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A FUZZY INFERENCE MODEL FOR DIAGNOSIS OF DIABETES AND LEVEL OF CARE

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ABSTRACT

Diagnosis of diabetes is a complex decision-making process. The creation of diabetes diagnosis models is vital in the decision-making process and requires adequate information for fast detection and treatment. Diabetes is detected from a set of symptoms. The symptoms data are an important reference to diagnose diabetes which are collected and stored in datasets. Diabetes datasets are prone to vagueness and uncertainty. In addition, insufficient information on the diagnosis of diabetes exists and this problem is not addressed in previous research. This research work analyzes a simulated diabetes treatments dataset that were validated by medical expert [1]. A new fuzzy inference model based on Mamdani method is designed to provide interpretable understanding and sufficient information on diabetes diagnosis which is combied with the level of care to support the vagueness, uncertainty, and insufficient information problems.
Keywords: *Decision-Making, Fuzzy Inference Model, Dataset, Diagnosis Of Diabetes, Level Of Care*

1. INTRODUCTION

Diabetes is a chronic disease when the pancreas cannot produce enough insulin, or the body cannot use the insulin it produced effectively. More and more people are suffering from diabetes regardless of age. Diabetes can lead to further complications including stroke, kidney failure, and blindness if not treated fast. Early detection of diabetes can save life and an effective decision-making plays an important role in diabetes diagnosis [1]-[3].

Diabetes can be detected from several symptoms, called as the predictor variables. Based on these predictor variables, the diagnosis of diabetes can be determined by the target variable. It is essential to capture these variables of the diabetes dataset to be stored in a database as a reference to diagnose diabetes. The Pima Indians Diabetes Dataset (PIDD) is developed by the National Institute of Diabetes and Digestive and Kidney Diseases [4] and widely used in most research [5]-[9]. The simulated diabetes treatments dataset [1] is a new dataset developed to assist decision-making in healthcare.

Logic is significant in the medical science area. Fuzzy logic is a variable processing approach which allows multiple possible truth values to be represented through the same variable. Fuzzy logic models the human thinking capability to satisfy for vague and uncertain situations. Medical data are exposed to these kinds of situations and reducing them via fuzzy logic can improve the decision-making process. Fuzzy logic has been utilized in diabetes diagnosis and research are ongoing to improve the models [10]-[14]. Fuzzy technology in diabetes diagnosis is challenging research and provides more room to be extended in the field of data analytics, modeling, simulation, visualizations, and etc.

Our research work is motivated due to the importance of diabetes diagnosis in decision-making and the approach of fuzzy logic towards human-interpretable understanding. The problem with current research in diabetes management is that the issue of vagueness, uncertainty, and insufficient information on the diagnosis of diabetes is not tackled together. All medical data especially diabetes data are vague, and all numbers are uncertain or fuzzy. Furthermore, sufficient information on the diagnosis of diabetes is crucial because the diagnosis consists of several categories. The objective of this paper is to analyze a set of simulated diabetes treatments dataset that were validated by medical expert [1] and to produce the new design of a fuzzy inference model for decision-making that handles vagueness and uncertainty. The insufficient information on the diagnosis of diabetes is managed by combining diabetes diagnosis consisting of several categories with the appropriate level of care.

This paper is organized into six sections. Section 2 reviews the existing related works. Section 3 clarifies the design of the proposed fuzzy model based on fuzzy concepts. Section 4 presents the proposed fuzzy inference model implemented using MATLAB. Section 5 discusses the proposed fuzzy inference model that have been validated and verified. Finally, section 6 is the conclusion and future works.

2. RELATED RESEARCH

This section describes about the study on existing diabetes datasets, details about the combination of diabetes diagnosis and the level of care, and previous medical models closely related to our research work.

2.1 Diabetes Datasets

Data of diabetes patients is important and valuable in the research of diabetes management. The data refers to the predictor variables representing the symptoms of diabetes. The data also consists of the target attribute representing the diagnosis of diabetes. There are four types of diabetes namely diabetes type 1, diabetes type 2, diabetes gestational and autosomal inherited type of diabetes mellitus [15], [16]. Diabetes type 2 or also called as diabetes mellitus type 2 (T2DM) is the most common type of diabetes and is the focus of this research work. The Pima Indians Diabetes Dataset (PIDD) has been widely utilized in most of the research to diagnose diabetes type 2 [4]-[9]. The objective of PIDD is to diagnose whether a patient has diabetes or not based on the predictor variables in the dataset. The content of PIDD consists of several predictor variables and one target variable. The predictor variables in PIDD consists of pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function and age. The target variable is the outcome to determine whether the patient has diabetes or not.

This research work analyzed a simulated diabetes treatments dataset that were validated by medical expert [1], with a set of its own predictor variables and additional target variable compared to PIDD. The additional information is the diagnosis of diabetes combined with the level of care for diabetes type 2.

2.2 Diabetes and Level of Care

Table 1 shows a sample of data from medical expert [17] used as the basis to create the simulated diabetes treatments dataset [1].

Table 1: Data Example from Medical Expert [1]

Pemeriksaan Fizikal	Laporan Makmal									
Acanthosis Nigricans	A1c(mmol/mol)	FPG	RPG	OGTT	HDL	TG	Sejarah penyakit jantung	Diagnosis		Peringkat Penjagaan
Y	36	5.2	8.7	Nil	1.4	1.2	T	Sihat	Prediabetes	Peringkat Primer
Y	40	6.1	10	6.3(FPG)	1.3	2.8	T	IFG	Diabetes	Peringkat Primer
Y	48	7.3	12.3	Nil	0.9	2.8	T	T2DM	Diabetes	Peringkat Primer
T	60	8.8	16	Nil	0.9	3	Y	T2DM	Diabetes	Peringkat Sekunder
T	55	7.5	13	Nil	1	2.8	Y	T2DM	Diabetes	Peringkat Sekunder
Y	43	6.4	9.8	9.8 (2-hr PPG)	1.2	2	T	IGT	Prediabetes	Peringkat Primer

Diagnosis of diabetes type 2 consists of several categories, for example a patient can be healthy but, in the prediabetes, category as shown in Table 1. The diabetes predictor variables in Table 1 comprises of acanthosis nigricans, a1c, fpg, rpg, ogtt, hdl, tg, and history of heart disease. In real life, the process of healthcare decision-making is closely related to each other, as in diabetes diagnosis. The target variable in Table 1 is the diagnosis which is related to the level of care. The level of care refers to the stages of healthcare consisting of primary care, secondary care, tertiary care, quaternary care, and palliative care [1]. However, the scope of this research in designing the fuzzy inference model emphasize on the primary and secondary care for the category of diabetes type 2 which is based on the simulated diabetes treatments dataset [17].

2.3 Previous Medical Models

Fuzzy diagnosis models for various diseases have been created in previous research to support the decision-making process. An insulin advisory system based on Mamdani fuzzy inference have been developed to assist an artificial pancreas for

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clinical diabetes type 1 patients [18]. An intelligent fuzzy inference rule-based predictive diabetes model using Mamdani technique is proposed which provides content recommendations to patients with diabetes that applies the Pima Indians Diabetes Dataset (PIDD) [19]. A fuzzy rule-based system combined with the cosine amplitude method and fuzzy classifier has been designed for the classification of diabetes also utilize the PIDD [20]. Authors proposed the design and implementation in MATLAB of a fuzzy expert system to identify the current stage of Chronic Kidney Disease (CKD), using CKD predictor variables approved by a team of specialist [21]. A fuzzy expert system that applies Mamdani fuzzy inference structure has been invented to diagnose type 2 diabetes using PIDD [2]. Besides fuzzy method, multi-agent method and the simulated diabetes treatments dataset is used to produce a healthcare model [1]. In addition, recent research works [5], [6] used data mining method with PIDD and other datasets.

Type-2 fuzzy system has the capability to deal with a high level of vagueness and uncertainty in medical data and diagnose diseases compared to the traditional type-1 fuzzy systems. Due to type-2 fuzzy systems capability, it is chosen as an effective model in medical diagnosis [11], [22] and utilized in our research work.

Table 2 shows the comparison between previous models and our proposed model. Most of the medical models used fuzzy method and PIDD dataset. None of the previous model can handle the three important issues which are uncertainty, vagueness, and insufficient information issues. The uncertainty and vagueness issues are catered in fuzzy type-2 models as proposed in our research work. Our proposed model handles the insufficient information problem by providing extended diagnosis relating the diabetes diagnosis with the level of care. Previous research built fuzzy models just to diagnose whether patients are diabetic or non-diabetic but does not relate the model with extended diagnosis. This extended diagnosis is essential to assist decision-making because diabetes type 2 consists of several categories namely healthy prediabetes, IFG diabetes, T2DM diabetes and IGT prediabetes. Each diabetes category has different ways to treat patients, for example whether the patient with T2DM needs primary care or secondary care. Therefore, previous research does not provide sufficient information about diabetes diagnosis compared to our proposed model. Our proposed model deals with the three important issues mentioned compared to previous models.

Table 2: Comparison between Previous Models

Previous models	Application	Method	Dataset	Can handle uncertainty and vagueness	Provides extended diagnosis
[1]	Healthcare	Multi-agent	Simulated Diabetes Treatments	No	Yes
[2]	Diabetes diagnosis	Fuzzy Mamdani type-1	PIDD	No	No
[5]	Diabetes Prediction	Data mining	PIDD	No	No
[6]	Diabetes detection and classification	Data Mining	Indian demographic & health survey 2016	No	No
[11]	Diabetes classsification	Fuzzy Sugeno type-2 and Neural Network	PIDD	Yes	No
[18]	Insulin advisory system	Fuzzy Mamdani type-1	Biological variables	No	No
[19]	Recommendation system	Fuzzy Mamdani type-1	PIDD	No	No
[20]	Fuzzy rule-based system	Fuzzy Mamdani type-1	PIDD	No	No
[21]	CKD diagnosis	Fuzzy Mamdani type-1	CKD	No	No
[22]	Medical diagnosis	Fuzzy Mamdani type-2	PIDD and open datasets	Yes	No
Proposed Model	Diabetes diagnosis and level of care	Fuzzy Mamdani type-2	Simulated Diabetes Treatments	Yes	Yes

Fuzzy logic deals with the fuzziness of the data and the data is described by the fuzzy membership function (MF). MF is a function that specifies the degree to which a given input that belongs to a set. MF are used in the fuzzification and defuzzification steps of a fuzzy logic system to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. MF consists various types namely the of triangular, trapezoidal, gaussian, singleton, sigmoid, etc. Triangular, trapezoidal and gaussian are widely applied in research because it produced good performance [23], [24]. Our research work utilized the triangular MF.

2.4 Fuzzy Inference Process

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Figure 1 shows the fuzzy inference process block diagram adopted in Mamdani method. Mamdani method is used in our research work because this method is widely accepted for capturing expert knowledge and applied in medical diagnosis. In addition, Mamdani method is more intuitive and more human-like manner. Other fuzzy method besides Mamdani is the Sugeno method, which works well in nonlinear systems.

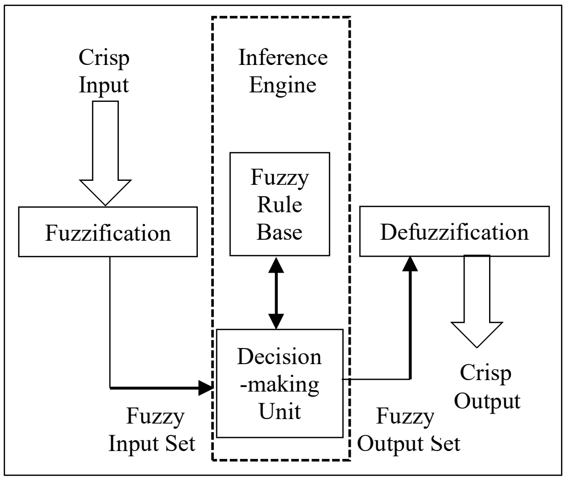

Figure 1: Fuzzy Inference Process Block Diagram

Based on Figure 1, Mamdani fuzzy inference process is performed in four steps as follows [25]:

i. Fuzzification of the input variables: take the crisp inputs and determine the degree to which these inputs belong to, for each of the appropriate fuzzy sets.

ii. Rule evaluation in fuzzy rule base: take the fuzzy input and apply them to the antecedence of the fuzzy rules. If a fuzzy rule has multiple antecedence, the fuzzy operator OR or AND is used to obtain a single number that represents the result of the antecedent evaluation. This number which is the truth value is then applied to the membership function (MF). The OR fuzzy operation is applied to evaluate the disjunction of the rule antecedents using the fuzzy operation union:

$$\mu_A \cup \mu_B(x) = \max[\mu_A(x), \mu_B(x)] \quad (1)$$

Similarly, the AND fuzzy operation is applied to evaluate the conjunction of the rule antecedents using the fuzzy operation intersection:

$$\mu_A \cap \mu_B(x) = \min[\mu_A(x), \mu_B(x)] \quad (2)$$

iii. Aggregation of the rule outputs in decision-making unit: The process of unification of the outputs of all rules. The MF of all rules are combined into a single fuzzy set. The input of the aggregation process is the list of consequent membership functions, and the output is one fuzzy set for each output variable.

iv. Defuzzification: Fuzziness helps to evaluate the rules, but the final output of a fuzzy system is a crisp number. The input for the defuzzification process is the aggregated output fuzzy set and the output is a single number. There are several defuzzification methods, the most popular one is the centroid technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. This center of gravity (COG) is calculated as follows:

$$COG = \frac{\int_a^b \mu_A(x)\, x\, dx}{\int_a^b \mu_A(x)\, dx} \quad (3)$$

A type-2 fuzzy system is defined by an upper and lower membership function (MF). Figure 2 shows the upper MF (red), lower MF (blue), and the footprint of uncertainty (FOU), the region between upper MF and lower MF for a type-2 triangular MF [26]. The triangle peak is represented by p in Figure 2.

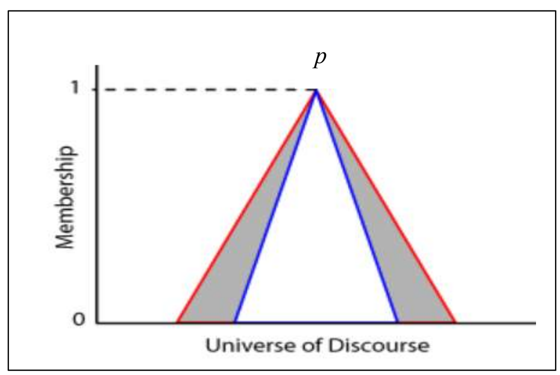

Figure 2: Type-2 Triangular Membership Function [26]

Input values for type-2 fuzzy inference system are fuzzified by finding the correspondence degree of upper MF and lower MF from the rule antecedents, which generates two fuzzy values for each type-2 MF. Figure 3 shows the fuzzification of membership value in upper MF (f_U) and lower MF (f_L) [26].

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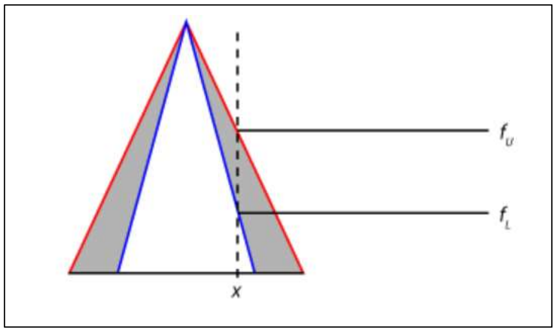

Figure 3: Fuzzification of Upper MF and Lower MF [26]

Applying the fuzzy operator to the fuzzified values of type-2 MF produced a range of rule strengths. The maximum value of this range (W_U) is the result of applying the fuzzy operator to the fuzzy values from the upper MF, while the minimum value (W_L) is the result of applying the fuzzy operator to the fuzzy values from the lower MF, shown in Figure 4 [26].

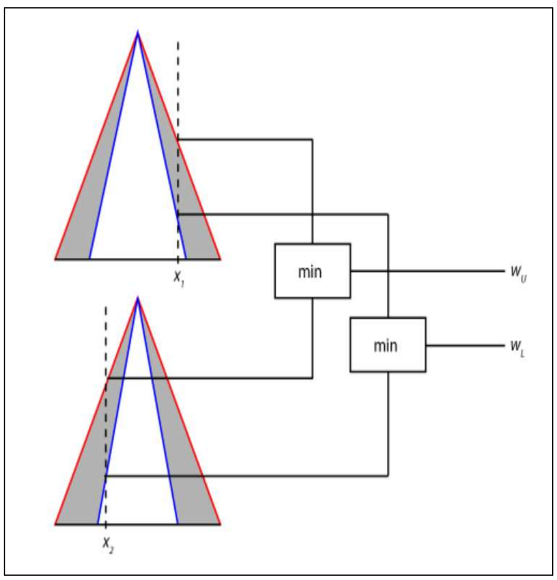

Figure 4: Fuzzified Minimum (W_L) and Maximum (W_U) Values [26]

3. DESIGN OF PROPOSED FUZZY MODEL

Figure 3 shows the diagnosis of diabetes and level of care decision-making process.

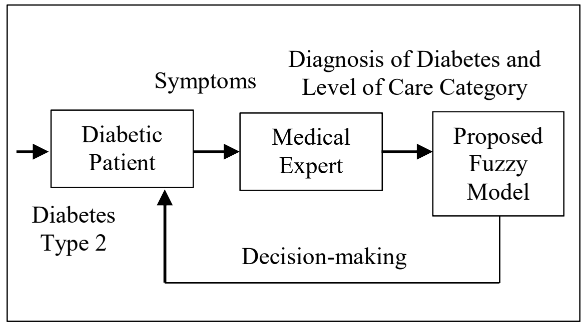

Figure 3: Diagnosis of Diabetes and Level of Care Decision-Making Process

Diabetes type 2 is detected from the symptoms experienced by a diabetic patient. The diabetic patient consults the medical expert and the medical expert identify the category of diabetes type 2 diagnosis and the level of care required by the patient. The proposed fuzzy inference model assists medical expert in decision-making. The symptoms experienced by the diabetic patient is updated every time the diabetic patient see the doctor for check-up. The diagnosis of diabetes type 2 and level of care is updated, meaning that the diabetic patients remain as the same diagnosis and level of care category or have changed to another category. Therefore, the medical expert can detect whether the condition of the diabetic patient has improved or worsen.

The following sections explain about the initializations of input and output variables; linguistic variables and membership functions; and fuzzy rules. An analysis of variables in the simulated diabetes treatments dataset [1] is made to produce the design of the proposed fuzzy model.

3.1 Input and Output Variable Initialization

The crisp input variables or predictor variables and output variables or target variable are initialized. The crisp input consists of thirteen predictor variables and the output consists of a target variable. The inputs are history of CVD, anemia, has CKD, A1c, FPG, RPG, FBS, two hours post-prandial, HDL, LDL, TG, Acanthosis Nigricans and OGTT; while the output is the diagnosis of diabetes and level of care, shown in Table 3. The description of each variable and number of labels is also explained in Table 3.

Table 3: Input and Output Variables

Num.	Variables	Description	Num. of labels
CRISP INPUT VARIABLES			
1	History of CVD	History of cardiovascular diseases of the person examined.	4
2	Anemia	Anemia disease of the person examined.	4
3	has CKD	Chronic Kidney Disease of the person examined.	4
4	Acanthosis Nigricans	Skin condition that causes a dark discoloration in body folds and creases of the person examined.	4
5	A1c	A test to measure the average amount of sugar in blood in percentage over the past few months of the person examined.	3
6	FPG	A test to measure fasting blood glucose in mmol/L of the person examined.	3
7	RPG	A test to measure random plasma glucose in blood in mmol/L of the person examined.	3
8	FBS	A test to measure fasting blood sugar in mg/dL of the person examined.	3
9	Two Hours Post-prandial	A test to measure post-prandial blood sugar in mmol/L exactly 2 hours after the start of a meal of the person examined.	3
10	HDL	Good cholesterol measured in mmol/L of the person examined.	2
11	LDL	Bad cholesterol measured in mmol/L of the person examined.	2
12	TG	Triglycerides measured in mmol/L of the person examined.	2
13	OGTT	A test to measure oral glucose tolerance in mmol/L of the person examined.	6
CRISP OUTPUT VARIABLE			
1	Diabetes Diagnosis	Diabetes type 2 category and the level of care of the person examined.	4

3.2 Linguistic Variables and Membership Function

The crisp input and output variables are then transformed to fuzzy linguistic variables and the terms are defined. In addition, the membership functions (MF) are constructed for each fuzzy variable as shown in Table 4.

Table 4: Linguistic Variables and Membership Functions

Num.	Fuzzy Variable	Fuzzy Range	Fuzzy Name	Upper Triangular MF
FUZZY INPUT VARIABLES				
1-4	History of CVD, Anemia, has CKD, Acanthosis Nigricans	[-0.3 1.3]	No	[-0.3 0 0.3]
			Weak No	[0.1 0.3 0.5]
			Weak Yes	[0.4 0.5 0.7]
			Yes	[0.6 1 1.3]
5	A1c	[0 25]	Normal	[4 5 6]
			Prediabetes	[5.7 6.05 6.4]
			Diabetes	[6.3 6.5 14]
6	FPG	[0 25]	Normal	[5 6 6.5]
			IFG	[6.1 6.5 6.9]
			DM	[6.6 7 14]
7	RPG	[0 25]	Normal	[3 7.7 9]
			OGTT	[8 9.5 11]
			Second RPG	[10 11.2 14]
8	FBS	[0 130]	Normal	[80 99 105]
			Prediabetes	[100 112.5 125]
			Diabetes	[120 126 130]
9	Two Hours Post-prandial	[0 25]	Normal	[5 7.7 8]
			IGT	[7.8 9.4 11]
			DM	[10 11.1 14]
10	HDL	[0 2]	Positive	[0 0.55 1.1]
			Negative	[1 1.5 2]
11	LDL	[0 1]	Negative	[0 1.3 2.6]
			Positive	[2.3 3.15 4]
12	TG	[0 1]	Negative	[0 0.85 1.7]
			Positive	[1.5 2.25 3]
13	OGTT	[0 25]	FPG Normal	[5 6 6.5]
			FPG IFG	[6.1 6.5 6.9]

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			FPG DM	[6.6 7 14]
			PPG Normal	[5 7.7 8]
			PPG IGT	[7.8 9.4 11]
			PPG DM	[10 11.1 14]
FUZZY OUTPUT VARIABLE				
14	Diabetes Mellitus Diagnosis	[-0.5 4.5]	Healthy Prediabetes and Primary Care	[-0.5 1 1.5]]
			IGT Prediabetes and Primary Care	[0.5 2 2.5]
			Diabetic in Control and Primary Care	[1.5 3 3.5]
			Diabetic Nephropathy and Secondary Care	[2.5 4 4.5]

The crisp input variable is taken from Table 3 to be the fuzzy variable in Table 4 and the degree of these input are associated to the fuzzy name and upper triangular MF. The lower MF scale factor for the fuzzy variables use the default value 1. The lower MF delay factor defines the point MF value starts increasing from zero based on the value of the upper MF. The lower lag in Table 3 uses the default value [0.1 0.1]. This means that a lag value of 0.1 indicates that the lower MF becomes positive when the upper MF has a value of 0.1.

3.3 Fuzzy Rules

Fuzzy rules are constructed in Table 5, based on the defined fuzzy name for each fuzzy variable in Table 4. Ten non-fuzzy rules are identified by referring to academic and Ministry of Health Malaysia sources [15], [17]. These non-fuzzy rules are converted to fuzzy rules to design the proposed fuzzy model. The fuzzy rules have multiple antecedents and the fuzzy operator OR is used for rule evaluation.

Table 5: Fuzzy Rules for Diagnosis of Diabetes and Level of Care

	History of CVD	Anemia	has CKD	A1c	FPG	RPG	FBS	Two Hours Post-prandial	HDL	LDL	TG	AC	OGTT	Diabetes Mellitus Diagnosis
1	Yes	Yes	Yes	-	-	-	-	-	-	-	-	-	-	Diabetic Nephropathy and Secondary Care
2	-	-	-	Diabetes	DM	Second RPG	Diabetes	DM	-	-	-	-	-	Diabetic in Control and Primary Care
3	-	-	-	Prediabetes	IFG	OGTT	Prediabetes	IGT	+ve	+ve	+ve	-	-	IGT Prediabetes and Primary Care
4	No	No	No	Normal	Normal	Normal	Normal	Normal	-ve	-ve	-ve	-	-	Healthy Prediabetes and Primary Care
5	No	-	-	Normal	Normal	OGTT	-	-	+ve	-	+ve	Yes	-	Healthy Prediabetes and Primary Care
6	No	-	-	Normal	IFG	OGTT	-	-	+ve	-	+ve	Yes	PPG IGT	IGT Prediabetes and Primary Care
7	No	-	-	Normal	IFG	OGTT	-	-	+ve	-	+ve	Yes	FPG IFG	Diabetic in Control and Primary Care
8	No	-	-	Normal	DM	Second RPG	-	-	+ve	-	+ve	Yes	-	Diabetic in Control and Primary Care
9	Yes	-	-	Normal	DM	Second RPG	-	-	+ve	-	-ve	No	-	Diabetic Nephropathy and Secondary Care
10	Yes	-	-	Normal	DM	Second RPG	-	-	+ve	-	+ve	No		Diabetic Nephropathy and Secondary Care

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4. IMPLEMENTATION OF PROPOSED FUZZY MODEL

Design of the proposed fuzzy model is implemented using the MATLAB Fuzzy Logic Designer application. The Mamdani type-2 and triangular membership function (MF) are utilized. The upper triangular MF value is defined based on sources from academic and Ministry of Health Malaysia [15], [17]. The following explains about the MF which relates to Table 4.

The MF for history of CVD, anemia, had CKD, and acanthosis nigricans is shown in Figure 4, with four defined fuzzy names: no, weak no, weak yes, and yes. 0, 0.3, 0.5, and 1 are the middle values in the range of each fuzzy names defined, which is represented by the triangle peak.

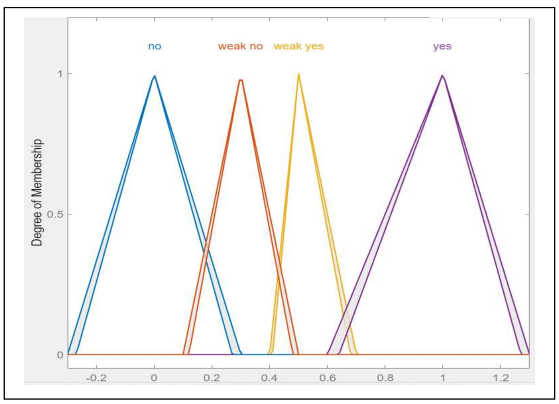

Figure 4 History of cvd, anemia, had ckd and acanthosis nigricans Membership Function

The MF for a1c is shown in Figure 5, with three defined fuzzy names: normal, prediabetes, and diabetes, where normal indicates the value 5, prediabetes the value 5.7 to 6.4 and diabetes 6.5 above. Middle values 5, 6.05, and 6.5 in the range of each fuzzy names defined is represented by the triangle peak.

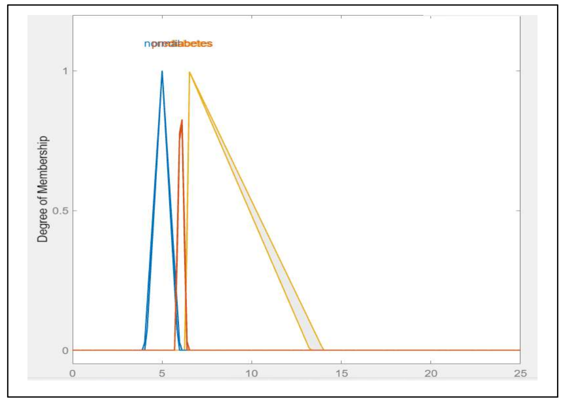

Figure 5: A1c Membership Function

The MF for fpg is shown in Figure 6, with three defined fuzzy names: normal, ifg and dm. The normal value is less than 6.1, ifg is 6.1 to 6.9, and dm is above 7. Middle values 6, 6.5, and 7 in the range of each fuzzy names defined is represented by the triangle peak.

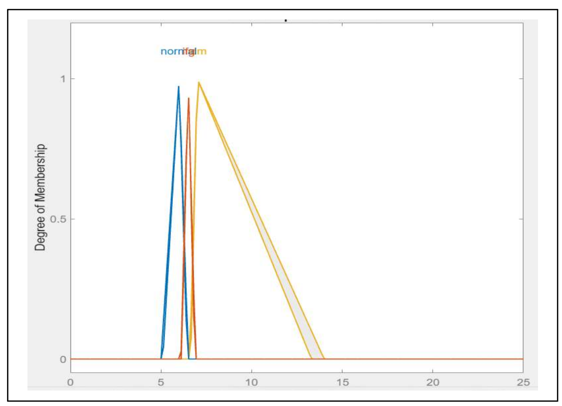

Figure 6:Fpg Membership Function

The MF for rpg is shown in Figure 7, with three defined fuzzy names: normal, ogtt and second rpg. The normal value is less than 7.8, ogtt is 7.8 to 11, and second rpg is above 11.1. Middle values 7.7, 9.5, and 11.2 in the range of each fuzzy names defined is represented by the triangle peak.

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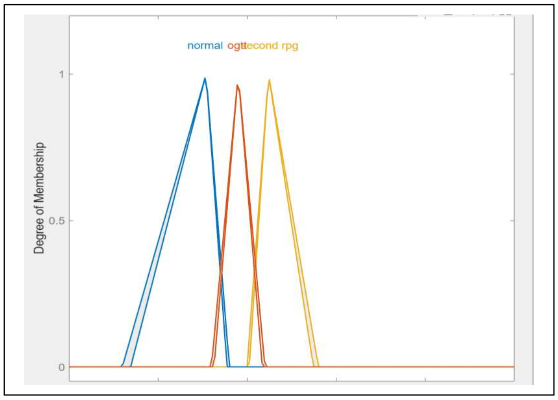

Figure 7: Rpg Membership Function

The MF for fbs is shown in Figure 8, with three defined fuzzy names: normal, prediabetes and diabetes. The normal value is 99 or below, prediabetes is 100 to 125, and diabetes is above 126. Middle values 99, 112.5, and 126 in the range of each fuzzy names defined is represented by the triangle peak.

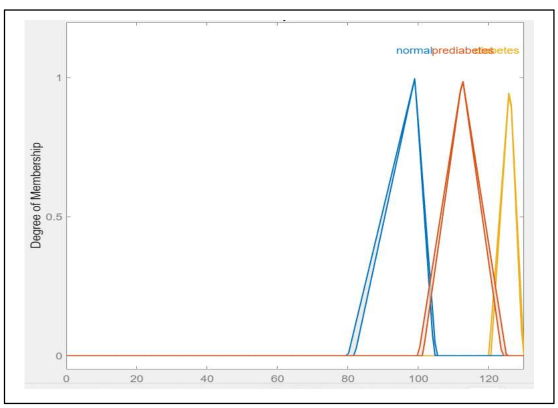

Figure 8: Fbs Membership Function

The MF for two hours post-prandial is shown in Figure 9, with three defined fuzzy names: normal, igt and dm. The normal value is below 7.8, igt is 7.8 to 11, and dm is above 11.1. Middle values 7.7, 9.4, and 11.1 in the range of each fuzzy names defined is represented by the triangle peak.

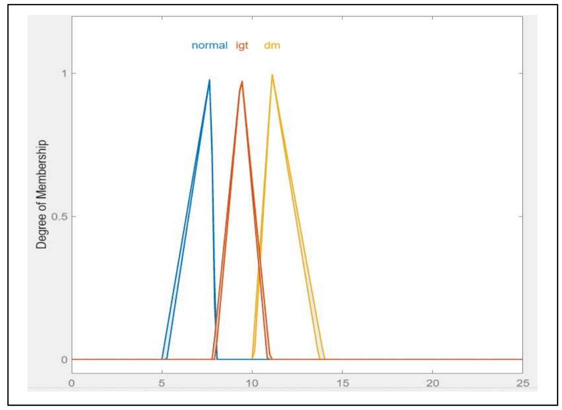

Figure 9: Two Hours Post-Prandial Membership Function

The MF for hdl is shown in Figure 10, with two defined fuzzy names: positive and negative where positive range is below 1.1 and negative above 1.1. Middle values 0.55 and 1.5 in the range of each fuzzy names defined is represented by the triangle peak.

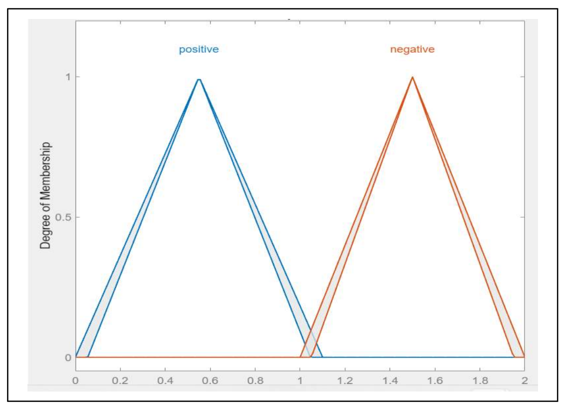

Figure 10: Hdl Membership Function

The MF for ldl is shown in Figure 11, with two defined fuzzy names: negative and positive where negative range is below 2.6 and positive above 2.6. Middle values 1.3 and 3.15 in the range of each fuzzy names defined is represented by the triangle peak.

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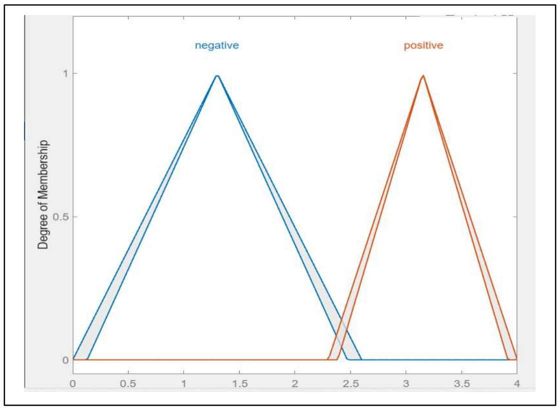

Figure 11: Ldl Membership Function

The MF for tg is shown in Figure 12, with two defined fuzzy names: negative and positive where negative range is below 1.7 and positive above 1.7. Middle values 0.85 and 2.25 in the range of each fuzzy names defined is represented by the triangle peak.

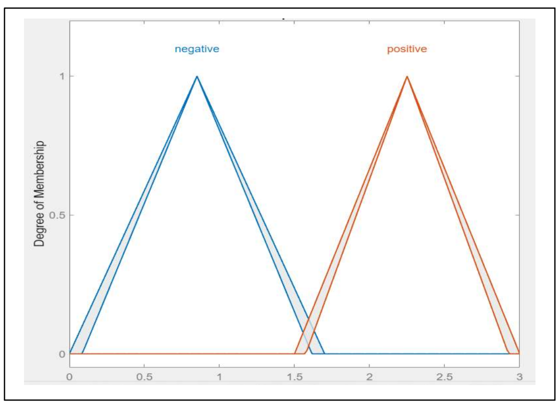

Figure 12: Tg Membership Function

The MF for ogtt is shown in Figure 13, with six defined fuzzy names: fpg normal, fpg ifg, fpg dm, ppg normal, ppg igt and ppg dm. fpg normal value is below 6.1, fpg ifg value is 6.1 to 6.9, fpg dm value is above 7, ppg igt is below 7.8, ppg igt is 7.8 to 11 and ppg dm is above 11.1. Middle values 6, 6.5, 7, 7.7, 9.4 and 11.1 in the range of each fuzzy names defined is represented by the triangle peak.

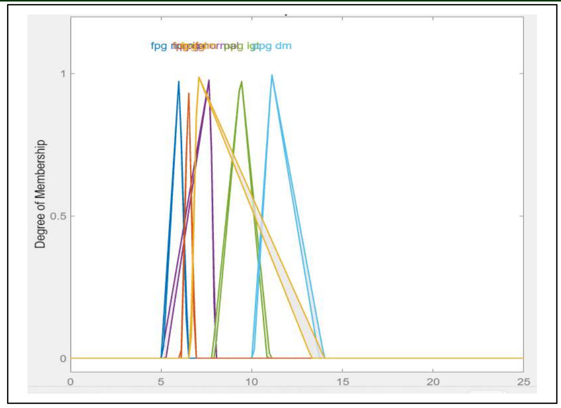

Figure 13: Ogtt Membership Function

The MF for fuzzy output diagnosis is shown in Figure 14, with four defined fuzzy names: healthy prediabetes and primary care; igt prediabetes and primary care; diabetic in control and primary care; and diabetic nephropathy and secondary care, which are set as middle values 1 to 4 in the range of each fuzzy names defined is represented by the triangle peak. This is the most crucial part of the model that combines the diagnosis of diabetes with the level of care which provides sufficient information for decision making.

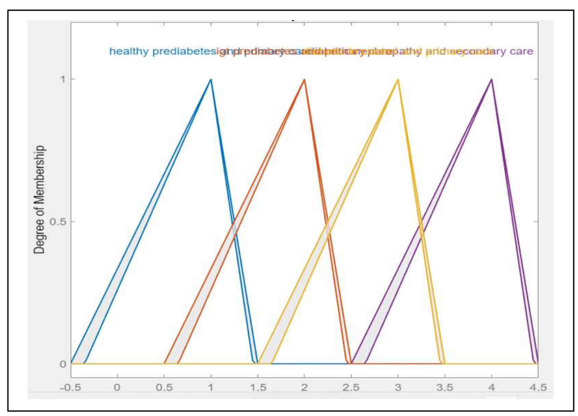

Figure 14:Dignosis of Diabetes and Level of Care Membership Function

The whole fuzzy inference model is clarified in Figure 15, with thirteen inputs and ten rules processed by Mamdani inference, and produced the output, diagnosis of diabetes and level of care. The ten fuzzy rules are shown in Figure 16. The rule inference in Figure 17 is generated based on the fuzzy rules.

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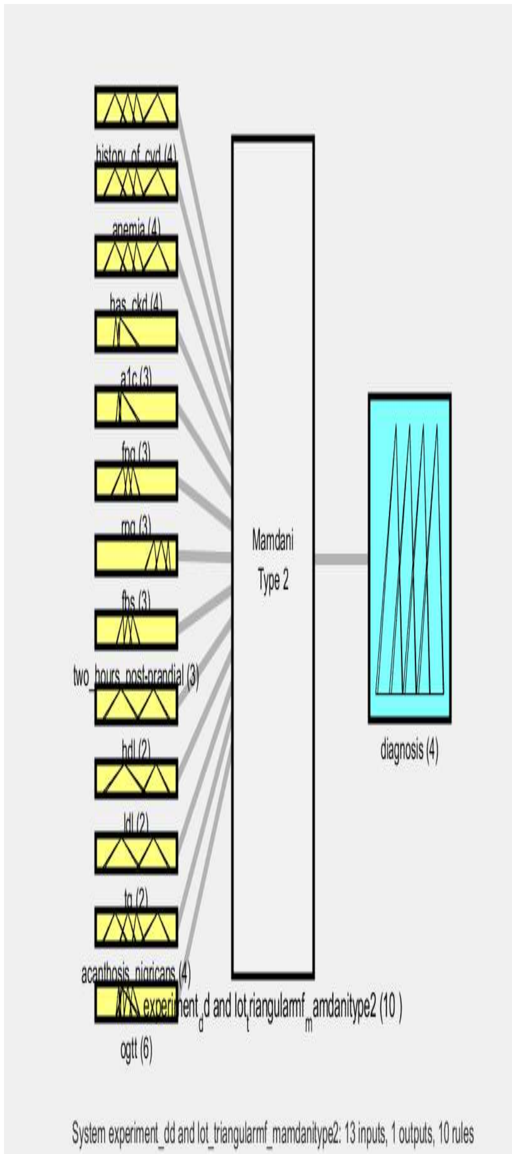

Figure 15: Fuzzy Inference Model for Diagnosis of Diabetes and Level of Care

	Rule	Weight	Name
1	If history_of_cvd is weak no or anemia is weak no or has_ckd is weak no then diagnosis is diabetic nephropathy and secondary care	1	rule1
2	If a1c is diabetes or fpg is dm or rpg is second rpg or fbs is diabetes or two_hours_post-prandial is dm then diagnosis is diabetic in control and primary care	1	rule2
3	If a1c is prediabetes or fpg is ifg or rpg is ogtt or fbs is prediabetes or two_hours_post-prandial is igt or hdl is negative or ldl is positive or tg is positive then diagnosis is igt prediabete...	1	rule3
4	If history_of_cvd is no or anemia is no or has_ckd is no or a1c is normal or fpg is normal or rpg is normal or fbs is normal or two_hours_post-prandial is normal or hdl is positive or ldl...	1	rule4
5	If history_of_cvd is no or a1c is normal or fpg is normal or rpg is ogtt or hdl is negative or tg is positive or acanthosis_nigricans is no then diagnosis is healthy prediabetes and primar...	1	rule5
6	If history_of_cvd is no or a1c is normal or fpg is ifg or rpg is ogtt or hdl is negative or tg is positive or acanthosis_nigricans is no or ogtt is ppg igt then diagnosis is igt prediabetes and...	1	rule6
7	If history_of_cvd is no or a1c is normal or fpg is ifg or rpg is ogtt or hdl is negative or tg is positive or acanthosis_nigricans is no or ogtt is fpg ifg then diagnosis is diabetic in control a...	1	rule7
8	If history_of_cvd is no or a1c is normal or fpg is dm or rpg is second rpg or hdl is negative or tg is positive or acanthosis_nigricans is no then diagnosis is diabetic in control and prim...	1	rule8
9	If history_of_cvd is weak no or a1c is normal or fpg is dm or rpg is second rpg or hdl is negative or tg is negative or acanthosis_nigricans is weak no then diagnosis is diabetic nephr...	1	rule9
10	If history_of_cvd is weak no or a1c is normal or fpg is dm or rpg is second rpg or hdl is negative or tg is positive or acanthosis_nigricans is weak no then diagnosis is diabetic nephro...	1	rule10

Figure 16: Created Fuzzy Rules for Diagnosis of Diabetes and Level of Care

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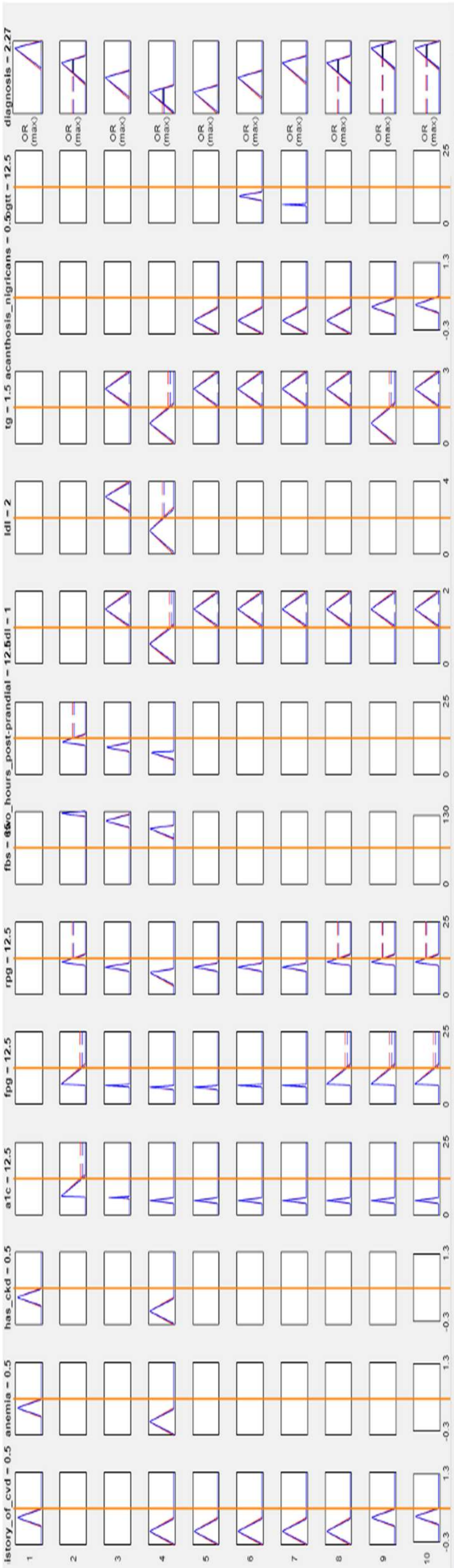

Figure 17: Rule Inference for Diagnosis of Diabetes and Level of Care

Figure 18 shows some of the generated control surface of the fuzzy model output value for the combinations of the input variables selected. Figure 18 (a) and (b) shows the three-dimensional control surface of a thirteen inputs reference where two variables are selected in the control surface plot. Figure 18 (c) and (d) illustrate a control surface for two inputs where the output is plotted against an input variable chosen.

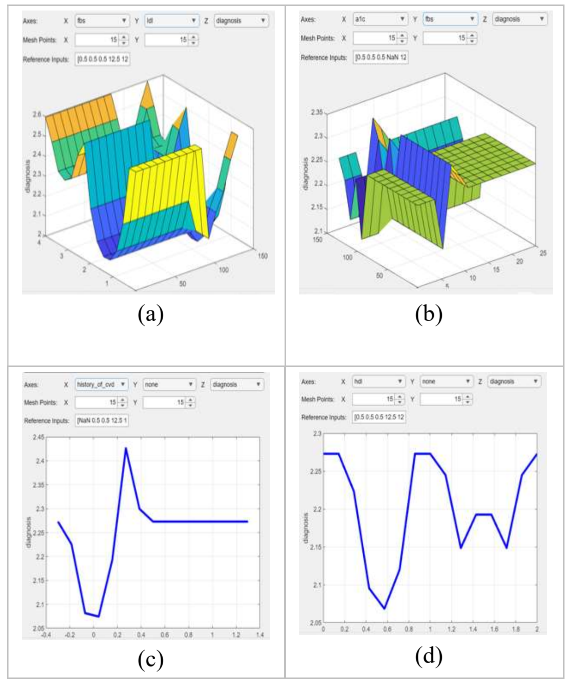

Figure 18:Control Surface of the Proposed Fuzzy Model

5. RESULTS AND DISCUSSION

The membership functions (MF) and rule base in our proposed fuzzy inference model for the diagnosis of diabetes and level of care has been designed. Evaluation is done based on the generated rule inference in Figure 17. The sliders in the rule inference are used to model different settings of the thirteen input values. The OR fuzzy operation is applied to evaluate the disjunction of each rule antecedents using the fuzzy operation union and must be true before making decision about the diagnosis of diabetes and level of care. The fuzzified thirteen inputs activate the second until ten rules by generating firing strength for both upper and lower MF for the type-2 Mamdani method shown in Figure 17. The resulting output MF are aggregated and defuzzified using the centroid technique. The value of the final output 2.27 is calculated using the center of gravity (COG) formula. The output MF for each rule shown at the most right-hand side in Figure 17 is associated to Figure 14 showing different diagnosis of diabetes and level of care. Based on our observation, to verify the performance of the proposed model, for each input, the model produced correct corresponding output for the ten fuzzy rules. Therefore, to validate, the proposed model is working as expected.

Recent research works [5], [6], applied data mining method but our research work applied fuzzy method which are two different methods. By using fuzzy method, the issues of uncertainty and vagueness can be solved because fuzzy method is easy to understand by human with the construction of fuzzy variables and fuzzy rules. Furthermore, eliminate the uncertainty and vagueness in medical datasets. A recent fuzzy Mamdani type-1 for an insulin advisory system developed by [18] used biological variables as the input values to detect diabetes type 1 patients with long-term high glucose level. We used fuzzy Mamdani type-2 with different fuzzy input values, output value and rules to diagnose diabetes type-2, compared to the insulin advisory system developed [18]. These features proposed in our research work handles the insufficient information problem.

The simulated diabetes treatments dataset [1] which contain uncertain and vague data has been converted to fuzzy linguistic variables for a more understandable manner to produce a new design of a fuzzy inference model. This feature solves the uncertainty and vagueness problem. For the insufficient information issue, the proposed model provides extended diagnosis combining diabetes diagnosis with appropriate level of care.

6. CONCLUSION AND FUTURE WORKS

A novel fuzzy inference model for the diagnosis of diabetes and level of care have been successfully proposed based on the generated rule inference and control surface. The proposed model catered the vagueness and uncertainty issues by utilizing the fuzzy concepts which are human interpretable. The simulated diabetes treatments dataset [1] which contains vague and uncertain data is improved by representing the data with fuzzy linguistic terms for the predictor and target variables as well as fuzzy rules. The model provides the diagnosis of diabetes combined with the level of treatment to support sufficient decision-making. Our model is a new fuzzy model that caters vagueness, uncertainty, and insufficient diagnosis information which fulfills the objective of this research.

The proposed fuzzy inference model is the initial model and future works can be done to enhance the model by combining it with other techniques. It is suggested that the proposed fuzzy model is combined with Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). In addition, more test needs to be implemented to verify and validate the improved model.

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