Fuzzy-based Risk Prediction Model for Cardiovascular Complication of Patient with Type 2 Diabetes Mellitus and Hypertension

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ABSTRACT

Cardiovascular diseases are chronic diseases that cause serious morbidity and mortality worldwide. Unfortunately, the patients with type 2 diabetes mellitus and hypertension have a high risk of having a cardiovascular complication. For these reasons, patients with type 2 diabetes mellitus and hypertension should be aware of cardiovascular complication along their healthcare journey. To prevent cardiovascular complication from diabetes and hypertension, accurate risk prediction is required for a long term self-management process. Consequently, this paper proposes a fuzzy logic based method for predicting cardiovascular risk particularly for a patient with type 2 diabetes mellitus and hypertension. This paper also proposes a set of factors based on the patient's lifestyle as the key factors besides clinical factors because of their implicit impact on the quality of life of the patient. The proposed model thus employs 15 predictors for both clinical and lifestyle risk factors. Additionally, the proposed model is constructed based on the scientific data and implicit knowledge of the experts. The experiment with 121 patients shows that the proposed prediction model provides 96.69% accuracy compared to those decided by the experts.

Keywords: Cardiovascular, Fuzzy Logic, Patient with Type 2 Diabetes Mellitus and Hypertension, Risk Prediction Model

1. INTRODUCTION

Chronic diseases (CDs), which are known as Non-communicable diseases (NCDs), are one of the serious health problems worldwide. They are a major cause of morbidity and mortality. There are increasing numbers of CD patients worldwide. In 2017, the World Health Organization (WHO) reported that 71% of all deaths each year were the responsibility of CDs [1], [2]. Additionally, 41 million people die each year because of CDs [1]. Consequently, CDs have become a leading cause that affects healthcare costs because these diseases generally have a slow progression and require lifelong treatment duration.

Cardiovascular diseases (CVDs) are the top disease causing deaths among all CDs. More people die from CVDs than from other CDs every year. Most people with CVD deaths take place at an age of less than 70 years old in the middle and lower income countries [3]. Moreover, the WHO has reported that 17.9 million people died from CVDs in 2016 [3] and the numbers of dead CVD people are expected to reach 23.6 million by 2030 [4]. Therefore, CVDs are a major public health problem faced all over the world because they have a great effect on society and the nation's economy.

Diabetes mellitus, one of the main types of CDs, killed 1.6 million people in 2016 [5] and the number of patients with diabetes mellitus has been rising from 108 million people in 1980 to 422 million people in 2014 [5], [6]. Nowadays, the type 2 diabetes mellitus is the most frequent of the three main types including type 1 diabetes mellitus, type 2 diabetes mellitus, and gestational diabetes mellitus [5]. Patients who have type 2 diabetes mellitus have a higher chance of getting high blood pressure than those without diabetes mellitus. They also have more chances to get serious complications including cardiovascular, kidney failure, blindness, and lower limb amputation. In addition, the major mortality cause of patients with diabetes mellitus is cardiovascular complication [7]. Furthermore, hypertension will be able to push patients with type 2 diabetes mellitus to have cardiovascular complication faster [7], [8]. Consequently, patients with type 2 diabetes mellitus and hypertension have an extremely higher risk of having a cardiovascular complication.

The above evidence indicates that the prevention from cardiovascular complication is important and immediately required for the patients with type 2 diabetes mellitus and hypertension, but it is challenging to do so because there are many factors involved for conducting long term treatment. For these reasons, this paper thus mainly focuses on preventing the pa-

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tient with type 2 diabetes mellitus and hypertension from having any cardiovascular complication.

The paper is organized as follows. Section 2 describes the literature reviews. Section 3 proposes the research methodology. Section 4 shows the experimental results. Section 5 presents the discussion. Section 6 is the conclusion of this paper.

2. LITERATURE REVIEWS

Type 2 diabetes mellitus and hypertension are chronic diseases that can only be treated, not cured. Therefore, the patients must receive proper treatment and follow up during their life. The healthcare professional may need to adjust the treatment periodically to suit the condition of the patients in each period. This is because of the high blood sugar and high blood pressure levels can lead to the serious circumstance of arteriosclerosis and eventually leads to clogging of blood vessels. Accordingly, patients who have both type 2 diabetes mellitus and hypertension can have a greater chance of having the CVDs problem than patients who have only type 2 diabetes mellitus or hypertension alone. Based on many studies, patients who have both type 2 diabetes mellitus and hypertension always have one type of increased risk to have CVDs [9] and they get a high risk of mortality from CVDs [7], [8], [10], as well. Consequently, these patients should be aware of and prevent themselves from getting CVDs. Nowadays, prevention from various diseases have been managed widely to reduce dramatically morbidity and mortality. One of the most innovative and interesting management approaches is to employ risk prediction.

The risk prediction has normally been proposed for preventing people from getting many diseases including CVDs. These research works mainly focus on primary prevention that depends on the early detection of the diseases [11-24]. Those works provide benefits for people to prepare themselves from being exposed to CVDs. However, there are not enough research works that currently focus on preventing the patient from having complications from cardiovascular problems when suffering from type 2 diabetes mellitus and hypertension [25-31], tragically resulting in an increasing number of patient deaths worldwide. Moreover, the existing CVDs prevention research works used scientific data which is mainly more clinical data than lifestyle data for prediction. Based on the fact that the lifestyle can explicitly affect the patient condition causing the changing of clinical data and impacting patients' life quality, the lifestyle factors are also used for constructing a risk prediction model in this paper in addition to the clinical data. Because the lifestyle of each patient is different according to the patients' different context, this paper also employs implicit knowledge from experts including doctors, nurses, and nutritionists to construct a risk prediction model to deal with the specific condition for the patients' particular contexts. Moreover, several methods have been developed previously for the prevention of CVDs risk events over a specified time period and area. Nevertheless, most of these methods have been using datasets that are not able to deal with the dynamic behavior of the patient and allowed more opinions or natural representations of implicit knowledge from experts to be considered for practical medical application.

Fuzzy logic is well known in dealing with uncertain data which represents uncertainty to generate decisions, dynamic behavior, and opinions or natural representation of knowledge from experts [32], [33]. Furthermore, the fuzzy logic is generally used in various areas such as e-commerce [34], life insurance [35], control systems [36], and healthcare [31-33], [37-40], etc. For the healthcare area, fuzzy logic is used for all processes including risk prediction and diagnosis. As fuzzy logic is applied widely for disease risk prediction [31], [37], [39], [40], this paper adopted its advantage to deal with uncertain CVDs data. Finally, the fuzzy logic can thus represent CVDs predicted knowledge by using the available data and experts' opinions in uncertainty terms [41]. The detail of the proposed risk prediction model is described in the next section. For these reasons, the contribution of this paper will not only be useful for applying to other disease complications, but the constructed risk prediction model can be applied to other different patients' contexts e.g. workforce or activities of daily living (ADLs) that affect to the mobility of the patients.

3. RESEARCH METHODOLOGY

In this paper, the fuzzy-based risk prediction model is proposed for preventing patients with type 2 diabetes mellitus and hypertension from having a cardiovascular complication. The clinical factors, lifestyle factors, and cardiovascular complications risk levels are used for modeling the scientific data and implicit knowledge of the experts. The methodology of the proposed risk prediction model is shown in Fig. 1. It can be seen that the methodology consists of three main processes which are data gathering, model construction, and model validation.

3.1 Data Gathering

From Fig. 1, the data used for modeling includes clinical data, lifestyle data, and cardiovascular complication's risk levels. The data comes mainly from the WHO [15] and Framingham [11] sources, where the standard of CVDs is referred. Besides that, this list of the data was approved by the invited medical experts (four doctors, five nurses, and two nutritionists). The clinical data includes Sex, Age, Body Mass Index (BMI), Total Cholesterol (TC), High Density Lipoprotein (HDL) Cholesterol, Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Low Density Lipoprotein (LDL) Cholesterol, Hemoglobin

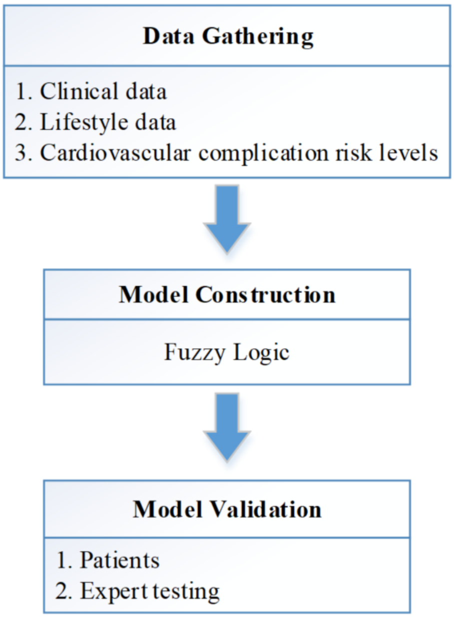

Fig. 1: *Methodology of Proposed Risk Prediction Model.*

A1c (HbA1c), Fasting Plasma Glucose (FPG), and Diabetes. At the same time, lifestyle data includes Smoking behavior, Medical compliance, Calories balance, and Physical activity. All fifteen factors are classified into different classes of cardiovascular complication's risk levels according to the scientific data and implicit knowledge from experts. In addition, categorization of cardiovascular complication from Framingham [11] is used for determining the level of risk in a cardiovascular complication which can be classified into four categories: very low, low, moderate, and high.

3.2 Model Construction

To obtain an accurate risk prediction model for the prevention of cardiovascular complication, the proposed method was able to deal with dynamic behavior from the patients and implicit knowledge from experts, both of which were required. This process constructs the model based on the scientific data and implicit knowledge from the experts by using fuzzy logic. The fuzzy logic is organized into four main steps which are fuzzification, fuzzy rule evaluation, aggregation, and defuzzification as shown in Fig. 2.

First, the fifteen selected factors are used as input variables for model construction. The level of risk in cardiovascular complication is used as an output variable for this construction process. These fifteen factors are factors related to cardiovascular complication's risk levels for patients who have both type 2 diabetes mellitus and hypertension, all of which are defined in the data gathering process.

Second, **the Fuzzification step** transfers these input variables and the output variable with crisp values to fuzzy sets using linguistic variables, linguistic values, and membership functions. This step is used to design crisp input values together with fuzzifying all values. The sixteen variables, including fifteen input variables and one output variable, are used to design fuzzy sets and membership functions. The fuzzy sets with their range values of fifteen factors as input variables are given in Table 1.

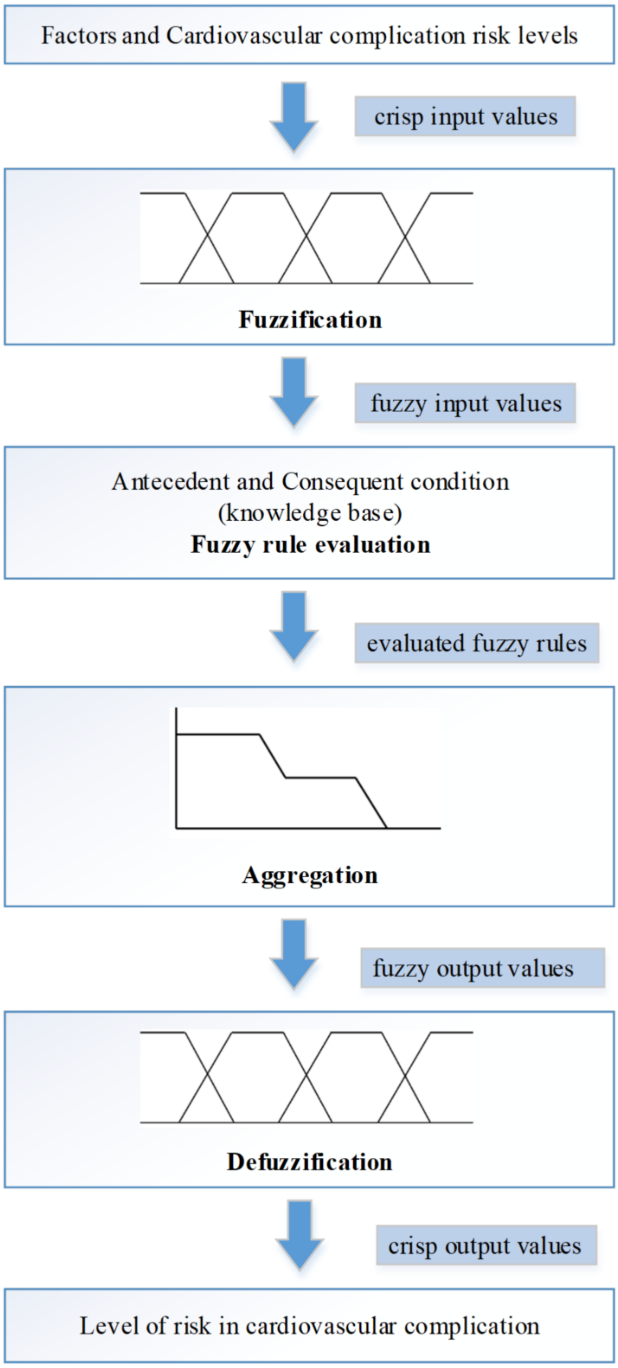

Fig. 2: *Steps of Model Construction Process based on Fuzzy Logic Conception.*

The fuzzy sets with their range values of each risk

Table 1: *Fuzzy Sets of Factors.*

No.	Variables	Range values	Fuzzy sets
1	Sex	0.5 1	Male Female
2	Age (Male) Age (Female)	30-34 35-39 40 - 44 45 - 49 50 - 54 55 - 59 60 - 64 65 - 69 70 - 74 $\geq$ 75 30 - 34 35 - 39 40 - 44 45 - 49 50 - 54 55 - 59 60 - 74 $\geq$ 75	Range1 Range2 Range3 Range4 Range5 Range6 Range7 Range8 Range9 Range10 Range1 Range2 Range3 Range4 Range5 Range6 Range7 Range8
3	BMI (Male and Female)	< 18.5 18.5 - 24.9 25.0 - 29.9 > 29.9	Underweight Healthy Overweight Obese
4	TC (Male and Female)	< 160 160 - 199 200 - 239 240 - 279 $\geq$ 280	Protected* Normal High Very High Extremely High
5	HDL Cholesterol (Male and Female)	$\geq$ 60 45 - 59 35 - 44 < 35	Protected Normal Very High Extremely High
6-7	SBP / DBP (Male) SBP / DBP (Female)	$\leq$ 129 and $\leq$ 84 $\leq$ 139 and $\leq$ 89 $\leq$ 159 and $\leq$ 99 $\leq$ 200 and $\leq$ 150 $\leq$ 120 and $\leq$ 80 $\leq$ 139 and $\leq$ 89 $\leq$ 159 and $\leq$ 99 $\leq$ 200 and $\leq$ 150	Normal High Very High Extremely High Protected Normal Very High Extremely High
8	LDL Cholesterol (Male and Female)	$\leq$ 100 101 - 140 > 140	Protected High Very High
9	HbA1c (Male and Female)	$\leq$ 6.5 6.6 - 7.0 > 7.0	Protected Normal High
10	FPG (Male and Female)	$\leq$ 60 61 - 80 81 - 130 131 - 140 > 140	Very Low Low Protected High Very High
11	Diabetes (Male) Diabetes (Female)	0.3 0.6 0.3 1	Normal Very High Normal Extremely High
12	Smoking (Male and Female)	0.5 1	Normal Very High
13	Medical compliance (Male and Female)	0.5 1	Regular Irregular
14	Calories balance (Male and Female)	0.3 0.6 1	Under Normal Over
15	Physical activity (Male and Female)	120 - 150 20 - 119 0 - 19	Protected Low Sedentary

* "Protected" = in medical field means "very healthy"

level in cardiovascular complication used as output variables are shown in Table 2.

Table 2: *Fuzzy Sets of Cardiovascular Complication's Risk levels.*

No.	Variables	Range values	Fuzzy sets
1	Male and Female	< 10 11 - 14 15 - 20 21 - 100	Very Low Low Moderate High

The membership functions of all input and output variables are defined by the membership of objects in the fuzzy set. The trapezoidal membership functions are presented by the following equation.

$$\mu_A(x) = \begin{cases} 0 & x \leq a \\ (x-a)/(b-a) & a < x < b \\ 1 & b \leq x \leq c \\ (d-x)/(d-c) & c < x < d \\ 0 & x \geq d \end{cases} \tag{1}$$

where; A is the fuzzy set
x is a member of fuzzy set A
μ_A is the membership function of a fuzzy set A
a, b, c and d are the parameters

The example of trapezoidal membership functions for HDL cholesterol is presented in Fig. 3. From Table 1, the HDL cholesterol consists of four fuzzy sets including Protected, Normal, Very High, and Extremely High, respectively with their range values.

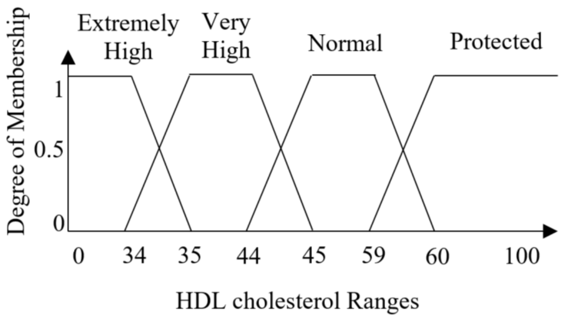

Fig.3: *Trapezoidal Membership Function of "HDL cholesterol".*

The trapezoidal membership function in (1) for the HDL cholesterol is as follows:

$$\mu_{Protected}(HDL)=\begin{cases}0 & HDL \le 59\\ (HDL-59)/(60-59) & 59<HDL<60\\ 1 & 60\le HDL\le 100\end{cases}$$

$$\mu_{Normal}(HDL)=\begin{cases}0 & HDL\le 44\\ (HDL-44)/(45-44) & 44<HDL<45\\ 1 & 45\le HDL\le 59\\ (60-HDL)/(60-59) & 59<HDL<60\\ 0 & HDL\ge 60\end{cases}$$

$$\mu_{VeryHigh}(HDL)=\begin{cases}0 & HDL\le 34\\ (HDL-34)/(35-34) & 34<HDL<35\\ 1 & 35\le HDL\le 44\\ (45-HDL)/(45-44) & 44<HDL<45\\ 0 & HDL>45\end{cases}$$

$$\mu_{ExtremelyHigh}(HDL)=\begin{cases}1 & 0\le HDL\le 34\\ (35-HDL)/(35-34) & 34<HDL<35\\ 0 & HDL\ge 35\end{cases}$$

where; Protected, Normal, Very High, and Extremely High are the fuzzy set
HDL is cholesterol values
$\mu_{Protected}$, μ_{Normal}, $\mu_{VeryHigh}$, and $\mu_{ExtremelyHigh}$ are the membership functions of the fuzzy set

Therefore, the fuzzy sets and the membership functions are designed completely to a degree of membership of each input and output variables that are produced.

Third, **Fuzzy rule evaluation step** is operated by a fuzzy inference process, which is designed based on a set of formulated rules for getting the quality of antecedent and consequent conditions. The values of the degree of membership for all input and output variables are assessed in the fuzzy rules. It will translate the existing knowledge into the model. These fuzzy rules are produced from fuzzy sets and membership functions based on scientific data and implicit knowledge from the experts for getting the desired quality of the result. Therefore, the fuzzy algorithm has utilized the rules for analyzing factors that cause the patients who have type 2 diabetes mellitus and hypertension from getting different levels of risk in cardiovascular complication. The examples of fuzzy rules followed by medical convention will be mentioned in the experimental results section.

After that, the **Aggregation step** integrates evaluated fuzzy rule-related sets according to fuzzy input values. The results of the aggregation are the membership functions of the fuzzy rule that relate to a level of risk in cardiovascular complication. The fuzzy rules aggregation is calculated using the union operation as shown in the following equation:

$$u_s(R) = \max\{u_1(R), u_2(R), \ldots, u_n(R)\} \qquad (2)$$

where; n is the total number of evaluated fuzzy rule-related sets
u_s is the fuzzy state for R
R is the risk level of cardiovascular complication

Finally, **the Defuzzification step** converts the result of rules aggregation from the fuzzy output value into a crisp output value form which can be used practically. The output value represents the risk level in cardiovascular complication. This process uses the mean-max-membership defuzzification, which is also called the mean of maximum (mom), in order to set the area of membership functions within the range value of the output variable. The mom defuzzification can be calculated using the following equation:

$$mom = \sum\nolimits_{i=1}^{n} \frac{mom_i}{n} \qquad (3)$$

where; n is the number of times the output distribution reaches the maximum level
mom is the mean of maximum
mom_i is the point at which the membership function is maximum

The result of mom defuzzification is constructed to follow the fuzzy sets of cardiovascular complication's risk levels that include very low, low, moderate, and high as shown in Table 3.

Table 3: *Description of MOM Defuzzification Result.*

No.	Results	Description
1	4.5	This patient has very low-risk level to get cardiovascular complication
2	12.0	This patient has low-risk level to get cardiovascular complication
3	17.5	This patient has moderate-risk level to get cardiovascular complication
4	60.5	This patient has high-risk level to get cardiovascular complication

Hence, the example of a trapezoidal membership function of a high-risk level is calculated by the mom defuzzification equation (3).

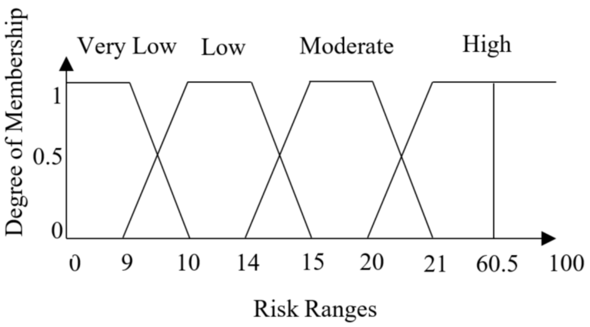

Fig.4: *Trapezoidal Membership Function of "High-Risk Level of Cardiovascular Complication".*

From Fig. 4, the example of the value range for the high-risk level is between more than 20 and 100 as shown in Table 2. Therefore, the mom defuzzification between more than 20 and 100 is 60.5, which is (21+100)/2 which is regarded as a high-risk level.

3.3 Model Validation

The result of this process shows the accuracy between the model construction and the ground truth from experts' decision. The risk prediction model is validated on the data from the patients who have type 2 diabetes mellitus and hypertension in Chiang Rai, which is the northernmost province of Thailand. In this study, the one hundred twenty-one patients consisted of fifty-three males and sixty-eight females aged between thirty-five to sixty-three years old. They are mostly contractors, merchants, and farmers. Then, the medical diagnostic made by the eleven experts, who are doctors, nurses, and nutritionists, is compared with those made by the constructed model for analyzing the proposed model performance.

4. EXPERIMENTAL RESULTS

4.1 Constructed Rules

The sixty-five fuzzy rules are constructed for evaluating the patients who have type 2 diabetes mellitus and hypertension for identifying a level of risk in cardiovascular complication. The four examples of fuzzy rules elicited from the medical convention are shown in Table 4.

Table 4: *Examples of Fuzzy Rules of Cardiovascular Complication's Risk Levels.*

Rule	Description
1	**If** (Sex is Male) and (Age is Range 1) and (BMI is Healthy) and (TC is Protected) and (HDL is Protected) and (SBP is High) and (DBP is High) and (LDL is Protected) and (HbA1c is Protected) and (FPG is Very Low) and (Diabetes is Very High) and (Smoking is Normal) and (Medical compliance is Regular) and (Calories balance is Normal) and (Physical activity is Protected) **then** (Risk level is Very Low)
2	**If** (Sex is Female) and (Age is Range 2) and (BMI is Healthy) and (TC is Normal) and (HDL is Normal) and (SBP is Very High) and (DBP is Very High) and (LDL is Protected) and (HbA1c is Normal) and (FPG is Low) and (Diabetes is Extremely High) and (Smoking is Normal) and (Medical compliance is Regular) and (Calories balance is Normal) and (Physical activity is Low) **then** (Risk level is Low)
3	**If** (Sex is Female) and (Age is Range 4) and (BMI is Overweight) and (TC is High) and (HDL is Very High) and (SBP is Very High) and (DBP is Very High) and (LDL is High) and (HbA1c is High) and (FPG is High) and (Diabetes is Extremely High) and (Smoking is Normal) and (Medical compliance is Regular) and (Calories balance is Over) and (Physical activity is Sedentary) **then** (Risk level is Moderate)
4	**If** (Sex is Male) and (Age is Range 7) and (BMI is Obese) and (TC is Extremely High) and (HDL is Extremely High) and (SBP is Extremely High) and (DBP is Extremely High) and (LDL is Very High) and (HbA1c is High) and (FPG is Very High) and (Diabetes is Very High) and (Smoking is Very High) and (Medical compliance is Regular) and (Calories balance is Over) and (Physical activity is Sedentary) **then** (Risk level is High)

4.2 Model Validation Results

Simulation Testing: The one hundred twenty-one patients' data, defined by fifteen input factors, was used for testing the proposed risk prediction model. The accuracy results of the evaluation show that the proposed model can achieve a correct prediction 94.21% of the time, and an incorrect prediction 5.79% of the time, when compared with the ground truth. The results are shown in Table 5.

Expert Consideration Testing: The decisions made by the proposed model were compared with those made by eleven experts. There were one hundred twenty-one patients invited for testing. The results show that the constructed risk prediction model provides 96.69% accuracy for a sample of one hundred seventeen patients when being compared to the decisions made by the experts. Table 5 presents the accuracy results from both simulation testing and experts for evaluating the model.

Table 5: *Accuracy Result of Both Testing Scenarios.*

Scenarios	Number of patient cases		Accuracy	
	Correct	Incorrect	Correct	Incorrect*
Simulation Testing	114	7	94.21%	5.79%
Experts Consideration testing	117	4	96.69%	3.31%

*accepted error rate is 6% [31], [33].

In Table 5, the accuracy result of risk decision for one hundred twenty-one patient cases is presented. The proposed model can deliver the correct result on one hundred fourteen patient cases, which is 94.21% of accuracy on the simulation testing. The expert consideration resulted in 96.69% accuracy. Furthermore, examples of those decisions for both the proposed model and experts decisions are shown in Table 6.

Table 6 shows that the risk decision between the constructed model and experts is different. The result of the fifth patient case was decided by the constructed model to be a low-risk level, whereas the experts have assigned a very low-risk level. Besides, the result of the sixth patient case was decided by the constructed model to be a moderate-risk level, whereas the experts have assigned a low-risk level.

5. DISCUSSION

The validation results from the constructed risk prediction model are determined by the efficiency of the patient cases and expert testing. The one hundred twenty-one patients who have type 2 diabetes mellitus and hypertension were tested with the proposed model which showed one hundred seventeen patient cases are correctly predicted whereas four patient cases are incorrectly predicted. Therefore, the sixty-five rules of the constructed model are sufficient for the risk prediction model. However, there are also a few incorrect predictions because the testing data was too limited in this study. Therefore, an evaluation with more patient cases is required as future work. To have higher accuracy, the rules need to be enhanced. Furthermore, the results show 96.69% accuracy of the model when being compared to those decisions from the experts. Therefore, the risk prediction model construction is nearly as accurate as the decisions from the experts. However, the result of validation between the simulation testing and experts consideration testing are different because the numbers of patient cases and experts are not enough. In order to have higher accuracy, more patient cases and more expert decisions need to be gathered.

Consequently, the constructed rules have a high potential to be used as the risk prediction model for the cardiovascular complication of patients with type 2 diabetes mellitus and hypertension. However, the incorrect prediction on constructed rules and the difference in experts' opinions are important. Therefore, future studies should be focusing on adjusting the model based on the number of rules from more experts to cover the results of other cases. Therefore, the number of patient cases and experts should be increased to enhance the accuracy of the proposed model.

6. CONCLUSION

This paper proposes a fuzzy logic based method for predicting cardiovascular complication's risk levels of a patient who has type 2 diabetes mellitus and hypertension. The proposed model uses fifteen predictors including clinical and lifestyle factors. The model is constructed based on scientific data and implicit knowledge from experts. The evaluation results with one hundred twenty-one patient cases show that the proposed risk prediction model achieves 96.69% accuracy when compared to the result decided by the eleven experts who are doctors, nurses, and nutritionists. This accuracy is higher than the accepted error rate by the other prediction model mentioned Table 5. Therefore it can be concluded that the proposed risk prediction model has a high potential for predicting cardiovascular complication's risk levels affecting patients who have type 2 diabetes mellitus and hypertension. It will be useful for personalized long-term healthcare management which allows the patients to have a higher quality of life along their healthcare journey. Furthermore, patients can apply the risk prediction model with mobile application to identify themselves from getting complication at any time when they want to have health check-up without queueing in the hospital. They can know their risk and ways to prevent trouble sooner. However, the model still requires more adjustment in terms of accuracy enhancement, such as fuzzy rule reduction, and testing with more patient cases.

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Table 6: *Example Decision of Constructed Model and Experts.*

Variables	Patient cases					
	1	**2**	**3**	**4**	**5**	**6**
Sex	0.5	1	1	0.5	1	0.5
Age	34	39	45	65	34	40
BMI	19.5	20	26.5	30	18.5	19
TC	145	176	230	283	148	170
HDL	63	52	40	30	63	48
SBP	139	142	152	155	140	138
DBP	88	90	95	104	90	86
LDL	95	98	117	144	95	87
HbA1c	6.2	6.7	7.4	7.6	6.5	6.8
FPG	55	65	135	143	54	76
Diabetes	0.6	1	1	0.6	1	0.6
Smoking	0.5	0.5	0.5	1	0.5	0.5
Medical compliance	0.5	0.5	0.5	0.5	0.5	0.5
Calories balance	0.6	0.6	1	1	0.6	0.6
Physical activity	130	90	15	10	100	80
Risk decision						
Proposed Model	very low	low	moderate	high	low	moderate
Experts	very low	low	moderate	high	very low	low

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