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A FUZZY LOGIC MODEL FOR ASSESSING OBESITY RISK LEVELS AMONG UNIVERSITY STUDENTS

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Abstract:

The global prevalence of obesity remains high, with statistics showing that in 2022, one in eight individuals worldwide were living with obesity. Obesity is associated with various health risks, including diabetes, hypertension, sleep apnea, and mental and emotional issues. Addressing obesity during adolescence is crucial for preventing related health problems in adulthood. Consequently, this study focuses on early obesity risk screening among university students using a Fuzzy Logic Model. Key input factors such as Body Mass Index (BMI), parental history, exercise habits, fibre intake, and fast-food consumption were collected from 30 students at UiTM Perlis Branch. The data were analyzed using 162 IF-THEN rules to classify obesity risk into low, medium, and high categories, demonstrating the flexibility and accuracy of fuzzy logic in handling vagueness and uncertainty in health assessments. The survey results indicated that 97% of the respondents were categorized as having a "medium" obesity risk, though at varying degrees within that category. Some students with healthy BMI values still fell into this category due to sedentary lifestyles and frequent consumption of fast food. This study successfully develops and implements a fuzzy logic model to evaluate risk levels of developing obesity. This model could aid the public and healthcare professionals in early diagnosis of obesity risk and could be further enhanced by incorporating additional obesity-related input factors.

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Keywords:

Fuzzy Logic, Obesity Risk Level, Body Mass Index, Parental History, Exercise Habit, Fibre Consumption, Fast Food Consumption

Introduction

Obesity is defined by an excessive accumulation of body fat that can have serious negative effects on an individual's health. In adults, Body Mass Index (BMI) serves as a standard measure: a BMI below 18.5 is classified as underweight, a BMI between 18.5 and 24.9 indicates a healthy weight, and a BMI from 25 to 29.9 is categorized as overweight. Obesity is diagnosed when BMI reaches 30 or higher, and it is further divided into three classes: Class I (mild obesity, BMI 30–34.9), Class II (moderate obesity, BMI 35–39.9), and Class III (severe obesity, BMI over 40) (WHO,2022). Research indicates that individuals with a BMI greater than 30 kg/m² are nine times more likely to develop hypertension compared to those with a normal BMI (Upadhyay et al., 2018). On a global scale, obesity remains a critical public health concern. In 2022, approximately one in every eight people worldwide was living with obesity. Around 2.5 billion adults aged 18 and over were classified as overweight, with over 890 million of them falling into the obese category. This means that 43% of adults (43% of men and 44% of women) were considered overweight, a significant increase compared to 1990, when only 25% of the adult population was categorized as overweight (WHO, 2024).

Excessive body weight greatly increases the risk of developing chronic conditions such as diabetes and cardiovascular diseases (Hales et al., 2017). Diabetes mellitus poses significant health risks for individuals with obesity, often leading to complications like heart disease and elevated cholesterol levels, which in turn heighten the likelihood of stroke and paralysis. A heart attack can occur when the coronary arteries, responsible for supplying oxygen and nutrients to the heart, become blocked, cutting off oxygen supply to the heart muscle and resulting in tissue death and potentially fatal consequences. Fat abnormally accumulates in organs such as the muscles, liver, and heart. This ectopic fat buildup can lead to severe outcomes, including heart failure, β-cell dysfunction in the pancreas, and insulin resistance in liver and muscle tissues. The presence of excessive fat in abdominal organs significantly raises the risk of developing life-threatening conditions like heart disease and diabetes mellitus (Nawarycz et al., 2015).

Obesity not only increases the risk of life-threatening diseases and reproductive health issues but also contributes to chronic conditions such as chronic venous disease and respiratory complications, affecting both adults and children. Upadhyay et al. (2018) reported that obesity significantly contributes to higher mortality rates by being associated with life-threatening diseases such as non-alcoholic fatty liver disease, stroke, severe pancreatitis, and cancers of the breast, colon, and uterus, among others. Additionally, obesity can exacerbate reproductive health issues; for instance, individuals with polycystic ovary syndrome (PCOS) often experience more difficulty conceiving compared to those with a healthy weight. Langan et al., (2023) indicate that obesity has being one of the factors that contribute to the pathophysiology of chronic venous disease. Chronic Venous Diseases (CVD) occurs when the veins in the body do not function properly by not returning blood to the heart. Normally, these things happen in the legs and cause various other problems such as swelling (Edema), cramps and fatigue and many more. Edema usually happens in legs and ankles that are caused by accumulation of

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excess fluid. Most who suffered from obesity had high chances to suffer from asthma, chronic inflammation, liver disease and dyslipidaemia (Shaban Mohamed et al., 2022).

Diet is a major modifiable factor influencing obesity. High-calorie, ultra-processed foods rich in sugars, fats, and refined carbohydrates contribute significantly to weight gain. Diets low in fibre and high in energy density often result in excessive calorie intake. Some people frequently consume junk foods such as sausages, soft drinks, pizza, and other fast foods, which are high in salt, fat, and sugar ingredients that can have harmful effects on the body's health systems (Wongprawmas et al., 2022). Although these foods may provide immediate satisfaction, they are often deficient in essential nutrients like fibre, vitamins, and minerals, potentially leading to digestive problems such as constipation. Increasing dietary fiber intake has been shown to offer structural, physicochemical, and site-specific gastrointestinal benefits, playing a significant role in both the prevention and management of obesity (Deehan et al., 2024; Van de Vijver et al., 2009; Smith, 1987). According to Nurohmat and Nughara (2024), consuming foods high in carbohydrates and fiber while low in fat can support a balanced diet, whereas shifting to a diet low in carbohydrates and high in fat may contribute to nutritional imbalances. Beyond diet, other contributing factors to obesity include a sedentary lifestyle, unhealthy eating behaviors, genetic factors, certain medications, and chronic stress.

Obesity is closely linked to exercise habits, as highlighted in several studies (Kang & Hee, 2021; Kim & Woo, 2022; Li et al., 2024). Regular physical activity has consistently been recognized as one of the strongest predictors of successful weight management and long-term weight maintenance. In addition to its role in controlling body weight, regular exercise significantly improves overall physical fitness. Research has shown that even if individuals remain overweight, enhanced fitness levels achieved through consistent physical activity can substantially reduce the risk of cardiovascular diseases and lower overall mortality rates (McInnis, 2000). Furthermore, adopting active lifestyles can lead to better metabolic health, improved mental well-being, and a reduced incidence of obesity-related comorbidities over time.

Other factors such as parental obesity, gender, and socio-academic status are also factors influencing the obesity. Numerous studies have demonstrated a significant positive relationship between parental obesity and the likelihood of obesity in their children. For instance, research by Bahreynian et al. (2017) and Jiang (2013) found that children with obese parents were significantly more likely to be overweight or obese compared to those with normal-weight parents, highlighting the impact of both genetic predispositions and shared family environments. Gender also plays a crucial role in the analysis of obesity. Studies indicate that men are generally more prone to developing obesity than women, although these trends can vary according to geographical regions and the level of economic development (Muscogiuri et al., 2024). Biological differences, such as variations in body composition, fat distribution, and metabolism, are largely influenced by hormonal factors, contributing to these disparities. Additionally, sex hormones have been found to affect eating behaviors differently in men and women, further influencing obesity risk (Muscogiuri et al., 2024). Socioeconomic status is another significant determinant of obesity. According to Wang and Beydoun (2007), lower socioeconomic status is often associated with higher obesity prevalence, particularly in developed countries, due to factors such as reduced access to healthy foods, limited opportunities for physical activity, and higher levels of stress. Moreover, lower educational

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attainment can correlate with reduced awareness of healthy lifestyle practices, contributing to unhealthy behaviors that promote weight gain.

Given the numerous health risks associated with obesity, this study aims to assess obesity risk levels among university students using Fuzzy Logic. University students often experience busy schedules that contribute to poor lifestyle choices and irregular eating habits. This research could act as an early screening tool to identify individuals at risk of developing obesity. Early interventions during adolescence are essential to prevent the progression of obesity-related health issues later in life.

Primary data related to obesity were collected from 30 students aged 18 to 24 years from various faculties at Universiti Teknologi MARA (UiTM), Perlis Branch. The data included height and weight (used to calculate BMI), parental history of obesity, exercise habits, fibre intake, and fast-food consumption. The BMI, exercise habits, fibre intake, and fast-food consumption were categorized into three linguistic levels: Low, Medium, and High. Parental history of obesity was classified into two categories: present or not present. A total of 162 IF-THEN rules were applied to analyze the data and classify the students' obesity risk into Low, Medium, or High categories. The use of fuzzy logic in this study demonstrates its effectiveness in managing the vagueness and imprecision commonly found in health assessments. Unlike conventional method, fuzzy logic approach is capable to integrate complex interaction of several input data to predict the outcome (Nurohmat & Nughara, 2024; Khanna et al., 2015).

Fuzzy Logic

Fuzzy logic is a computational method that imitates human reasoning by allowing for degrees of truth, instead of just "true" or "false" values (Langan et al., 2023). It is especially useful in situations involving uncertainty, vagueness, or imprecision, where traditional logic systems struggle (Sabri). Developed by Lotfi A. Zadeh in 1965, fuzzy logic uses membership functions to show how strongly an element belongs to a set. Instead of dealing only with strict yes/no decisions, it assigns membership values between 0 and 1, reflecting partial truth or belonging.

Let S be a non-empty universe set and $A \subset S$. A characteristic function of classical set theory is defined as

$$\mu_A(x) = \begin{cases} 1; & \text{if } x \in A \\ 0; & \text{otherrwise} \end{cases}$$

In fuzzy logic, the concept of absolute truth is discarded, as it operates based on "partial truth" or degrees of membership. Unlike classical sets, membership in a fuzzy set is defined as follows:

$$\mu_A : S \to [0,1]$$

The closer a membership value is to 1, the stronger the degree of association with a particular set. This flexibility makes fuzzy logic especially well-suited for scenarios that require human judgment or involve ambiguity and "gray areas".

Fuzzy logic systems typically have four main components: fuzzification, fuzzy rules, inference, and defuzzification (refer to Figure 1). In the fuzzification step, a crisp (exact) input is converted into a fuzzy value. Then, fuzzy rules are applied to these fuzzy values, and the

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inference process mimics human decision-making. Finally, the defuzzification step converts the fuzzy result back into a crisp output. Sari et al. (2021) further explain that fuzzy logic involves three basic elements: basic commands, a database, and reasoning mechanisms. In fuzzy rules, the basic structure follows the pattern: if A (antecedent) happens, then B (consequent) will follow.

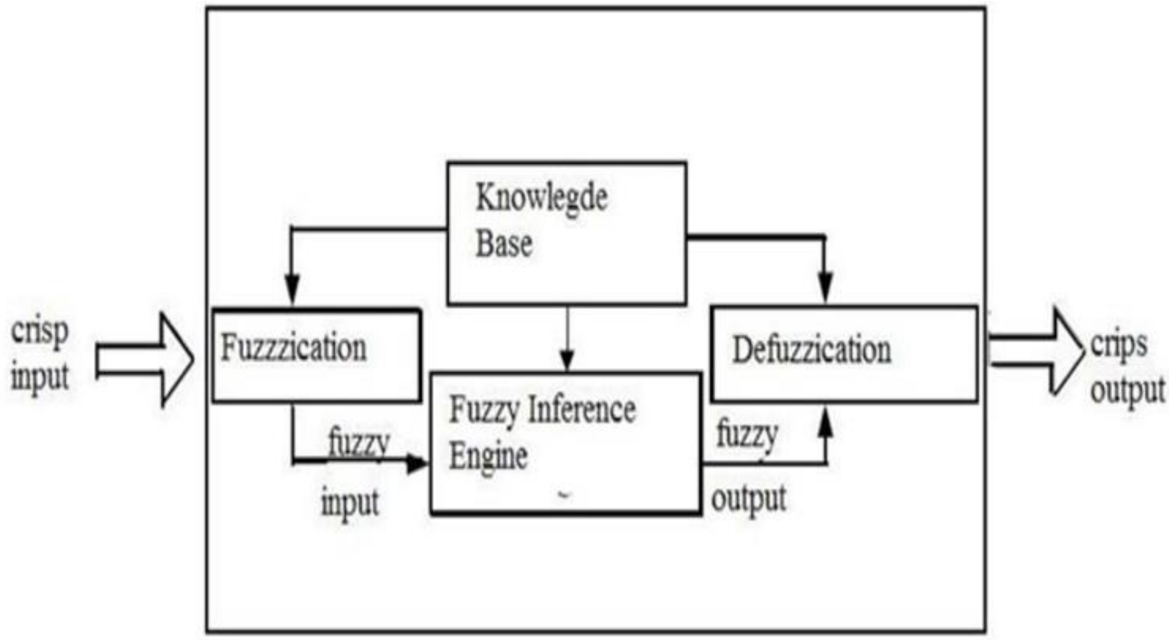

Figure 1: Fuzzy Logic Model

Fuzzy logic has proven to be an effective technique for addressing imprecision, ambiguity, partial truths, and situations without clear boundaries (Singh et al., 2013; Sabri et al., 2013). Since human capabilities are naturally limited in handling uncertainty, fuzzy logic offers a powerful tool to solve problems that involve vague or unclear conditions. This approach has been successfully applied in a wide range of research and development fields, including engineering (Skrzek et al., 2024; Belu et al., 2013), computer science (Almseidin et al., 2021; Buriboev et al., 2019; Chopra & Bedi, 2017), healthcare management (Suzuki & Negishi, 2024; Jahantigh, 2019), aerospace (Ooi et al., 2015), and many other areas.

Methodology

In this study, primary data on BMI, exercise habits, fast-food consumption, fibre intake, and parental history of obesity were collected from 30 students aged 18 to 25 years at UiTM Arau Branch during the October 2024 semester to evaluate their obesity risk levels. The data were analysed using a fuzzy logic approach to classify the level of obesity risk. Variables such as low fibre intake or high exercise habits inherently involve ambiguity and vagueness in determining their exact degree. Therefore, the fuzzy logic model is considered an ideal method for producing accurate obesity risk assessments, utilizing five input variables across various fuzzy sets.

The following are four main steps of fuzzy logic implementations:

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Step 1: Fuzzification

In this study, the crisp values of the five input variables are transformed into fuzzy values using predefined fuzzy membership functions, either triangular or trapezoidal in shape. The fuzzy numbers and linguistic variables adopted are summarized in Table 1 and are consistent with those used in the study by Nurohmat and Nugraha (2024).

Table 1: Fuzzy Number for Input and Output Variables and Linguistic values

Linguistic Variables		Fuzzy Number	Linguistic Value	Range
Inputs	Body Mass Index (BMI)	(0, 0,12,15)	Low	[0,30]
		(12,15,22,26)	Medium	
		(22,26,30,30)	High	
	Fibre Consumption	(0,0,10,40)	Low	[0,110]
		(10,40,70,100)	Medium	
		(70,100,110,110)	High	
	Fast-Food Consumption	(0,0,10,40)	Low	[0,110]
		(10,40,70,70)	Medium	
		(70,100,110,110)	High	
	Exercise Habit	(0,0,10,40)	Low	[0,110]
		(10,40,70,70)	Medium	
		(70,100,110,110)	High	
	Parents History	(0,0,50,100)	Yes	[0,110]
		(50,100,110,110)	No	
Output	Risk Level	(0,0,10,40)	Low	[0,110]
		(10,40,70,700	Medium	
		(70,100,110,110)	High	

BMI, exercise habits, fibre intake, and fast-food consumption were categorized into three linguistic levels or fuzzy sets: Low, Medium, and High. Parental history of obesity was classified into two categories: either present or not present. The membership values for each fuzzy set in this study were adopted from Nurohmat and Nugraha (2024) and are defined as follows:

Membership Functions for BMI Index

$$\mu_{Low}(x) = \begin{cases} 1; & x < 12 \\ \dfrac{15-x}{3}; & 12 \le x \le 15 \\ 0; & x > 15 \end{cases}$$

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$$\mu_{Medium}(x)=\begin{cases} 0; & x<12 \ , \ x>26 \\ \dfrac{x-12}{3}; & 12\le x\le 15 \\ 1; & 15<x<22 \\ \dfrac{26-x}{4}; & 22\le x\le 26 \end{cases}$$

$$\mu_{High}(x)=\begin{cases} 0; & x<22 \\ \dfrac{x-22}{4}; & 22\le x\le 26 \\ 1; & x>26 \end{cases}$$

Membership Functions for Parental History of Obesity

$$\mu_{yes}(x)=\begin{cases} 1; & x<50 \\ \dfrac{x-50}{50}; & 50\le x\le 100 \\ 0; & x>100 \end{cases}$$

$$\mu_{No}(x)=\begin{cases} 1; & x<50 \\ \dfrac{100-x}{50}; & 50\le x\le 100 \\ 0; & x>100 \end{cases}$$

Membership Functions for Fibre, Fast Food Consumptions, Exercise Habits and Output Obesity Risk

$$\mu_{Low}(x)=\begin{cases} 1; & x<10 \\ \dfrac{40-x}{30}; & 10\le x\le 40 \\ 0; & x>40 \end{cases}$$

$$\mu_{Medium}(x)=\begin{cases} 0; & x<10 \ , \ x>100 \\ \dfrac{x-10}{30}; & 10\le x\le 40 \\ 1 & 40<x<70 \\ \dfrac{100-x}{30}; & 70\le x\le 100 \end{cases}$$

$$\mu_{High}(x)=\begin{cases} 0; & x<70 \\ \dfrac{x-70}{30}; & 70\le x\le 100 \\ 1; & x>100 \end{cases}$$

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Step 2: Inference

In fuzzy logic systems, a fuzzy controller known as a fuzzy rule-base relies on a collection of fuzzy IF-THEN rules to perform decision-making and infer conclusions. Each rule connects input conditions (premises) to corresponding outputs (consequences) based on degrees of truth rather than absolute values. In this study, the truth values of the premises for several rules, along with their resulting implications, are shown in Table 2. By evaluating these fuzzy rules, the system can manage imprecision and uncertainty, enabling it to mimic human-like reasoning and make more flexible, adaptive decisions. The use of a comprehensive set of IF-THEN rules ensures that a wide range of input conditions can be appropriately mapped to meaningful outcomes, thereby enhancing the accuracy and reliability of the obesity risk assessment model.

Table 2: Some of IF-THEN-Rules

	IF-THEN Rules and Implications
1	If BMI is high, and parental history is yes, and exercise habit is high, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high.
2	If BMI is high, and parental history is no, and exercise habit is high, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high
3	If BMI is high, and parental history is yes, and exercise habit is medium, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high.
4	If BMI is high, and parental history is no, and exercise habit is medium, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high.
5	If BMI is high, and parental history is yes, and exercise habit is low, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high.
6	If BMI is high, and parental history is no, and exercise habit is low, and fibre consumption is high, and fast-food consumption is high, then obesity risk level is high.
7	If BMI is high, and parental history is yes, and exercise habit is low, and fibre consumption is high, and fast-food consumption is medium, then obesity risk level is high.
8	If BMI is high, and parental history is no, and exercise habit is low, and fibre consumption is high, and fast-food consumption is medium, then obesity risk level is medium.
9	If BMI is high, and parental history is yes, and exercise habit is medium, and fibre consumption is high, and fast-food consumption is medium, then obesity risk level is medium.
10	If BMI is high, and parental history is no, and exercise habit is medium, and fibre consumption is high, and fast-food consumption is medium, then obesity risk level is medium.

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Step 3: Composition

The fuzzy inference engine is responsible for processing all the fuzzy rules and generating the corresponding fuzzy output, often referred to as the fuzzy region. During this stage, the engine evaluates each rule based on the input data to produce an overall fuzzy output for each output variable. This process involves the aggregation of all fuzzy subsets associated with the output variables.

Aggregation is performed by combining the fuzzy outputs of individual rules using logical operators such as **"AND"** and **"OR."** When rules are connected by the **"AND"** operator, the fuzzy inference engine applies the *intersection* method, typically using the **minimum** operator, following the Mamdani implication approach. This determines the degree of fulfillment for each rule. The membership value of the resulting fuzzy output is calculated using the following expression:

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

Conversely, when rules are connected using the **"OR"** operator, the *union* of the fuzzy sets is taken, commonly using the **maximum** operator:

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

Step 4: Defuzzification

Defuzzification is the final step in the fuzzy inference process, where the aggregated fuzzy output is converted into a single crisp value that can be interpreted for decision-making. In this study, the **centroid method**, also known as the **centre of gravity (COG)** technique, was employed for defuzzification. This method calculates the centre of the area under the curve of the aggregated fuzzy set, providing a balanced and representative output value.

The centroid defuzzification formula is given by:

$$x^* = \frac{\int \mu_A(x).x\,dx}{\int \mu_A(x)dx}$$

The MATLAB Fuzzy Logic Toolbox is a valuable tool for implementing fuzzy inference systems, particularly due to its intuitive interface and robust functionality. Figure 2 demonstrates a Mamdani-type fuzzy inference system that incorporates five key input parameters: Body Mass Index (BMI), parental history of obesity, exercise habits, fibre intake, and fast-food consumption. These inputs are processed through a set of predefined rules and membership functions within the system. By entering relevant values for each input, the system can effectively evaluate and predict an individual's risk of obesity as shown in Figure 3. This approach facilitates a more nuanced, human-like reasoning process, making it especially useful in health risk assessment and decision-support applications.

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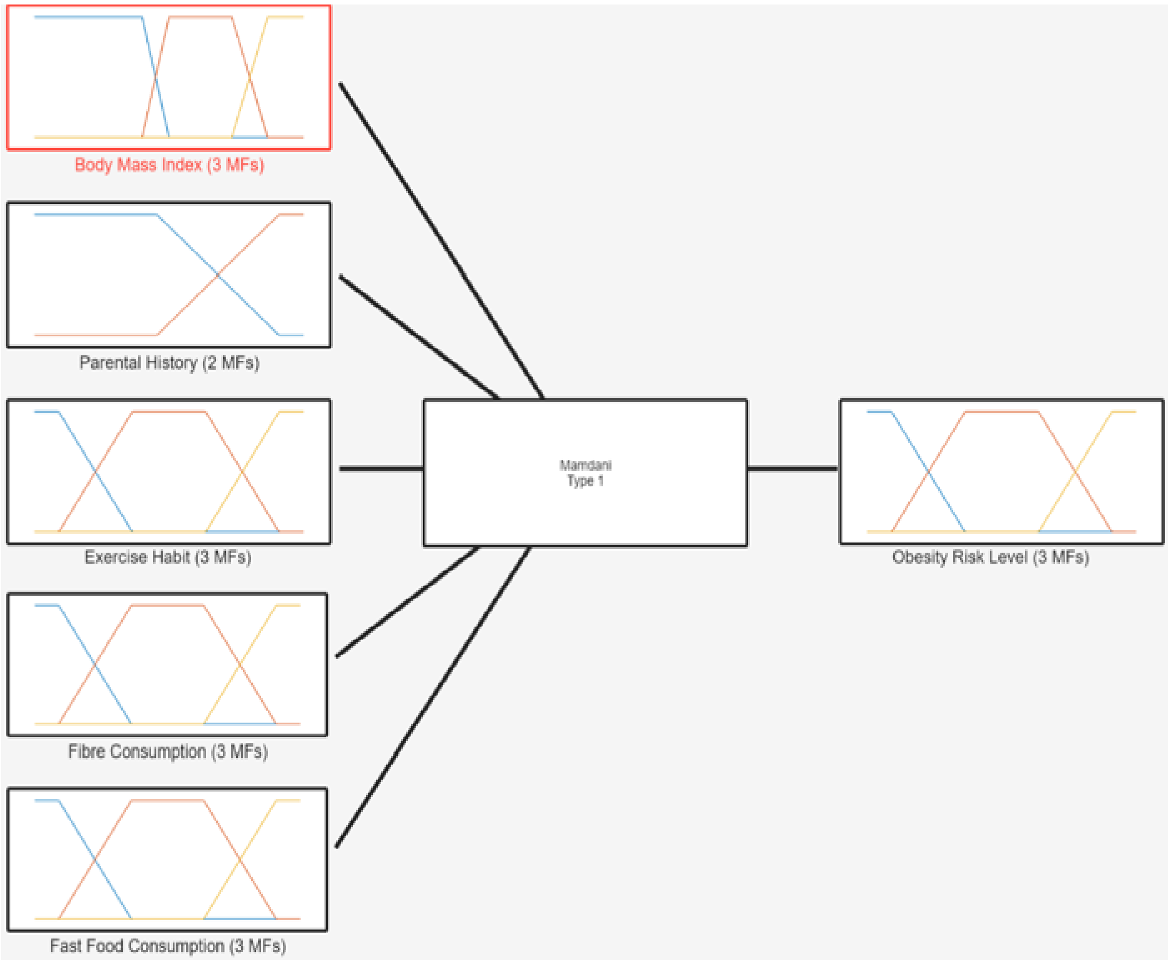

Figure 2: Mamdani Fuzzy Inference System

Figure 3 illustrates the Fuzzy Inference System (FIS) developed using the MATLAB Fuzzy Logic Toolbox. The input values provided to the system are [18.3,100,100,29,29, corresponding to the following factors: Body Mass Index (BMI) = 18.3, Parental History of Obesity = 100 (indicating "Yes"), Exercise Habit = 100, Fibre Consumption = 29, and Fast-Food Consumption = 29. Based on these inputs, the system computes an Obesity Risk Level of **60**, which places the individual in the **medium risk** category, with a **membership value of 1**, indicating full membership in that risk level.

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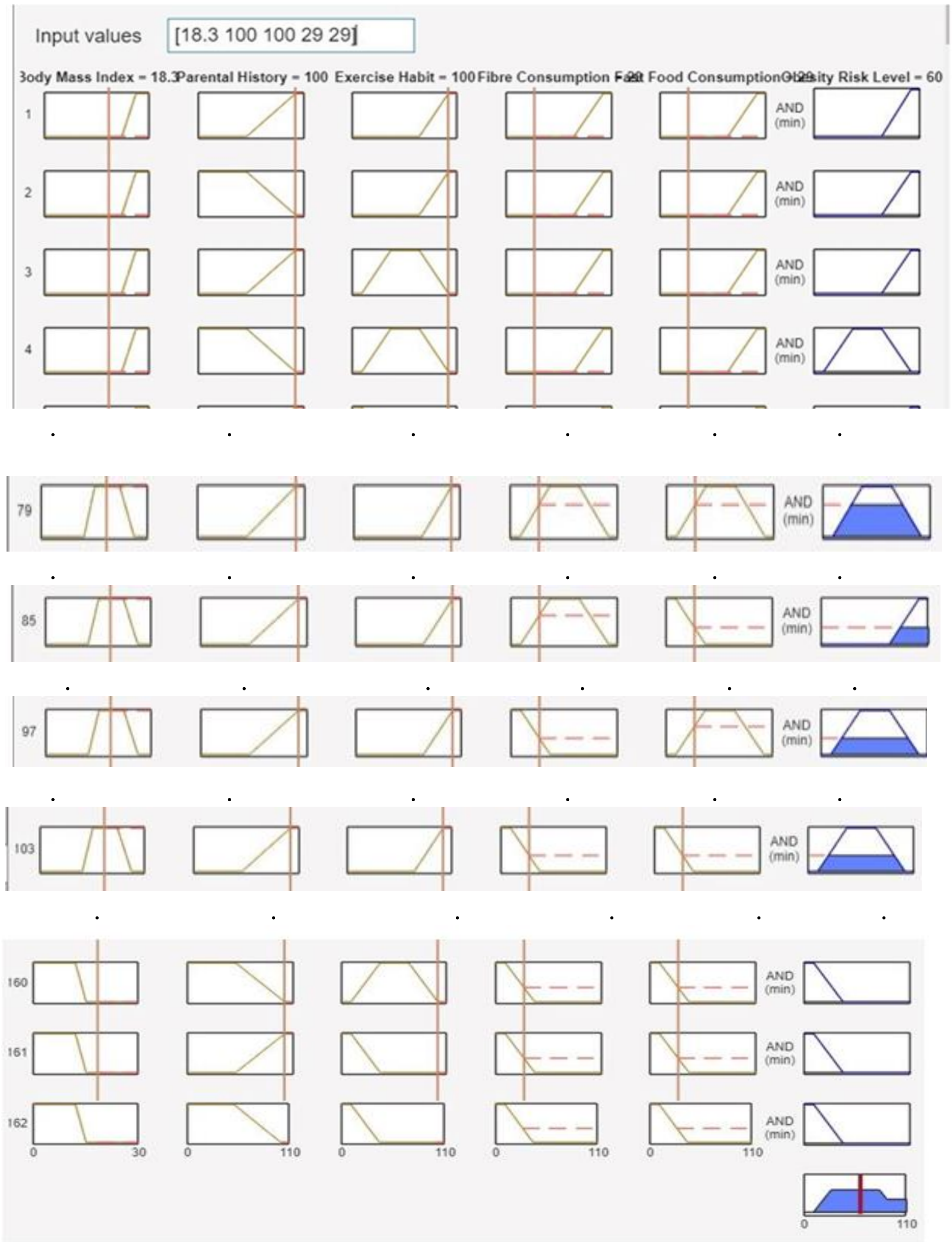

Figure 3: Sample Output From MATLAB Fuzzy LogicToolbox

Numerical Example

The sample data chosen is a-22 year old male student with the weight 56 kg and the height 175 cm. He has a family member with obese problem. He exercises edequately everyday but consume a little amount of fibre in a week; only 2 days in a week. He takes a little amount of fast food in a week; only 2 days in a week. All the collected crisp data will be assingned the membership value where there are beloging as shown in Table 3.

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Table 3: The Fuzzy Membership Values

Input	**Membeship values**		
BMI	μ_{BMI}Low [18.3] = 0	μ_{BMI}Medium [18.3] = 1	μ_{BMI}High [18.3] = 0
Exercise Habit	μ_{EH} Low[100] = 0	μ_{EH} Medium[100] = 0	μ_{EH} High[100] = 1
Parental Obesity	μ_{PH} Yes[100] = 1	μ_{PH} No[60] = 0	
Fast Food Consumption	μ_{FFC} Low[29] = 0.3667	μ_{FFC} Medium[29] = 0.6333	μ_{FFC} High[29] = 0
Fibre Intake	μ_{FI} Low[29] = 0.3667	μ_{FI} Medium[29] = 0.6333	μ_{FC} High [29] = 0

In performing the Mamdani Max-Min implication, only four rules resulted in non-zero fuzzy output regions, specifically rules 79, 97, 85, and 103. These rules were activated based on the given input values, contributing to the final inference result. The active rules are as follows:

Rule 79: If BMI is Medium (μ = 1) and Fibre Consumption is Medium (μ =0.633) and Fast-Food Consumption is Medium (μ =0.633) and Exercise Habit is high (μ =1) and Parental History exist(μ =1) then the obesity risk is Medium (μ = 0.633).

Rule 85: BMI is Medium (Medium=1) and Fibre Consumption is Low(Low=0.3667) and Fast Food Consumption is Medium (μ =0.633) and Exercise Habit is High(μ =1) and Parental History is High (μ =1) then the obesity risk is Medium (μ =0.3667).

Rule 97: BMI is Medium (μ =1) and Fibre Consumption is Medium (μ =0.633) and Fast Food Consumption is Low (μ =0.3667) and Exercise Habit is high (μ =1) and Parental History exists (μ =1) then the obesity risk is High (μ =0.3667).

Rule 103: BMI is Medium(μ =1) and Fibre Consumption is Low (L=0.3667) and Fast Food Consumption is Low (μ =0.3667) ∩ Exercise Habit is high (μ =1) and Parental History exists (μ =1) then the obesity risk is Medium (μ =0.3667).

The outputs from the four activated rules are aggregated using the Mamdani OR operator (maximum function), based on the defined membership functions of the output variable. This aggregation results in a single fuzzy output region representing the overall obesity risk. The combined fuzzy set, illustrating this aggregated output, is depicted in Figure 5.

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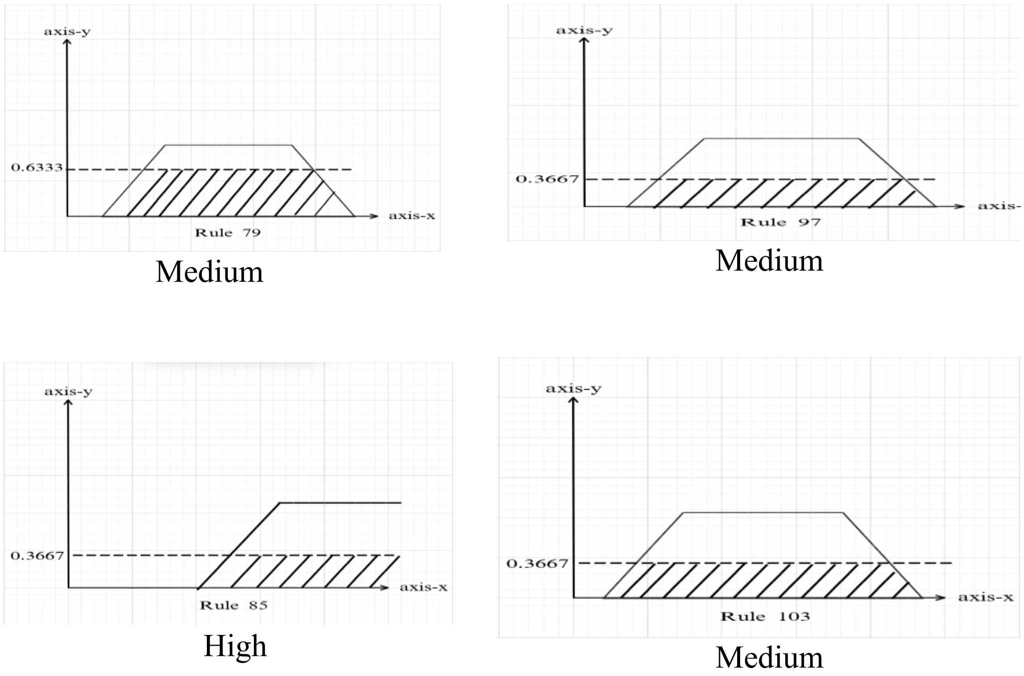

Figure 4: Output for IF-THEN Rules

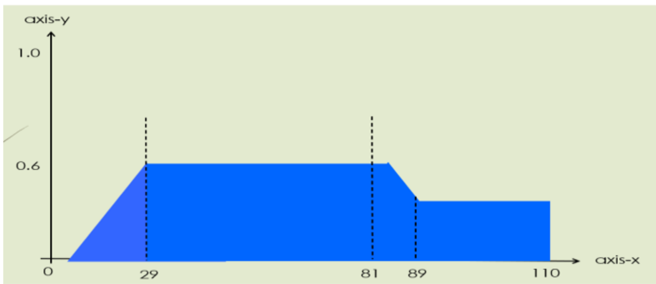

Figure 5: Fuzzy Obesity Risk Output

The final stage is to find the centre of gravity of the region or in other word to covert fuzzy output into crisp result.

$$x^{*}=\frac{\int \mu_A(x).x\,dx}{\int \mu_A(x)dx}$$

$$=\frac{\int_{10}^{29}\left(\frac{x}{30}-\frac{1}{3}\right)x\,dx+\int_{29}^{81}\frac{19}{30}x\,dx+\int_{81}^{89}\left(\frac{10}{3}-\frac{x}{30}\right)x\,dx+\int_{89}^{110}\frac{11}{30}x\,dx}{\int_{10}^{29}\left(\frac{x}{30}-\frac{1}{3}\right)dx+\int_{29}^{81}\frac{19}{30}dx+\int_{81}^{89}\left(\frac{10}{3}-\frac{x}{30}\right)dx+\int_{89}^{110}\frac{11}{30}dx}$$

$$\approx 60$$

With the respondent's inputs BMI, physical exercise, fibre and fast food consumption and parential history of obesity, the sample falls in category obesity of degree 60 and fall in medium risk with the membership 1.

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Conslusion and Discussion

In this study, a Fuzzy Logic Model was successfully implemented to evaluate the risk of obesity among UiTM students, based on five key input variables: Body Mass Index (BMI), physical activity level, fibre intake, fast-food consumption, and parental history of obesity. Table 4 displays the categorized obesity risk levels along with their respective membership values for each student.

Table 4: Summary of Obesity Risk Level and Membership Value

No	Input					Output	
	BMI	Parental History	Exercise Habit	Fibre Consumption	Fast-Food Consumption	Obesity Risk Level	Membership (Category)
1	18.3	100	100	29	29	60	1 (M)
2	23.8	60	14	29	29	35	0.8333(M)
3	19.8	60	14	43	14	32	0.7333(M)
4	24.8	60	29	43	57	50	1 (M)
5	29.9	60	14	14	43	36	0.8667(M)
6	26	100	14	7	14	56	1 (M)
7	26.3	60	29	43	14	55	1 (M)
8	18.3	60	57	57	43	55	1 (M)
9	15.9	100	0	57	43	13	0.90 (L)
10	20.3	60	29	43	29	49	0.7333(M)
11	27.4	60	57	57	43	55	1 (M)
12	17.4	60	43	100	57	55	1 (M)
13	19.9	100	14	14	43	53	1 (M)
14	24.4	60	29	43	43	49	1 (M)
15	27.8	100	71	29	57	55	1 (M))
16	19	60	100	14	14	53	1 (M)
17	19.6	60	29	29	14	41	1 (M)
18	19	60	14	71	43	28	0.6(M)
19	24.1	60	29	57	14	46	1 (M)
20	20.5	60	14	57	43	28	0.6(M)
21	20	60	100	100	14	55	1 (M)
22	23.7	60	100	100	71	51	1 (M)
23	17.4	60	29	71	29	49	1 (M)
24	17	60	14	14	43	32	0.7333(M)
25	17.7	60	71	100	29	55	1 (M)
26	17.7	60	43	86	43	55	1 (M)
27	19.7	60	29	14	29	49	1 (M)
28	20	60	43	43	43	55	1 (M)
29	21	60	71	14	29	53	1 (M)
30	20.9	100	29	57	43	49	1 (M)

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The overall findings, indicating that 29 out of 30 respondents were categorized as having a “Medium” risk of obesity, while only one respondent was classified under the “Low” risk category. The membership value represents the extent to which individuals belong to a specific risk group. In medium risk category, 76% of respondents demonstrated full membership (value of 1) in the medium-risk category, while the remaining participants, though only partial members, still showed a strong association with the medium-risk group (refer to Figure 6).

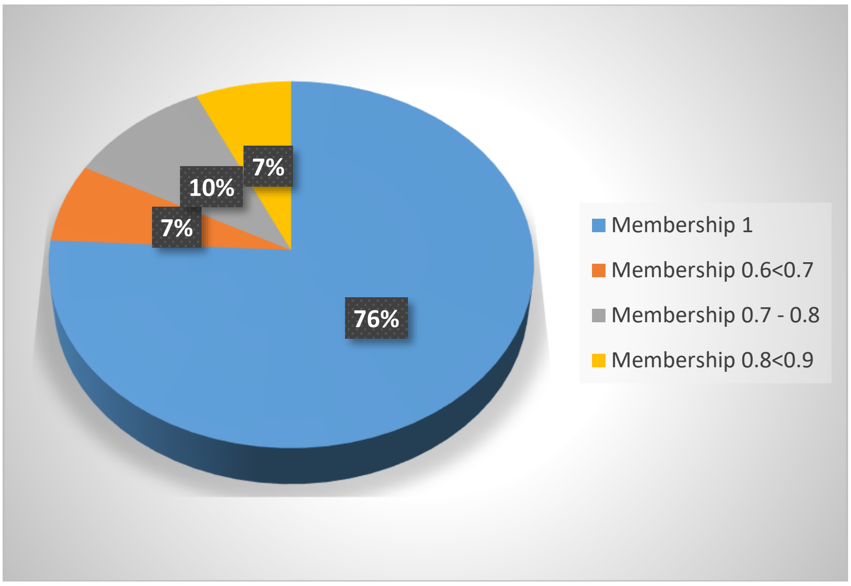

Figure 6: Percentage Respondents With Different Degrees in Medium Obesity Risk

Although many participants had a normal BMI ranging from 18.5 to 24.9 kg/m², as defined by the WHO, their risk of obesity remained at a medium level due to significant contributing factors, including limited physical activity, frequent consumption of fast-food, and insufficient fibre intake. These findings underscore the need for healthier lifestyle choices. Students are encouraged to focus on their well-being by consuming balanced, nutritious meals and maintaining regular physical activity to reduce the risk of obesity. The analysis effectively employed the Fuzzy Logic Technique using five input variables: Body Mass Index (BMI), parental history of obesity, exercise habits, fast food consumption, and fibre intake to assess obesity risk levels. Early identification and management of obesity risks are crucial to preventing related health problems later in life.

Several previous studies have been conducted on obesity among college students, though the number remains limited. One notable study by Umoh and Isong (2015) successfully developed a Fuzzy Expert System for diagnosing and managing obesity using only three input variables: Body Mass Index (BMI), Body Fat, and Waist Circumference. In contrast, Nurohmat and Nugraha (2024) utilized six input variables: BMI, exercise habits, fiber intake, fast food consumption, gender, and parental history of obesity to assess obesity risk among Polindra students in Indonesia. Their results showed that 66% of students were categorized as "Low" risk and 34% as "Medium" risk. These findings are comparable to those in the present study, despite this study using only five input variables, excluding gender. Another relevant study by Patil and Ghazali (2022), conducted among university students in Sarawak, reported a high prevalence of overweight and obesity. The surge in weight gain was attributed to the movement control restrictions during the COVID-19 pandemic in 2020, which led to reduced physical activity and increased caloric intake as students were confined to their homes. This highlights how external factors, such as public health emergencies, can significantly impact students' health behaviors and contribute to obesity risks. Overall, these comparative studies reinforce the effectiveness of Fuzzy Logic-based models in assessing obesity risk and emphasize the importance of lifestyle factors in shaping health outcomes among university students.

Although this study has successfully applied a fuzzy logic model to categorize students by their risk of obesity, the model still has room for improvement to enhance its predictive accuracy. For future research on obesity, it is recommended to incorporate additional input variables that significantly influence obesity risk, such as emotional well-being, sleep patterns, age, and gender. For instance, emotional stress can lead to unhealthy eating habits and disrupted sleep, both of which are associated with increased appetite and excessive food consumption. These behaviors can negatively affect adherence to healthy dietary guidelines, such as the food pyramid, and reduce motivation for maintaining a balanced lifestyle. By including such factors, future studies can achieve a more comprehensive understanding of obesity and generate more accurate risk assessments. Additionally, expanding the sample size to include a more diverse and representative population would enhance the generalizability of the findings. To further improve the accuracy and effectiveness of a fuzzy inference system, collaboration with healthcare professionals such as doctors, nutritionists, and hospital staff is crucial. These experts bring valuable insights into the complex relationship between obesity and various health conditions, as well as practical knowledge of effective prevention and treatment strategies. Their contributions can also help refine data collection tools, such as questionnaires, ensuring they reflect real-world conditions and clinical observations. Ultimately, expert involvement will enhance the system's reliability, accuracy, and practical applicability.

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