the insured person have to be evaluated, $X_1 = 25$; $X_2 = 38$; and $X_3 = 2.5$(say). 2) Fuzzification of the crisp values of inputs:

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Cardiovascular risk of diabetes mellitus type 2

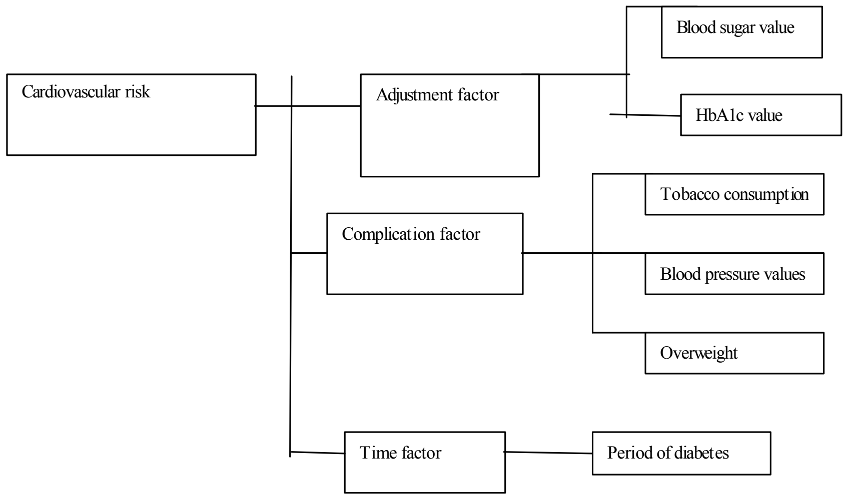

Fig. 1: Model structure for the current studies regarding insurer is diabetic

Through the use of membership functions defined for each fuzzy set for each linguistic variable (Fig. 1) the degree of membership of a crisp value in each fuzzy set is determine as follows:

$\mu_G (X_1) = 0.33$ $\mu_N(X_1) = 0.66$ $\mu_B (X_1) = 0$
$\mu_G (X_2) = 0$ $\mu_N (X_2) = 0.4$ $\mu_B (X_2) = 0.3$
$\mu_G (X_3) = 0.5$ $\mu_N (X_3) = 0.33$ $\mu_B (X_3) = 0$

3) Fire the rule bases that correspond to these inputs, based on the value of the fuzzy membership function. For the example under consideration, the following rules apply:

Rule 4: If X_1 is GOOD, X_2 is NORMAL and X_3 is GOOD, then Y is NORMAL RISK (NR).

Rule 5: If X_1 is GOOD, X_2 is NORMAL and X_3 is NORMAL, then Y is NORMAL RISK (NR).

Rule 7: If X_1 is GOOD, X_2 is BAD and X_3 is GOOD, then Y is HIGH RISK (HR).

Rule 8: If X_1 is GOOD, X_2 is BAD, X_3 is NORMAL, then Y is HIGH RISK (HR).

Rule 13: If X_1 is NORMAL, X_2 is NORMAL, X_3 is GOOD, then Y is NORMAL RISK (NR).

Rule 14: If X_1 is NORMAL, X_2 is NORMAL, X_3 is NORMAL, then Y is NORMAL RISK (NR).

Rule 16: If X_1 is NORMAL, X_2 is BAD, X_3 is GOOD, then Y is HIGH RISK (HR).

Rule 17: If X_1 is NORMAL, X_2 is BAD, X_3 is NORMAL, then Y is HIGH RISK (HR).

4) Execute the Inference Engine. We use the "root sum squares" (RSS) method to combine the effects of all applicable rules. The respective output membership function strengths (range: 0-1) from the possible rules (R1-R27) are:

"HIGH RISK" = $\sqrt{\sum_{i \in HR} \left(\mu_{R_i}\right)^2} = \sqrt{(0.3)^2 + (0.3)^2 + (0.3)^2 + (0.3)^2} = 0.6$

"MODERATE RISK" = $\sqrt{\sum_{i \in NR} \left(\mu_{R_i}\right)^2} = \sqrt{(0.33)^2 + (0.33)^2 + (0.33)^2 + (0.4)^2}$ = 0.7078

"LOW RISK" = $\sqrt{\sum_{i \in LR} \left(\mu_{R_i}\right)^2} = 0$

5) Defuzzification. We use "fuzzy centroid algorithm" for defuzzification. The defuzzification of the data into crisp output is accomplished by combining the results of the inference process and then computing the "fuzzy centroid" of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the *sum f* the weighted member function strengths and the result is taken as the crisp output.

RESULTS AND DISCUSSION

The Output Factor of the Cardiovascular Risk for Diabetics Is Calculated by Adjustment Factor

Blood Sugar Level: Blood sugar levels are an important parameter for the diagnosis of diabetes. Blood sugar level is the level of sugar circulating in blood at a given time. Blood glucose levels vary at different time on various part of the day. Some factors that affect blood sugar levels are body composition, age, physical activity and sex. Males and females may also have differing blood sugar level.

Normal guidelines for blood sugar:	
On waking up (before breakfast)	80 to 120
Before meals	80 to 120
2 hours after meals	160 or less
At bedtime	100 to 140

While in most of the cases, blood sugar levels will be high in case of diabetes patients, its level can have adverse effect on the patient depending upon its severity and complications. A severely high level of blood sugar may result in various symptoms like breathlessness. It may also lead to complications involving the circulatory system and the blood vessels. A severely low blood sugar level may lead to unconsciousness. So if the blood sugar level is good then the risk of having severe disease is low. However, a lack of standardization in the methods used to measure glycated haemoglobin has produced wide variations among results and is among the current limitations to the effective use of HbA1c results in gauging a person's risk of these complications. When blood glucose remains higher than 200mg/dl for 8-10 weeks, the concentration of glycosylated hemoglobin (HbA1c) arises. A (HbA1c) measurement therefore reflects the blood glucose control over a preceding 2-3 months period, while the estimates of blood glucose indicate the glucose value at the time of blood test. HbA1c values between 6-7% indicate very good control on diabetes. If HbA1c values between 6-7% then there exist low risk of having severe disease like cardiovascular disease due to diabetes. High blood pressure (hypertension) is an important risk factor for the development and worsening of many complications of diabetes, including diabetic eye disease and kidney disease. It affects up to 60% of people with diabetes. Having diabetes increases your risk of developing high blood pressure and other cardiovascular problems, because diabetes adversely affects the arteries, predisposing them to atherosclerosis (hardening of the arteries). Atherosclerosis can cause high blood pressure, which if not treated, can lead to blood vessel damage, stroke, heart failure, heart attack, or kidney failure. Even high yet normal blood pressure or pre-hypertension (defined as 120-139/ 80-89) impacts your health. Studies show that people with normal yet high range blood pressure readings, over a 10 year period of follow up time, had a two to three fold increased risk of heart disease. If a person is diabetic and having high or low blood pressure then there exist high risk of mortality or having severe disease.

Overweight: Most people are overweight when they're diagnosed with type 2 diabetes. Being overweight or obese increases the risk for developing type 2 diabetes and if someone who already has type 2 diabetes gains weight, it will be even harder to control blood sugar levels. People with type 2 diabetes have a condition called insulin resistance. They're able to make insulin but their bodies can't use it properly to move glucose into the cells. So the amount of glucose in the blood rises. The pancreas then makes more insulin to try to overcome this problem. Eventually, the pancreas can wear out from working overtime and may no longer be able to produce enough insulin to keep blood glucose levels within a normal range. People with insulin resistance are often overweight and don't exercise very much. But weight loss, eating healthier foods and controlling portion sizes and getting exercise can actually reverse insulin resistance. For people with type 2 diabetes, doing so makes it easier to reach target blood sugar levels and, in some cases, the body's ability to control blood sugar may even return to normal. People who don't have diabetes can have insulin resistance, but they're at a higher risk for developing the disease. For overweight people without type 2 diabetes, losing weight and exercising can cut their risk of developing the disease. Overweight is complicating problem. The risk increases if a person is diabetic and overweight.

Time Factor (Period of Diabetes): As the period of diabetes increases the risk of having severe disease or mortality increases

The process starts by information from the insured person and from various other sources which is obtained from a standard form that is used by insurance company. This information contains different sections such as adjustment factors, complication factors and time factors and each section is also containing a set of information. Now the expert system generates the various measures.

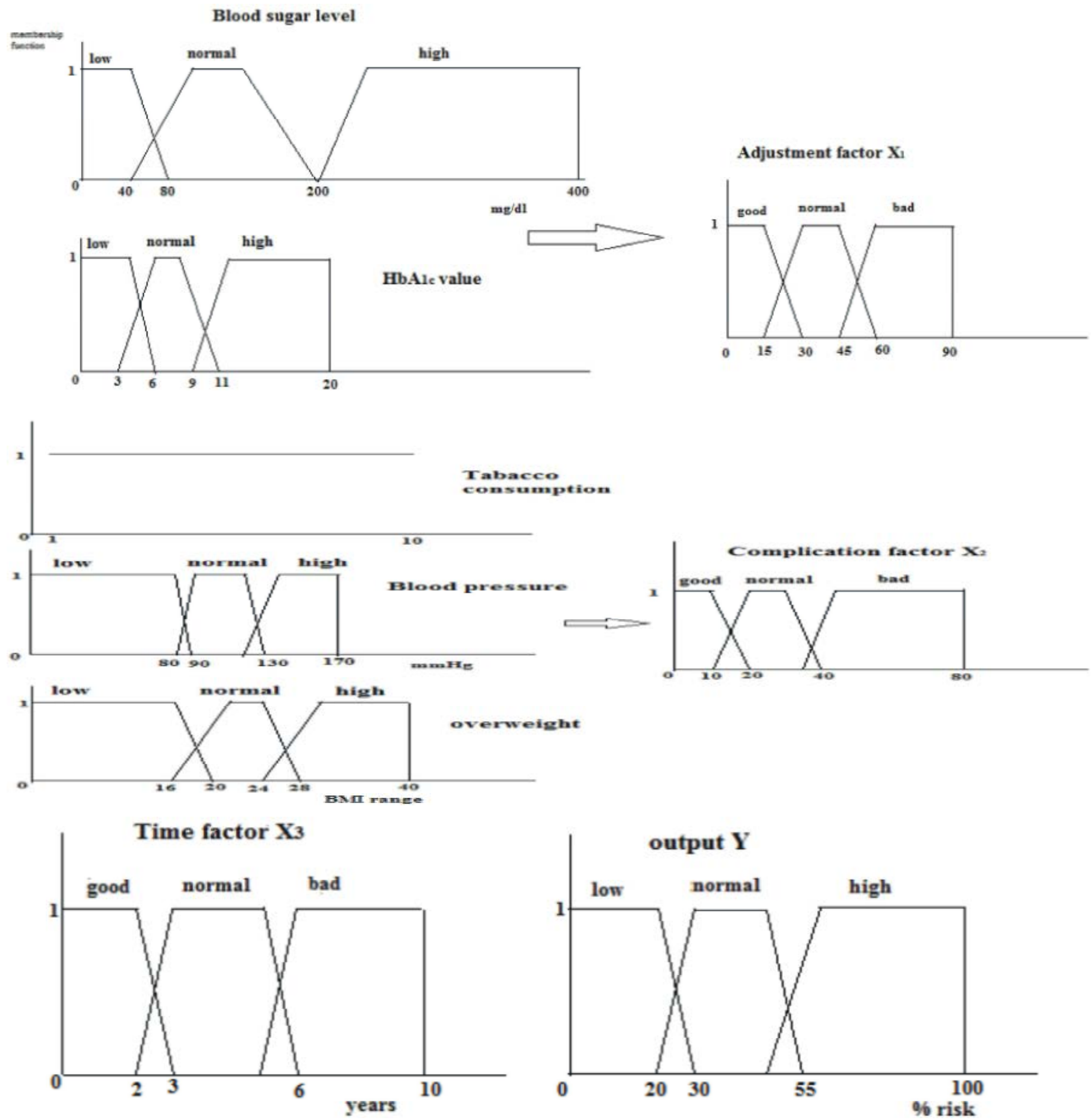

Fig. 2: Membership function of inputs and outputs functions

These qualitative measures are quantified and converted into linguistic variables with corresponding membership functions. For example, the adjustment factors for the information section i[th] is given by

$$X_1 = \frac{\left(\sum_{i=1}^{I}\sum_{j=1}^{J} W_{ij}\Delta_{ij}\right)}{I}$$

where W_{ij} is the weightage or impact factor given to the j[th] information of the i[th] section and Δ_{ij} is a 0-1 variable (where Δ_{ij} = 1, if there is any deviation/difference in the information furnished by the claimant and the one obtained by the auditor, 0 otherwise). All the weights for a set of information i_{th}, $\sum_{j=1}^{J} W_{ij}$ add to unity. Similarly, the values of the other inputs can be determined. The normalized values of these measures are used as inputs to the expert system. The degree of membership corresponding to a value of input is determined by the use of trapezoidal membership functions because of their simplicity and good result obtained by simulation. These membership functions are designed on the basis of available information. The Fig. 2. shows the definition of

Table 1: Sample rule base for the fuzzy logic based expert system

	Input			
Rule no.	Adjustment factor	Complication factor	Time factor	Output (additional risk)
1	G	G	G	LOW
2	G	G	N	LOW
3	G	G	B	LOW
4	G	N	G	NORMAL
5	G	N	N	NORMAL
6	G	N	B	NORMAL
7	G	B	G	HIGH
8	G	B	N	HIGH
9	G	B	B	HIGH
10	N	G	G	LOW
11	N	G	N	LOW
12	N	G	B	NORMAL
13	N	N	G	NORMAL
14	N	N	N	NORMAL
15	N	N	B	NORMAL
16	N	B	G	HIGH
17	N	B	N	HIGH
18	N	B	B	HIGH
19	B	G	G	NORMAL
20	B	G	N	NORMAL
21	B	G	B	HIGH
22	B	N	G	NORMAL
23	B	N	N	HIGH
24	B	N	B	HIGH
25	B	B	G	HIGH
26	B	B	N	HIGH
27	B	B	B	HIGH

the fuzzy sets of the input and the output functions. A rule base is then constructed which will be based on all the applicable input parameters and for each decision several rules are fired. Table 1 shows a sample rule base for the system under consideration. These rules result in an aggregate fuzzy set that represents a particular decision regarding the processing of claims. This fuzzy set is then converted into a crisp number, which depicts the degree of suitability of the decision regarding the cardiovascular risk. The rules aggregation is done using fuzzy centroid algorithm. Mamdani implication is used to represent the meaning of "*if-then*" rules. In this context, the statement "if X is A then Y is B" or $A \rightarrow B$ results in a relation R such that $\mu_X(X,Y) = \min(\mu_A(X), \mu_B(Y))$. This implication is precise, computationally simple and fits various practical applications. The *min* operator is a natural choice for the logical *AND*. Bellman and Giertz (1973) have devised a set of axioms that should be satisfied by the *AND* operator and have proved that *min* operator satisfies them.

The steps of expert system are summarized below:

Input: The crisp value of the adjustment factors, complication factors, time factors are obtained by various sources such as form filled by insurant, etc.

Evaluate the Input: Determine the adjustment factor X_1, complication factors X_2 and time factors X_3.

Fuzzify the Crisp Values of Inputs: Through the use of membership functions defined for each fuzzy set and for each linguistic variable (Fig. 2), determine the degree of membership of a crisp value in each fuzzy set. Each of these three indices has been divided into three fuzzy sets (LOW - L, NORMAL - M and HIGH - H). The equation for computing memberships are:

$$\mu(X_1) = \begin{cases} \max\left\{0, \dfrac{X_1 - a}{c - a}\right\} & \text{if } X_1 < c \\ 1 & \text{if } c \le X_1 \le d \\ \max\left\{0, \dfrac{b - X_1}{b - d}\right\} & \text{if } d < X_1 \end{cases} \tag{1}$$

$$\mu(X_2) = \begin{cases} \max\left\{0, \dfrac{X_2 - a}{c-a}\right\} & \text{if } X_2 < c \\ 1 & \text{if } c \le X_2 \le d \\ \max\left\{0, \dfrac{b - X_2}{b-d}\right\} & \text{if } d < X_2 \end{cases} \qquad (2)$$

$$\mu(X_3) = \begin{cases} \max\left\{0, \dfrac{X_3 - a}{c-a}\right\} & \text{if } X_3 < c \\ 1 & \text{if } c \le X_3 \le d \\ \max\left\{0, \dfrac{b - X_3}{b-d}\right\} & \text{if } d < X_3 \end{cases} \qquad (3)$$

where a, b, c, d, are the vertices of the trapezoidal membership function and L, N & H represent the fuzzy set for LOW, NORMAL and HIGH, respectively.

Fire the Rule Bases That Correspond to These Inputs: All expert systems which are based on fuzzy logic uses *if-then* rules. Since all the three inputs have three fuzzy sets (LOW – L, NORMAL – M and HIGH – H) therefore 27 (3×3×3) fuzzy decisions are to be fired. There are three outputs: LOW RISK- LR, NORMAL RISK- NR and HIGH RISK- HR.

Execute the Inference Engine: Once all crisp input values have been fuzzified into their respective linguistic values, the inference engine will access the fuzzy rule base of the fuzzy expert system to derive linguistic values for the intermediate as well as the output linguistic variables. The two main steps in the inference process are the aggregation and composition. Aggregation is the process of computing the values of the *if* (antecedent) part of the rules while composition is the process of computing the values of the *then* (conclusion) part of the rules. During aggregation, each condition in the *if* part of a rule is assigned a degree of truth based on the degree of membership of the corresponding linguistic term.

Defuzzification: The last phase in the fuzzy expert system is the defuzzification of the linguistic values of the output linguistic variables into crisp values. The most common techniques for defuzzification are center-of-maximum (CoM) and center-of-area (CoA). CoM first determines the most typical value for each linguistic term for an output linguistic variable and then computes the crisp value as the best compromise for the typical values and respective degrees of membership. The other common method is CoG, or sometimes called center-of-gravity.

Output of the Decision of the Expert System: In our case, the types of the outputs are: LR, NR and HR. The specific features of each controller depend on the model and performance measure. However, in principle, in all the fuzzy logic based expert system, we explore the implicit and explicit relationships within the system by mimicking human thinking and subsequently develop the optimal fuzzy control rules as well as knowledge base. Fig. 3. Shows, the output of the expert system and here the crisp output is 50%. The crisp output belongs to the set of NR more than the set of HR or LR (as evident from its membership function), which shows that the risk of having severe disease (cardiovascular disease) in future is 50%. Which indicate that the mortality of the insurer is 50%. Output of the decisions of the expert system.

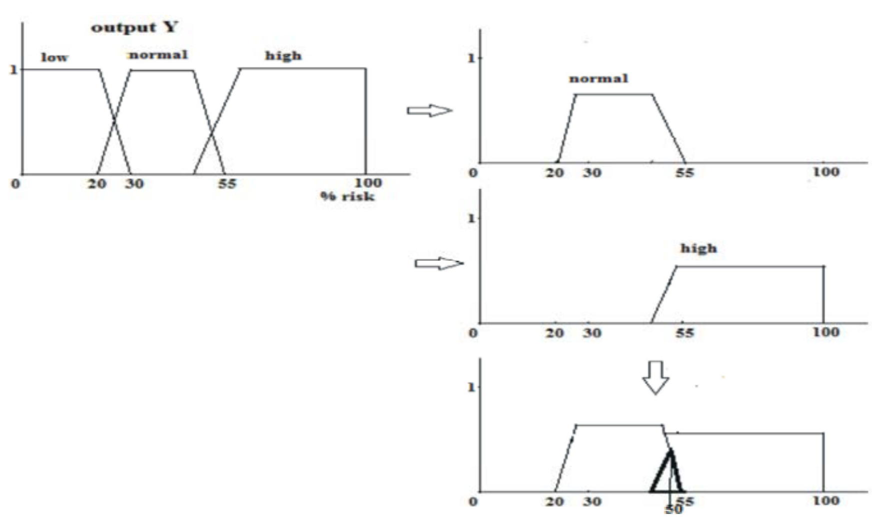

Fig. 3: Output of the expert system involved in when insurer is diabetic

CONCLUSION

The development of a fuzzy based expert system for life insurance underwriting when insurer is diabetic, is reported through this work. Identifying and quantifying risks will increasingly be viewed as the best way to control costs in insurance programs. By this model insurance company find the mortality of diabetic insurer and can change the underwriting process accordingly. Our future efforts will be on the improvement of the performance of the system by adjusting the membership function of the inputs.

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