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Selection of Aggregation Function in Fuzzy Inference System for Metabolic Syndrome

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***Abstract*— Metabolic syndrome (MetS) has long-term, very detrimental effects, including chronic kidney disease, cardiovascular disease, stroke, and diabetes mellitus. Therefore, early detection of MetS is very important. Numerous global health organizations have made some Metabolic Syndrome (MetS) diagnosis criteria, but they are still mostly in a dichotomous form. On the other hand, a continuous MetS risk score has been proven to be more sensitive and with less risk of error. This study aims to build a Fuzzy Inference System (FIS) model. MetS diagnostic criteria issued by NCEP-APT III are used as a reference for generating rules. This model uses max, probor, and additive functions to obtain membership values as a result of rules aggregation in seven steps: 1) Identification of variables; 2) Determination of fuzzy sets and their membership functions; 3) Knowledge base generation; 4) Implementation of the implication functions; 5) Fuzzy rules aggregation; 6) Defuzzification; 7) Performance testing of the model and selecting the best aggregation function. The findings show the max function as the most suitable function for the aggregation process with an accuracy, sensitivity, specificity, and precision value of 100% according to the measurement results with NCEP-ATP III. A continuous risk score between 0% and 99.99% is considered a non-high risk, whereas a score of 100% indicates a high risk. This function also has an ideal risk value distribution according to the neighborhood level of the NCEP-ATP III diagnostic criteria.**

***Keywords*— Metabolic syndrome; risk score; fuzzy; aggregation function; performance.**

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I. INTRODUCTION

Age and modern lifestyle can lead to increased health problems for humans. Factors like depression, workloads requiring a person to sit frequently for a long period, immobility by body systems, and unhealthy diets may trigger a series of health problems, including central obesity, increased blood sugar levels, blood pressure, and cholesterol increased triglycerides [1]. These health problems, which may occur simultaneously, are known as Metabolic Syndrome (MetS). MetS greatly affects patients to have an increased risk of complications [2]–[8], even more so in the case of COVID-19, where MetS patients are at a higher risk of death [9]. Several researchers have analyzed the relationship between metabolic syndrome and the emergence of other health problems, including the relationship with hyperplasia [10], chronic kidney disease [11], HIV [12], periodontal [13], and coronary heart [14].

MetS diagnosis is carried out by considering several criteria. Numerous health organizations such as the World Health Organization (WHO), European Group for the Study of Insulin Resistance (EGIR), National Cholesterol Education Program Adult Treatment Panel III (NCE-ATP III), American Association of Clinical Endocrinologists (AACE), and International Diabetes Federation (IDF) have made some criteria for a proper clinical diagnosis of MetS [15] Research comparing different measurements of the level of risk for metabolic syndrome using various criteria has been carried out in many different countries such as in Thailand [16], Philippines [17], India [18], Malaysia [19], and South Korea [20]. However, these criteria are still mostly in a dichotomous form in which there are only two categories of risk for MetS, i.e., high risk and non-high risk. This binary classification could not indicate gradation or spectrum of increasing or decreasing levels of risk. As such, using a continuous MetS risk score offers more advantages as it is more sensitive and has a lower risk of error than the dichotomous approach [21]. According to NCEP-ATP III, a proper clinical diagnosis of MetS is when at least three out of five criteria, as shown in Table I are met [22].

TABLE I
DIAGNOSIS CRITERIA OF METS ACCORDING TO NCEP-ATP III

Criteria	Conditions
Central Obesity	WC ≥ 102 cm (male), WC ≥ 88 cm (female) In Asian: WC ≥ 90 cm (male), WC ≥ 80 cm (female)
Dyslipidemia Triglycerides (TG)	TG ≥ 150 mg/dL or medication
Dyslipidemia HDL	HDL-C < 40 mg/dL (male), HDL-C < 50 mg/dL (female), or medication
Blood Pressure (BP)	Systolic BP ≥ 130 mmHg or Diastolic BP ≥ 85 mmHg, or medication
Glucose	Fasting plasma glucose: ≥ 100 mg/dL or medication

Today, many researchers have used continuous rather than dichotomous data to analyze the relationship between physical activity, MetS, and its components. The measurement of MetS risk level using a Z-score has been carried out in certain domains [21]. This method shows high specificity (i.e., more than 96%) so that it can be used to strengthen the measurement of the risk level of MetS and to support the statement that a continuous measurement is considered better than a dichotomous one. Nonetheless, this study uses statistical approaches that are yet to accommodate oftentimes occurring situations that contain uncertainty. This research aims to build a MetS prediction model using a Fuzzy Inference System (FIS). Fuzzy logic is a reliable method for dealing with uncertainty problems. Generally, FIS uses the max method for aggregation. We use max, probabilistic or (probor), and additive (sum) functions for the rule-aggregation process to be compared with each other in order to get the one with the best performance.

II. MATERIALS AND METHOD

A. Materials

The model was tested on simulation data created by generating random numbers in Microsoft Excel to measure validity. This study's use of simulation data was possible because the gold standard for model testing was based on clear guidelines, i.e., the NCEP-ATP III diagnostic criteria. There were 1000 data used for the simulation process, which profile is shown in Table II.

TABLE II
THE PROFILE OF SIMULATION DATA SAMPLES

Criteria	Number of Samples		
	Male	Female	Total
Central Obesity	265	332	597
Dyslipidaemia			
• High triglycerides	118	97	215
• Low HDL	129	247	376
• TG medication	62	28	90
• HDL medication	36	28	64
High Blood Pressure			
• Systolic blood pressure	223	207	430
• Diastolic blood pressure	274	218	492
• Blood pressure medication	40	48	88
Glucose			
• High glucose	216	184	400
• Glucose medication	59	34	93

B. Method

In general, we adopted an inference flow in the fuzzy inference system in this study. The knowledge base containing fuzzy rules was generated from the NCEP-ATP III criteria with a combinatorial concept. The details of the proposed method are divided into seven stages as follows:

1) Stage 1, Identification of variables: We used MetS diagnostic criteria issued by the NCEP-ATP III as the variables used in this study [22]. The final result of this fuzzy inference system was the level of MetS risk, represented as a percentage, while MetS risk level became the output variable. As the input variables, four main factors are considered in the diagnosis of MetS according to NCEP-ATP III, namely:

- Central obesity. This factor was measured using the abdominal circumference, referred to as Waist Circumference (WC) variable. For Asians, a person is considered to have central obesity if WC ⩾ 90 cm (male) or WC ⩾ 80 cm (female).
- Dyslipidemia. This factor was measured by using four variables, namely:
  a) Triglyceride (TG). A person is considered to have dyslipidemia if TG ⩾ 150 mg/dL.
  b) TG medication, i.e., a condition in which a person is being treated for TG.
  c) High-Density Lipoprotein Cholesterol (HDL-C). A person is considered having dyslipidemia if HDL-C < 40 mg/dL (male) or HDL-C < 50 mg/dL (female).
  d) HDL-C medication, i.e., a condition in which a person is being treated for HDL-C.
- Blood Pressure (BP). This factor was measured using three variables, namely:
  a) Systolic blood pressure (SBP). A person is considered to have high blood pressure if SBP ⩾ 130 mmHg.
  b) Diastolic blood pressure (DBP). A person is considered to have high blood pressure if DBP ⩾ 85 mmHg.
  c) BP medication, i.e., a condition in which a person is being treated for blood pressure.
- Glucose. This factor was measured using two variables, namely:
  a) Fasting plasma glucose (FPG). A person is considered to have high glucose if FPG ⩾ 100 mg/dL.
  b) FPG medication, i.e., a condition in which a person is being treated for glucose.

The four factors became the dependent variable, which is influenced by the related independent variables. To facilitate computing, the dyslipidemia factor was divided into two, i.e., dyslipidemia caused by triglycerides (dyslipidemia TG) and dyslipidemia caused by HDL-C (dyslipidemia HDL-C). Hence, we had eleven independent variables, four dependent variables as intermediate variables, and one dependent variable as the output variable in this study.

2) Stage 2, Determination of fuzzy sets and membership functions: After determining the research variables, we identified which variables are fuzzy and non-fuzzy variables. A fuzzy variable is a mapping from an abstract space (called the pattern space) onto the real line [23]. The identification step yielded twelve fuzzy variables, as shown in Table III, and four non-fuzzy variables, as shown in Table IV.

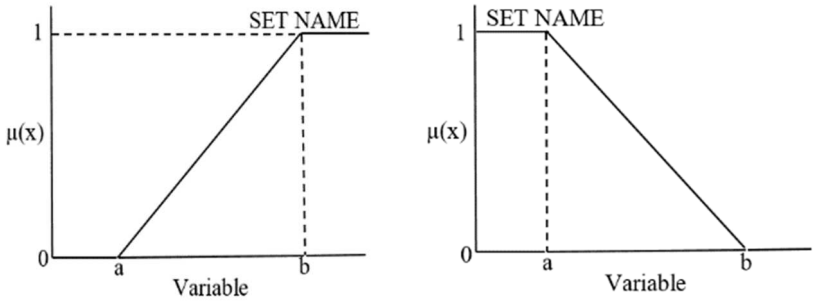
TABLE III
FUZZY VARIABLES, FUZZY SETS, AND MEMBERSHIP FUNCTION (MF)

Variable	Unit	Set Name	Parameter		MF	Parameter setting standards	
			Lower bound (a)	Upper bound (b)		Lower bound (a)	Upper bound (b)
Waist Circumference (WC)	cm	LARGE	80 (M); 70 (F)	90 (M); 80 (F)	LU	Central obesity category recommended by NCEP-ATP III minus 10 cm	Central obesity category recommended by NCEP-ATP III [24]
Triglycerides (TG)	mg/dL	HIGH	50	150	LU	High TG category recommended by NCEP-ATP III minus 100 mg/dL	High TG category recommended by NCEP-ATP III [24]
HDL-C	mg/dL	LOW	39 (M); 60 (F)	49 (M); 60 (F)	LD	Low HDL cholesterol category recommended by NCEP-ATP III [24]	Low HDL cholesterol category recommended by NCEP-ATP III plus 10 mg/dL [24]
Systolic Blood Pressure (SBP)	mmHg	HIGH	110	130	LU	Normal blood pressure category recommended by the American Heart Association [25]	High systolic blood pressure category recommended by NCEP-ATP III [24]
Diastolic Blood Pressure (DBP)	mmHg	HIGH	80	85	LU	Normal blood pressure category recommended by the American Heart Association [25]	High diastolic blood pressure category recommended by NCEP-ATP III [24]
Fasting Plasma Glucose (FPG)	mg/dL	HIGH	80	100	LU	High FPG category by NCEP-ATP III minus 20 mg/dL	High FPG category by NCEP-ATP III [24]
Central Obesity	-	HIGH	0	1	LU	-	-
Dyslipidaemia TG	-	HIGH	0	1	LU	-	-
Dyslipidaemia HDL-C	-	HIGH	0	1	LU	-	-
Bllod Pressure	-	HIGH	0	1	LU	-	-
Glucose	-	HIGH	0	1	LU	-	-
MetS Risk	%	HIGH	0	100	LU	-	-

TABLE IIV
NON-FUZZY VARIABLES

Variable	Value	Description
TG Medication	Yes/No	Currently on Triglycerides medication
HDL-C Medication	Yes/No	Currently on HDL-C medication
BP Medication	Yes/No	Currently on high blood pressure medication
Glucose Medication	Yes/No	Currently on glucose medication

Furthermore, for each fuzzy variable in Table III, we determined the relevant fuzzy set, i.e., the LARGE set for the WC variable, the LOW set for the HDL-C variable, and the HIGH set for other fuzzy variables. The fuzzy membership function for each set was represented by one of the two linear functions, i.e., linearly up (LU) and linearly down (LD). This function was chosen because every element in the domain would get the same treatment in the membership value range [26]. Graphically, this membership function can be seen in Fig 1.



(a) (b)

Fig. 1 Membership Function: (a) Linearly Up (LU); (b) Linearly Down (LD)

Both functions had two parameters i.e., the lower limit (a) and the upper limit (b). The membership function for the linearly up function is given in Eq 1 and the membership function for the linearly down function is given in Eq 2.

$$\mu(x) = \begin{cases} 0; & x \le a \\ \frac{x-a}{b-a}; & a < x < b \\ 1; & x \ge b \end{cases} \quad (1)$$

$$\mu(x) = \begin{cases} 1; & x \le a \\ \frac{b-x}{b-a}; & a < x < b \\ 0; & x \ge b \end{cases} \quad (2)$$

Determining parameters (a and b) was based on the international standard of each variable. An explanation of the parameter assignments for each membership function is presented in Table III. For non-fuzzy variables, it is only possible to have two membership values, i.e., 1 (Yes) or 0

(No). In other words, if a person was in a medical treatment period, the membership value was 1, but if a person was not currently undergoing treatment, the membership value was 0.

3) Stage 3, Knowledge base generation: We generated the knowledge base using a rule-based concept. Each knowledge is represented using the production rules (IF - THEN rule) according to the same format of "IF antecedent THEN consequence". Each antecedent can be a relation between several sets. In this research, only the operator "and" was used to make a relation between sets. If the "or" operator was required, a new rule would be created with the same consequence. Ten rules were designed to get the conditions of central obesity, dyslipidemia, high blood pressure, and high glucose. This rule was based on the diagnostic criteria provided by the NCEP-ATP III [22]. Details of the rules are shown in Fig 2.

R01:	IF	WC	is	LARGE	THEN	Central Obesity	is	HIGH
R02:	IF	TG	is	HIGH	THEN	Dyslipidemia TG	is	HIGH
R03:	IF	TG Medication	is	YES	THEN	Dyslipidemia TG	is	HIGH
R04:	IF	HDL-C	is	LOW	THEN	Dyslipidemia HDL-C	is	HIGH
R05:	IF	HDL-C Medication	is	YES	THEN	Dyslipidemia HDL-C	is	HIGH
R06:	IF	Systolic BP	is	HIGH	THEN	Blood Pressure	is	HIGH
R07:	IF	Diastolic BP	is	HIGH	THEN	Blood Pressure	is	HIGH
R08:	IF	BP Medication	is	YES	THEN	Blood Pressure	is	HIGH
R09:	IF	FPG	is	HIGH	THEN	Glucose	is	HIGH
R10:	IF	FPG Medication	is	YES	THEN	Glucose	is	HIGH

Fig. 2 Fuzzy Rules for Central Obesity, Dyslipidemia, High Blood Pressure, and High Glucose.

R11:	IF	Central Obesity	is	HIGH	and
		Dyslipidemia TG	is	HIGH	and
		Dyslipidemia HDL-C	is	HIGH	THEN
		MetS Risk	is	HIGH	
R12:	IF	Central Obesity	is	HIGH	and
		Dyslipidemia TG	is	HIGH	and
		Blood Pressure	is	HIGH	THEN
		MetS Risk	is	HIGH	
R13:	IF	Central Obesity	is	HIGH	and
		Dyslipidemia TG	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	
R14:	IF	Central Obesity	is	HIGH	And
		Dyslipidemia HDL-C	is	HIGH	And
		Blood Pressure	is	HIGH	THEN
		MetS Risk	is	HIGH	
R15:	IF	Central Obesity	is	HIGH	And
		Dyslipidemia HDL-C	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	
R16:	IF	Central Obesity	is	HIGH	And
		Blood Pressure	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	
R17:	IF	Dyslipidemia TG	is	HIGH	And
		Dyslipidemia HDL-C	is	HIGH	And
		Blood Pressure	is	HIGH	THEN
		MetS Risk	is	HIGH	
R18:	IF	Dyslipidemia TG	is	HIGH	And
		Dyslipidemia HDL-C	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	
R19:	IF	Dyslipidemia TG	is	HIGH	And
		Blood Pressure	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	
R20:	IF	Dyslipidemia HDL-C	is	HIGH	And
		Blood Pressure	is	HIGH	And
		Glucose	is	HIGH	THEN
		MetS Risk	is	HIGH	

Fig. 3 Fuzzy Rules for Central Obesity, Dyslipidemia, High Blood Pressure and High Glucose

Based on the NCEP-ATP III diagnostic criteria, a person is considered to have MetS if at least three out of five criteria (central obesity, dyslipidemia TG, dyslipidemia HDL-C, high blood pressure or high glucose) are met. The number of combinations of n objects taken r at a time was determined by using Eq 3.

$$C(n,r) = \frac{n!}{(n-r)!r!} \quad (4)$$

The formula was implemented for n = 5 and r = 3 for the ten rule combinations, as shown in Fig 3 (R11 – R20).

4) Stage 4, Implementation of the implication function: In this stage, we calculated the membership value obtained from the results of operations between fuzzy sets. This value was named fire strength (α). The operator "and" was represented by the operation of the intersection between sets, while the operator "or" was represented by the operation of the union between sets. The formula for calculating fire strength using the "and" and "or" operators were given as shown in Eq 4 and Eq 5 [26].

$$\mu_{A\cap B} = \min(\mu_A(x), \mu_B(y)) \quad (4)$$

$$\mu_{A\cup B} = \max(\mu_A(x), \mu_B(y)) \quad (5)$$

From the first rule (R01) to the 10th rule (R10), each rule would have the same fire strength as the membership value in the antecedent because each rule used only one variable in its antecedent. From the 11th rule (R11) to the 20th rule (R20), the fire strength of each rule was obtained by finding the minimum value for each membership value in the antecedent.

Monotonous reasoning was used as an implementation of the implication function. In monotonous reasoning, the consequence set must be represented using a monotonous membership function [26]. In this study, all fuzzy sets in the dependent variable were represented using a monotonous membership function (linearly up) so that monotonous reasoning could be implemented in this case. In monotonous reasoning, the output value in the k-rule (z_k) could be directly calculated based on the fire strength of the kth rule (α_k) obtained using the formula as shown in Eq 6.

$$z_k = \mathrm{a} + (b-a)(\alpha_k) \quad (6)$$

5) Stage 5, aggregation of fuzzy rule: Aggregation was implemented for the 11th rule to the 20th rule. The max functions, probor function, and additive functions [27] were used in the aggregation process. The max function is given in Eq 7, the probor function is given in Eq 8, and the additive

function is given in Eq 9. The aggregation process starts at the 2nd rule and was carried out sequentially for every two rules up to the last rule (i.e., α_{20}).

$$\alpha_k = max(\alpha_{k-1}; \alpha_k) \quad (7)$$

$$\alpha_k = \alpha_k + \alpha_{k-1} - (\alpha_k)(\alpha_{k-1}) \quad (8)$$

$$\alpha_k = min(1; \alpha_{k-1} + \alpha_k) \quad (9)$$

*6) Stage 6, Defuzzification:*The last process of the fuzzy inference system was defuzzification. In this section, MetS risk would be calculated based on the results of the aggregation of all rules with the formula as shown in Eq 10.

$$MetS\ Risk = (\alpha_{20})(100\%) \quad (10)$$

7) Stage 7, Performance testing and selecting the best aggregation function: Model performance testing was done by using the following five factors as shown in Eq 11-15 [28]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \quad (11)$$

$$Sensitivity = \frac{TP}{TP+FN}\ x\ 100\% \quad (12)$$

$$Specificity = \frac{TN}{TN+FP}\ x\ 100\% \quad (13)$$

$$Precision = \frac{TP}{TP+FP}\ x\ 100\% \quad (14)$$

$$Negative\ Predictive\ Value\ (NPV) = \frac{TN}{TN+FN}\ x\ 100\% \quad (15)$$

NCEP-ATP III	The proposed model +	The proposed model -
+	TP (True Positive)	FN (False Negative)
-	FP (False Positive)	TN (True Negative)

Fig. 4 Components of the Model Test

III. Results and Discussion

Table V shows the results of the risk level prediction. In the NCEP-ATP III diagnostic criteria, the number of samples for the high-risk level was calculated from the number of samples with the fulfilled criterion value (k) greater than or equal to 3. In the max, probor and additive functions, the number of samples for high risk levels was calculated from the number of samples where the degree of aggregation membership (α) was equal to 1.

TABLE V
THE RESULT OF THE RISK LEVEL PREDICTION

Method/function	Number of Samples		
	High risk	Non-high risk	k or aggregation membership value (α) for high risk
NCEP-ATP III	514	486	k=3
Max	514	486	$\alpha_{max} = 1$
Probor	514	486	$\alpha_{probor} = 1$
Additive (sum)	872	128	$\alpha_{sum} = 1$

The three functions had the same sensitivity and NPV values, i.e., 100% and 0%, meaning that all samples declared high risk in NCEP-ATP III were also declared high risk in the model. The max and probor functions had the highest accuracy (100%), while the additive functions had the lowest accuracy (64.20%). The max and probor functions had the highest specificity (100%), while the additive functions had the lowest specificity (26.34%). Likewise, the max and probor functions had the highest precision (100%), while the additive functions had the lowest precision (58.94%).

Table VI shows the membership values due to the aggregation of rules (α) using the max and probor functions for the non-high risk level, which were only at k = 0, 1, and 2. We divided the results into three categories, *i.e* $0.6667 \leqslant \alpha \leqslant 1$ (related to k=2); $0.3333 \leqslant \alpha < 0.6667$ (related to k=1);; and $0 \leqslant \alpha < 0.3333$ (related to k=0).

TABLE VI
THE MEMBERSHIP VALUE OF NON-HIGH RISK FOR MAX FUNCTION

k	Max Function			Probor Function		
	$0{,}6667 \leq \alpha < 1$	$0{,}3333 \leq \alpha < 0{,}6667$	**$0 \leq \alpha < 0{,}3333$**	$0{,}6667 \leq \alpha < 1$	$0{,}3333 \leq \alpha < 0{,}6667$	$0 \leq \alpha < 0{,}3333$
2	183 (61,82%)	96 (32,43%)	17 (5,74%)	286 (90,51%)	16 (5,06%)	14 (4,43%)
1	56 (34,15%)	75 (45,63%)	33 (20,12%)	112 (68,29%)	29 (17,68%)	23 (14,02%)
0	1 (3,85%)	13 (50%)	12 (46,15%)	11 (43,31%)	8 (30,77%)	7 (26,92%)

Applications of fuzzy logic as a function for disease prediction have been widely used [29], [30], [31], [32]. In the classical fuzzy inference system, the role of the knowledge base is very important. If the knowledge base has a number of rules with the same consequence, then the use of the union operator (aggregation using the maximum value) instead of a weighted average is recommended. The use of weighted average is more appropriate for rules with consequence differences in fuzzy sets [33], [34], [35] or using in Multi-Criteria Decision Making (MCDM) [35], [36], [37], [38], [39], [40], [32]. This research did not use weighted averages as a defuzzification method. Instead, we used the conversion of rules aggregation membership values into 0 - 100% range. Therefore, the selection of the aggregation function is critical so that the defuzzification results, which are the final result of this model, have the best performance.

Suppose αmax is the membership value as a result of rule aggregation using the max function. In that case, α_{probor} is the membership value as a result of rule aggregation using the probor function, and α_{sum} is the membership value as a result of rule aggregation using the additive function, the following relationship as shown in Equation 16 is obtained.

$$\alpha_{max} \leq \alpha_{probor} \leq \alpha_{sum} \quad (16)$$

Based on the model performance test results, the max function and probor function are proven to have the best performance with all of the accuracy, sensitivity, specificity, and precision at 100%. It means that these functions can be used as an alternative to predict the risk level of MetS in a continuous form. If a person has a high risk according to NCEP-ATP III, then the high-risk level as per this model will be 100%. However, if a person is not high-risk according to NCEP-ATP III, then the high-risk level as per this model will

be between 0% and 99.99%, depending on the level of closeness of each variable to the upper or lower limit of the risk condition. By using this function, people diagnosed as the non-high-risk of MetS based on NCEP-ATP III can learn how close they actually are to being high risk. The closer to 100% their score is, the closer to the high risk they are.

The results show that the max and probor functions have the best performance at 100% for accuracy, sensitivity, specificity, and precision. The additive function is not recommended because of its poor performance. Next, we will see the distribution of membership values based on the value of k. In the case of the max function with k=2, the membership value of the aggregation results is mostly in the range of 0.6667 to 1, i.e., 61.82%. It shows that if there are two criteria in accordance with the NCEP-ATP III diagnostic criteria, the possibility of having a high risk is quite high (between 66.67% and 99.99%). The same thing is also true, with a greater magnitude, in the case of the probor function with a greater percentage (90.51%). It makes sense that the increasing proximity of diagnostic criteria has implications to being high risk of MetS.

As for the max function with k=1, the membership value of the aggregation results is mostly in the range of 0.3333 to 0.6667, i.e., 45.63%. In other words, the fewer criteria match the NCEP-ATP III diagnostic criteria, the lower risk of MetS is (in the range of 33.33% to 66.66%). This condition does not occur in the probor function. This function has the membership value of the aggregation results mostly in the range of 0.6667 to 1 (68.49%). This, of course, becomes less than ideal.

Lastly, in the case of the max function with k=0, the membership value of the most aggregated results lies in the range of 0.3333 to 0.6667 (50%). However, the number of samples between 0 and 0.6666 is greater than that of $\geqslant$ 0.6667, i.e., 96.15%. Only one sample has a MetS risk level above 66.66%. In the probor function, the membership value of the aggregation results is at most in the range of 0.6667 to 1, i.e., 43.31%. Although the number of samples between 0 and 0.6666 is greater than that of $\geqslant$ 0.6667, it is not significant. Thus, for k=0, the max function is recommended over the probor function.

In this model, we do not need a threshold value (θ) indicating a minimum membership value to be considered high risk because the diagnostic criteria follow NCEP-ATP III where at least three criteria are met. In other words, the threshold value for this model is 1. If α=1, the high-risk level for MetS is equal to 100%.

This research contributes to the enrichment of models for the early detection of MetS with a continuous approach. Based on previous research, the continuous model is proven to provide better accuracy and precision than the dichotomous model. Another contribution is the model based on knowledge represented by rules (IF-THEN rules), so it can be understood very well. The proposed model does not use a complicated mathematical model, and we use a fuzzy inference system using a rule-based linguistic approach. So it can be implemented easily.

In the future, we will focus on measuring the risk level of complications when a person is diagnosed with MetS. These complications include chronic kidney problems, cardiovascular disease, and stroke. The measurement of the risk level of complications can also be done by using a similar fuzzy inference system by taking into consideration the variables that are directly related to the increase of risk level for each problem

IV. Conclusion

Many health organizations across the globe have made some Metabolic Syndrome (MetS) diagnosis criteria that are still mostly in a dichotomous form (i.e., high risk vs. non-high risk). A continuous MetS risk score offers more sensitivity and a lower risk of error than the dichotomous approach, which could not indicate a gradation or spectrum of increasing or decreasing levels of risk.

Using statistical approaches to implement a continuous MetS risk score cannot accommodate any situation with some level of uncertainty. A fuzzy inference system as the Implementation of a continuous MetS risk score could help people be more aware of how close they are to being at high risk of MetS by breaking down further the non-high-risk score to a value between 0% and 99% while keeping the high-risk score at 100%.

The max function offers better performance (i.e., accuracy, sensitivity, specificity, precision, and distribution of MetS risk score as per NCEP-ATP III diagnostic criteria) than probor and additive function as an aggregation function in this fuzzy inference system.

Nomenclature

α	fire strength
$\mu_A(x)$	membership value of x in A

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