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Diagnosing Stunting Risk in Toddlers Using Mamdani Method

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Abstract
Stunting remains a major public health problem that requires early and accurate risk assessment to support effective prevention strategies. This study proposed and evaluated a Mamdani-based fuzzy expert system to assess stunting risk in toddlers by integrating six key determinants: birth length, dietary diversity, protein intake, immunization status, infectious disease history, and breastfeeding practice. The system modeled uncertainty and partial membership through fuzzification, rule-based inference using the minimum operator, and centroid-based defuzzification to generate a quantitative stunting risk score and categorical risk level. We implemented a prototype of the fuzzy expert system and validated its behavior using representative hypothetical cases and a small set of anonymized real data provided by a local health center nutritionist. The fuzzy rule base was first verified to ensure logical consistency and intuitive outputs under extreme input conditions. Experimental results showed that the system correctly classified all evaluated cases in accordance with expert assessments, achieving 100% agreement in risk category assignment. For illustrative cases, the system produced a risk score of 80 (High Risk) for a child with multiple adverse factors and 17.62 (Low Risk) for a child with favorable nutritional and health conditions. These findings demonstrate that the proposed Mamdani fuzzy expert system can effectively handle uncertainty in stunting risk assessment and provide interpretable, nuanced outputs suitable for decision support. The approach shows strong potential for assisting healthcare workers in early screening and prioritization of interventions. Future work will focus on large-scale clinical validation, optimization of membership functions using empirical data, and deployment of the system in web-based or mobile platforms to support practical stunting prevention programs.

Keywords:
Expert System, Fuzzy Mamdani; Stunting, Anthropometry, Nutrition

1. Introduction

Stunting is a condition of chronic malnutrition in children under five, characterized by a height that is significantly below the age-appropriate standard. It remains a critical global health issue, with about 22% of under-five children worldwide classified as stunted in 2020 (approximately 150 million children) [1][2]. In Indonesia, the prevalence of stunting has been notably high. Around 30.8% of Indonesian toddlers were stunted in 2018 [3][4], prompting national strategic initiatives to reduce stunting as a top priority [4]. These efforts have yielded improvements; the stunting rate dropped to 21.6% by 2022 [5], yet this level is still above the World Health Organization (WHO) threshold for public health concern. Stunting is not only a growth issue but also has serious long-term consequences; it is associated with impaired cognitive development and reduced productivity in adulthood [6][7][8]. Therefore, early identification and intervention for children at risk of stunting are of paramount importance to mitigate irreversible damage.

The causes of stunting are multifactorial, arising from a combination of nutritional,

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health, and environmental factors [7]. Studies show that children born with shorter body length have a significantly higher likelihood of becoming stunted [9]. Inadequate dietary diversity is strongly associated with stunting; toddlers who do not receive a minimally diverse diet are more prone to growth faltering [10]. Insufficient protein intake is another critical factor; one study found that children consuming less protein than recommended had about four times greater risk of stunting compared to those with adequate protein intake [11][12][13]. Health-related factors also contribute, incomplete immunization has been linked to higher stunting rates, as children without full vaccines were observed to be more than twice as likely to be stunted [14]. This is partly because each episode of infectious disease (such as diarrhea or pneumonia) diverts energy away from growth and can exacerbate undernutrition [15]. Conversely, proper infant feeding practices improve growth outcomes, ensuring exclusive breastfeeding in the first six months and appropriate complementary feeding are protective against stunting [16] [9]. Given this range of risk factors, an effective stunting risk assessment must incorporate both anthropometric indicators and variables related to nutrition and health status.

Traditionally, monitoring of child growth in Indonesia has relied on tools like the Kartu Menuju Sehat (KMS) handbook. However, manual methods are prone to inconsistencies, for example, lost or improperly recorded KMS cards can impede accurate tracking of a child’s nutritional status [17]. Many parents and caregivers also seek a better understanding of whether their child’s feeding pattern is sufficient [17]. In this context, a computerized expert system can assist in early diagnosis of stunting risk by emulating the decision-making process of nutrition experts. Expert systems have been applied in healthcare to consistently analyze multiple criteria and offer recommendations. In particular, fuzzy logic is well-suited for this problem domain due to the inherent uncertainty and imprecision in nutritional assessments. Rather than using strict binary thresholds, fuzzy logic allows reasoning with linguistic terms (such as "a little," "enough," or "a lot) which better capture gradations in dietary intake and growth measurements [17]. The Mamdani fuzzy inference method provides an intuitive rule-based framework where expert knowledge can be encoded in if-then rules, and it handles vague inputs effectively by producing a graded risk score instead of a hard classification [14].

Motivated by these considerations, this paper proposes a Mamdani fuzzy expert system to diagnose the risk of stunting in toddlers based on key anthropometric and nutritional variables. The goal is to facilitate early detection by combining multiple risk factors into a single actionable risk level.

2. Related Works

Previous studies have examined the application of expert systems for nutritional status assessment and stunting detection using various methods. Several approaches have been used, namely those focused on the use of logical rules or classification algorithms. For example, a Rule-Based Reasoning-based application was developed to categorize nutritional status, including stunting, wasting, low body weight, and obesity [18]. In addition, the Random Forest Method has also been applied, utilizing eight attributes to detect stunting in both individuals and groups [19], as well as the C4.5 Algorithm to classify stunting and normalcy based on secondary data obtained from maternal cohort books and Excel-based nutritional data from the Sumberjambe Community Health Center [20].

Fuzzy logic systems are considered effective in dealing with data uncertainty, making them an ideal choice for diagnosing conditions where the category boundaries are not clear (gray cases). This approach integrates forward-chaining inference with Sugeno-type Fuzzy Logic to diagnose stunting [20]. In addition to Sugeno, the Mamdani Fuzzy Method has been widely applied to evaluate the nutritional status of toddlers based on the web [19].

Fuzzy logic systems are considered effective in handling data uncertainty, making them an ideal choice for diagnosing conditions where category boundaries are not clear-cut (“gray” cases). This approach integrates forward-chaining inference with Sugeno-type Fuzzy Logic to diagnose stunting [21]. In addition to Sugeno, the Mamdani Fuzzy Method has been widely applied to evaluate the web-based nutritional status of toddlers [22].

Other studies related to the application of the Mamdani Fuzzy Method have been conducted in several studies. One study shows that this method is capable of assessing stunting status with an accuracy of 80.87% compared to expert diagnosis, especially effective in cases where toddler health criteria are in the borderline area [23]. This approach is also used to determine the nutritional status of toddlers, including malnutrition, based on parameters such as weight, age, height, and upper arm circumference, with an accuracy of 90.2% [17]. Furthermore, the flexibility of the fuzzy system allows its application in public health data analysis, such as mapping the distribution of stunting prevalence in a region, which helps identify priority areas for intervention [24]. This demonstrates the flexibility of the fuzzy system, not only for individual diagnosis but also for public health data analysis.

Overall, previous studies have shown that the Mamdani Fuzzy-based expert system is highly effective in classifying nutritional status and detecting stunting, generally achieving an accuracy rate of between 80 and 90% [17][23]. This effectiveness stems from its ability to incorporate expert knowledge into a rule base and overcome uncertainty in input data. Considering these advantages, this approach motivated the development of this study, which focuses on the use of a similar fuzzy inference framework, specifically designed to diagnose the risk of stunting based on various risk factors.

3. Proposed Method

The proposed system is a rule-based expert system that utilizes the Mamdani fuzzy inference method to diagnose the risk level of stunting in toddlers. The overall system flow consists of several stages: (1) input acquisition, (2) fuzzification, (3) fuzzy inference using the rule base, (4) defuzzification, and (5) output of the stunting risk diagnosis. Fig. 1 (conceptual) illustrates this pipeline, starting from raw input data and ending with a crisp risk assessment.

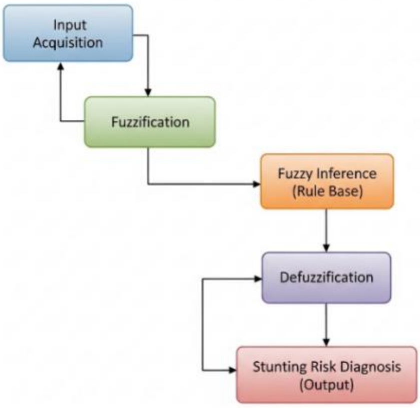

Fig. 1 System Flow of Fuzzy Logic

This study identifies six key input variables that represent major risk factors for stunting, based on established pediatric nutrition knowledge and prior research on stunting determinants. We treat all variables as inputs to the fuzzy inference system to capture their combined influence on stunting risk. These variables reflect both biological conditions at birth and postnatal environmental and nutritional factors that directly affect child growth and development.

The selected inputs include birth length, dietary diversity, protein intake, immunization status, infectious disease history, and breastfeeding practice. Birth length serves as an early biological indicator, as shorter length at birth is strongly associated with higher stunting risk. Dietary diversity and protein intake represent nutritional adequacy, where low diversity and insufficient protein contribute to micronutrient deficiencies and impaired linear growth. Immunization status and infectious disease history capture the child's exposure to illness, which can disrupt nutrient absorption and increase metabolic stress. Breastfeeding practice reflects early-life nutritional and immunological support, as exclusive and continued breastfeeding is widely recognized for its protective role against stunting. Together, these six variables provide a comprehensive and clinically relevant foundation for modeling stunting risk.

3.1 Fuzzification

Each input is represented by a fuzzy set with an appropriate membership function (generally trapezoidal or triangular). The membership functions are designed in consultation with pediatric nutrition experts so that they align with clinical judgment. Fig. 2-7 shows the membership function for each variable independent (input), and Fig. 8 show variable dependent (output). Table 1 shows the fuzzy set and range for each input and output.

Table 1. Membership Function of Variable Input and Output

Variables Input	Fuzzy Set	Range	Membership Function
Birth Length	Short	<48 cm	$\mu_{\text{Short}}(x) = \begin{cases} 1, & x \le 48 \\ \dfrac{50-x}{50-48}, & 48 \le x \le 50 \\ 0, & x \ge 50 \end{cases}$
	Normal	48 – 52 cm	$\mu_{\text{Normal}}(x) = \begin{cases} 0, & x \le 46, x \ge 60 \\ \dfrac{x-46}{50-46}, & 46 \le x \le 50 \\ 1, & 50 \le x \le 52 \\ \dfrac{60-x}{60-52}, & 52 \le x \le 60 \end{cases}$
	Long	≥ 52 cm	$\mu_{\text{Long}}(x) = \begin{cases} 0, & x \le 50, \\ \dfrac{x-50}{54-52}, & 50 \le x \le 54 \\ 1, & x \ge 54 \end{cases}$
Dietary Diversity	Very Low	≤1	$\mu_{\text{Very Low}}(x) = \begin{cases} 1, & x \le 1 \\ \dfrac{3-x}{3-1}, & 1 \le x \le 3 \\ 0, & x \ge 3 \end{cases}$
	Low	1-3	$\mu_{\text{Low}}(x) = \begin{cases} \dfrac{x-0}{2-0}, & 0 \le x \le 2 \\ 1, & 2 \le x \le 3 \\ \dfrac{5-x}{5-3}, & 3 \le x \le 5 \\ 0, & x \ge 5 \end{cases}$

	Median	3–4	$\mu_{\text{Median}}(x) = \begin{cases} 0, & x \leq 2 \\ \frac{x-2}{4-2}, & 2 \leq x \leq 4 \\ 1, & 4 \leq x \leq 5 \\ \frac{7-x}{7-5}, & 5 \leq x \leq 7 \end{cases}$
	High	≥4	$\mu_{\text{High}}(x) = \begin{cases} 0, & x \leq 4 \\ \frac{x-4}{6-4}, & 4 \leq x \leq 6 \\ 1, & x \geq 6 \end{cases}$
Protein Intake	Very Low	≤10 g/day	$\mu_{\text{Very Low}}(x) = \begin{cases} 1, & x \leq 8 \\ \frac{10-x}{10-8}, & 8 \leq x \leq 10 \\ 0, & x \geq 10 \end{cases}$
	Low	10-15 g/day	$\mu_{\text{Low}}(x) = \begin{cases} 0, & x \leq 8, x \geq 20 \\ \frac{x-8}{10-8}, & 8 \leq x \leq 10 \\ 1, & 10 \leq x \leq 15 \\ \frac{20-x}{20-15}, & 15 \leq x \leq 20 \end{cases}$
	Adequate	15-20 g/day	$\mu_{\text{Adequate}}(x) = \begin{cases} 0, & x \leq 15, x \geq 25 \\ \frac{x-15}{20-15}, & 15 < x \leq 20 \\ \frac{25-x}{25-20}, & 20 < x \leq 25 \\ 0, & x \geq 25 \end{cases}$
	High	≥20 g/day	$\mu_{\text{High}}(x) = \begin{cases} 0, & x \leq 20 \\ \frac{x-20}{25-20}, & 20 \leq x \leq 25 \\ 1, & x \geq 25 \end{cases}$
Immunization Status	Not Complete	<40%	$\mu_{\text{Not Complete}}(x) = \begin{cases} 1, & x \leq 40 \\ \frac{50-x}{50-40}, & 40 \leq x \leq 50 \\ 0, & x \geq 50 \end{cases}$
	Partial	40-80%	$\mu_{\text{Partial}}(x) = \begin{cases} 0, & x \leq 40, x \geq 80 \\ \frac{x-40}{50-40}, & 40 \leq x \leq 50 \\ 1, & 50 \leq x \leq 70 \\ \frac{80-x}{80-70}, & 70 \leq x \leq 80 \end{cases}$
	Complete	≥80%	$\mu_{\text{Complete}}(x) = \begin{cases} 0, & x \leq 70 \\ \frac{x-70}{80-70}, & 70 \leq x \leq 80 \\ 1, & x \geq 80 \end{cases}$
Infectious Disease History	Rarely	0 – 2	$\mu_{\text{Rarely}}(x) = \begin{cases} 1, & x \leq 2 \\ \frac{3-x}{3-2}, & 2 \leq x \leq 3 \\ 0, & x \geq 3 \end{cases}$
	Moderate	3 – 6	$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \leq 2, x \geq 7 \\ \frac{x-2}{3-2}, & 2 \leq x \leq 3 \\ 1, & 3 \leq x \leq 6 \\ \frac{7-x}{7-6}, & 6 \leq x \leq 7 \end{cases}$

	High Risk	7 – 13	$\mu_{\text{High Risk}}(x) = \begin{cases} 0, & x \le 6, x \le 14 \\ \frac{x-6}{7-6}, & 6 \le x \le 7 \\ 1, & 7 \le x \le 13 \\ \frac{14-x}{14-13}, & 13 \le x \le 14 \end{cases}$
	Very High Risk	≥14	$\mu_{\text{Very High Risk}}(x) = \begin{cases} 0, & x \le 13 \\ \frac{x-13}{14-13}, & 13 \le x \le 14 \\ 1, & x \ge 14 \end{cases}$
Breastfeeding Practice	Not Exclusive	<1 month	$\mu_{\text{Not Exclusive}}(x) = \begin{cases} 1, & x \le 0 \\ \frac{2-x}{2-0}, & 0 \le x \le 2 \\ 0, & x \ge 2 \end{cases}$
	Partial	1-6 months	$\mu_{\text{Partial}}(x) = \begin{cases} 0, & x \le 0, x \ge 7 \\ \frac{x-0}{2-0}, & 1 \le x \le 2 \\ 1, & 2 \le x \le 5 \\ \frac{7-x}{7-5}, & 5 \le x \le 7 \end{cases}$
	Exclusive	≥6 months	$\mu_{\text{Exclusive}}(x) = \begin{cases} 0, & x \le 5 \\ \frac{x-5}{7-5}, & 5 \le x \le 7 \\ 1, & x \ge 7 \end{cases}$

Variables Output	**Fuzzy Set**	**Range**	**Membership Function**
Stunting Risk	Low Risk	< 20	$\mu_{\text{Low Risk}}(x) = \begin{cases} 1, & x \le 20 \\ \frac{40-x}{40-20}, & 20 \le x \le 40 \\ 0, & x \ge 40 \end{cases}$
	Moderate Risk	20-60	$\mu_{\text{Moderate Risk}}(x) = \begin{cases} 0, & x \le 20, x \ge 80 \\ \frac{x-20}{40-20}, & 20 \le x \le 40 \\ 1, & 40 \le x \le 60 \\ \frac{60-x}{80-60}, 0, & 60 \le x \le 80 \end{cases}$
	High Riks	60-80	$\mu_{\text{High Risk}}(x) = \begin{cases} 0, & x \le 60 \\ \frac{x-60}{80-60}, & 60 \le x \le 80 \\ \frac{100-x}{100-80}, & 80 \le x \le 100 \end{cases}$
	Severely Risk	>80	$\mu_{\text{Severely Risk}}(x) = \begin{cases} 0, & x \le 80 \\ \frac{x-80}{100-80}, & \le< x \le 100 \\ 1, & x \ge 100 \end{cases}$

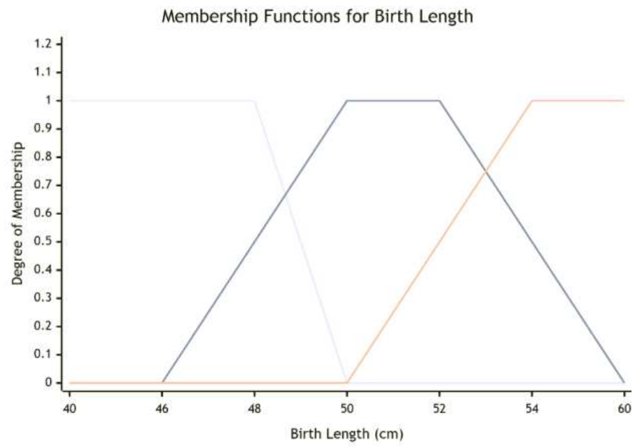

Fig. 2 Membership Function of Birth Length

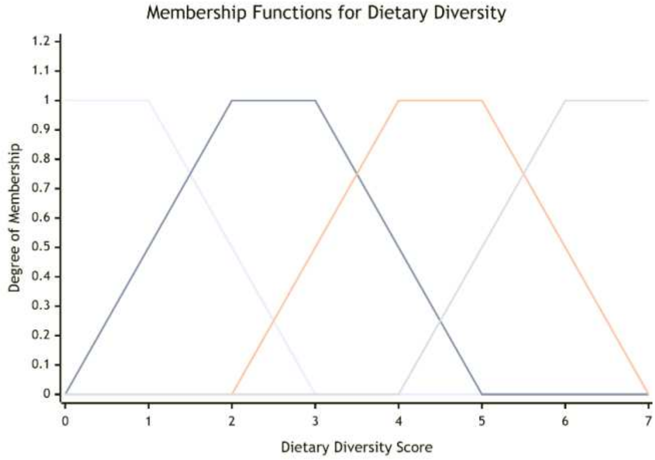

Fig. 3 Membership Function of Dietary Diversity

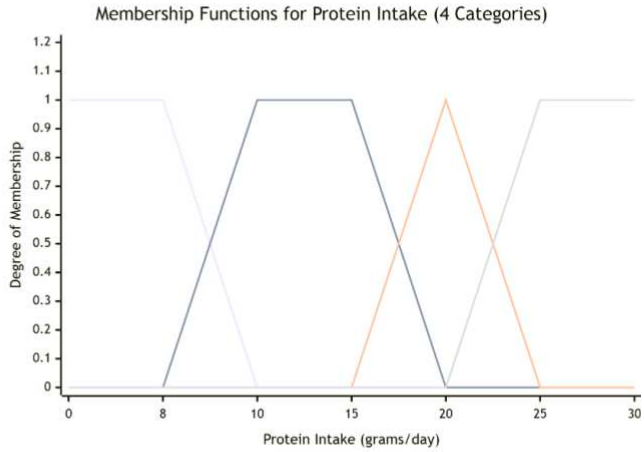

Fig. 4 Membership Function of Protein Intake

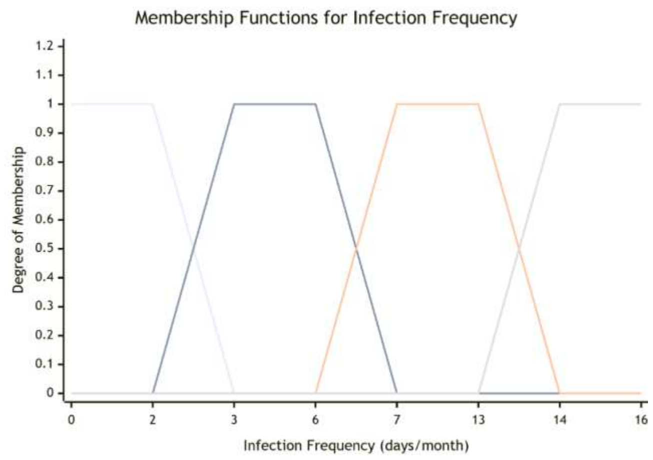

Fig. 5 Membership Function of Infectious Disease History

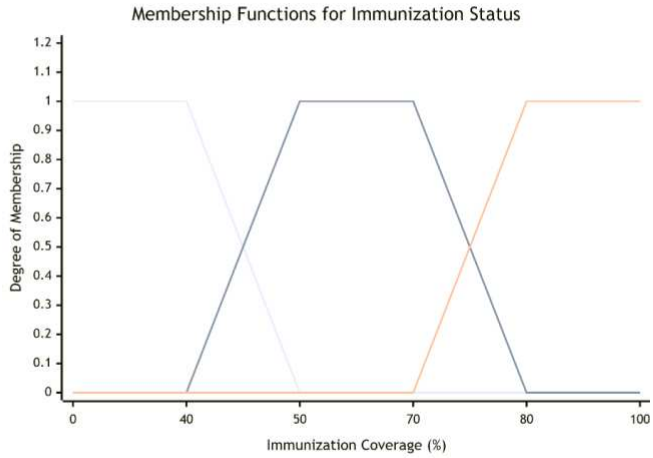

Fig. 6 Membership Function of Immunization Coverage

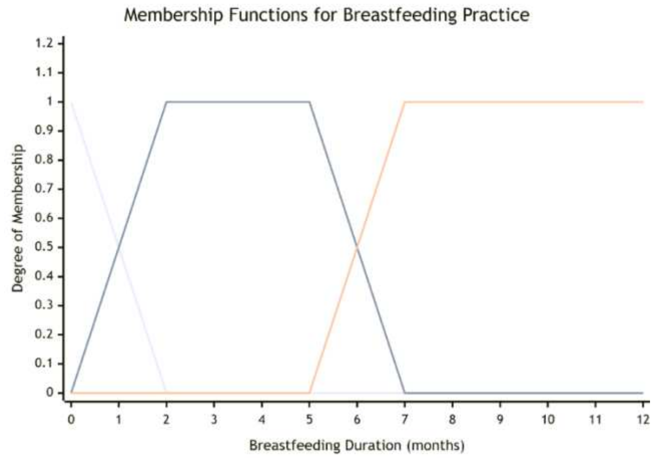

Fig. 7 Membership Function of Breastfeeding Duration

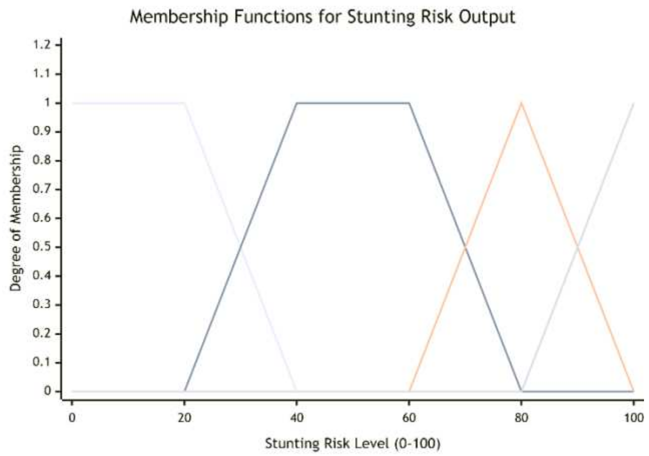

Fig. 8 Membership Function of Stunting Risk

3.2 Fuzzy Rule Base

The heart of the expert system is a collection of fuzzy IF-THEN rules that encapsulate expert knowledge about how the combination of various factors translates to a stunting risk level. We define the output variable risk of stunting as a fuzzy variable with linguistic values such as Low, Moderate, and High risk. The rule base is constructed with the help of a pediatric nutritionist and by reference to known risk factor interactions. Each rule antecedent is a combination of conditions on the input variables (using fuzzy sets), and the consequent is a fuzzy set for the output risk. A simplified excerpt from the rule base is given in Table 2.

Table 2. Fuzzy Mamdani Rules

No	IF (Input Conditions)	THEN (Output: Stunting Risk)
1	Birth Length = Short **AND** Dietary Diversity = Very Low **AND** Protein Intake = Very Low **AND** Immunization = Not Complete **AND** Infection = Very High Risk **AND** Breastfeeding = Not Exclusive	Severely Risk
2	Birth Length = Short **AND** Dietary Diversity = Low **AND** Protein Intake = Low **AND** Immunization = Partial **AND** Infection = High Risk **AND** Breastfeeding = Partial	High Risk
3	Birth Length = Short **AND** Dietary Diversity = Median **AND** Protein Intake = Adequate **AND** Immunization = Partial **AND** Infection = Moderate **AND** Breastfeeding = Partial	Moderate Risk
4	Birth Length = Short **AND** Dietary Diversity = High **AND** Protein Intake = Adequate **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive	Moderate Risk
5	Birth Length = Normal **AND** Dietary Diversity = Very Low **AND** Protein Intake = Low **AND** Immunization = Partial **AND** Infection = High Risk **AND** Breastfeeding = Not Exclusive	High Risk
6	Birth Length = Normal **AND** Dietary Diversity = Low **AND** Protein Intake = Adequate **AND** Immunization = Partial **AND** Infection = Moderate **AND** Breastfeeding = Partial	Moderate Risk
7	Birth Length = Normal **AND** Dietary Diversity = Median **AND** Protein Intake = Adequate **AND** Immunization = Complete **AND** Infection = Moderate **AND** Breastfeeding = Exclusive	Low Risk
8	Birth Length = Normal **AND** Dietary Diversity = High **AND**	Low Risk

	Protein Intake = High **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive	
9	Birth Length = Long **AND** Dietary Diversity = Very Low **AND** Protein Intake = Low **AND** Immunization = Not Complete **AND** Infection = Moderate **AND** Breastfeeding = Partial	High Risk
10	Birth Length = Long **AND** Dietary Diversity = Low **AND** Protein Intake = Adequate **AND** Immunization = Partial **AND** Infection = Moderate **AND** Breastfeeding = Exclusive	Moderate Risk
11	Birth Length = Long **AND** Dietary Diversity = Median **AND** Protein Intake = High **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive	Low Risk
12	Birth Length = Long **AND** Dietary Diversity = High **AND** Protein Intake = High **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive	Low Risk
13	Birth Length = Short **AND** Dietary Diversity = Very Low **AND** Protein Intake = Very Low **AND** Immunization = Partial **AND** Infection = High Risk **AND** Breastfeeding = Partial	High Risk
14	Birth Length = Short **AND** Dietary Diversity = Low **AND** Protein Intake = Low **AND** Immunization = Partial **AND** Infection = Moderate **AND** Breastfeeding = Partial	Moderate Risk
15	Birth Length = Normal **AND** Dietary Diversity = Very Low **AND** Protein Intake = Low **AND** Immunization = Partial **AND** Infection = High Risk **AND** Breastfeeding = Not Exclusive	High Risk
16	Birth Length = Normal **AND** Dietary Diversity = Median **AND** Protein Intake = Adequate **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive	Low Risk
17	Birth Length = Short **AND** Dietary Diversity = Very Low **AND** Protein Intake = Very Low **AND** Immunization = Not Complete **AND** Infection = High Risk AND Breastfeeding = Partial	High Risk

We utilized Mamdani fuzzy inference to evaluate the rules and aggregate the results. During inference, each rule is evaluated by calculating the fuzzy truth of its antecedent and then applying it to the consequent. We employ the standard Mamdani operators: the logical AND is implemented as the minimum of the memberships (min operator), OR as the maximum (max operator), and the implication uses the min operator (i.e., the rule's firing strength is the minimum of its antecedent conditions, and this strength is applied to the consequent set).

For example, in **Rule 1**, if a given child's fuzzified inputs yield membership values: *Short* (*Birth_Length*) = 0.8, Very_Low (*Diatary_Diversity*) = 1.0, Very_Low (*Protein_Intake*) = 0.7, Not Complete (Immunization_Status)=0,8, Very High (Infectious_Disease_History)=0,7, Not Exclusive (Breastfeeding_Practice)=0,9, then the rule's firing strength would be min (0.8, 1.0, 0.7, 0.8, 0.7, 0.9) = 0.7. This means the rule concludes *Stunting*_Risk is **Severe_Risk** with a truth of 0.7. Using Mamdani's inference, we then cut the fuzzy set **High** of risk at the level 0.7 (producing a truncated membership function for high risk).

This procedure is done for all active rules. The fuzzy outputs from all rules are then combined (aggregated) by taking the maximum union across rules for each output fuzzy set. Essentially, we accumulate contributions to the *Severe, High, Moderate, and Low* risk sets from every rule that fired.

3.3 Defuzzification

The final step is defuzzification, where the aggregated fuzzy output set is converted into a single crisp value representing the stunting risk score or category. We use the centroid (center of gravity) defuzzification method, which is one of the most commonly applied techniques in Mamdani systems due to its balanced representation of the information in the fuzzy set [17]. The centroid formula computes the output as shown in equation 1.

$$Z_0 = \frac{\int z\, \mu_{\text{Risk}}(z)\, dz}{\int \mu_{\text{Risk}}(z)\, dz} \tag{1}$$

where $\mu_{\text{Risk}}(z)$ is the aggregated membership degree of risk at output level z across the combined fuzzy sets (Severe, High, Moderate, Low). In practice, this is implemented by discretizing z over the universe of discourse (for example, risk could be defined on a scale 0 to 100) and computing the weighted average. The result Z_0 is a numeric risk score. We can interpret this score directly (e.g., as a percentage risk) or map it to a categorical label by seeing which fuzzy set has the highest degree. For instance, $Z_0 = 72$ on a 0–100 scale, that would correspond to a High-Risk classification (since it lies in the region where the High fuzzy set dominates). If $Z_0 = 30$, it would be a Moderate Rrisk. The centroid defuzzification ensures that all contributing rules influence the final result in proportion to their firing strength and the position of their output fuzzy sets.

The outcome of the defuzzification is presented as the system's diagnosis of stunting risk. For user interpretation, we might translate the numeric score into descriptors (e.g., score > 80 = "Severely Risk", 60–80 = "High Risk", "20-60 "Moderate", < 20 = "Low Risk"), while also possibly providing the numeric value for more nuanced understanding. The fuzzy rule-based approach yields a system that can say, for example, "Risk = 75 (High)" rather than a binary "Stunted/Not Stunted". This is valuable because a child who is not yet stunted but has a high-risk score can be flagged for preventive action.

4. Result and Analysis

We constructed a prototype of the proposed fuzzy expert system and conducted a simulation to validate its behavior using several test cases. Since obtaining a large clinical dataset was beyond the scope of this study, we designed representative hypothetical cases and also tested the system with a small sample of real anonymized data provided by a local health center nutritionist. The experimental setup involved the following steps:

1. **Fuzzy Rule Verification:** Before using the system on data, we performed a verification of the fuzzy rule base to ensure there were no logical conflicts or redundancies. This included checking that for extreme input conditions the rules produce intuitive results (e.g., a child with all risk factors at worst levels always yields High risk; a child with all factors at healthy levels yields Low risk). We also adjusted membership function parameters slightly during this phase to fine-tune the system's sensitivity, based on expert feedback.
2. **Sample Test Cases:** We prepared a set of test scenarios to simulate different combinations of risk factors. Table 3 shows two illustrative examples from these scenarios, including the input values and the output generated by the fuzzy system:

Table 3. Example Case

Case	Birth Length (cm)	Dietary Diversity (food groups)	Protein Intake vs RDA	Immunization	Infection History	Breastfeeding
1	46	2	9 g	35%	12	2 months
2	50	6	18 g	100%	1	8 months

Table 3. Example input data for two test cases and the resulting stunting risk output from the fuzzy expert system. (Note: Values in parentheses indicate the qualitative assessment corresponding to the numeric value, for clarity.)

The fuzzy Mamdani inference process was conducted in three main steps: fuzzification, rule evaluation, and defuzzification.

1. Fuzzification

Each input variable, Birth Length, Dietary Diversity, Protein Intake, Immunization Status, Infectious Disease History, and Breastfeeding Practice was mapped to its corresponding fuzzy set using the defined membership functions. For instance, Birth Length was classified into the fuzzy categories Short, Normal, or Long, with the degree of membership calculated based on linear triangular or trapezoidal functions.

Case 1

Birth Length=46

Short:1

Normal: 0

Long: 0

Dietary Diversity=2

Very Low: $\frac{3-x}{3-1} = \frac{3-2}{3-1} = \frac{1}{2} = 0{,}5$

Low: $\frac{x-0}{2-0} = \frac{2-0}{2-0} = \frac{2}{2} = 1$ and 1

Median: 0 and $\frac{x-2}{4-2} = \frac{2-2}{4-2} = \frac{0}{2} = 0$

High: 0

Protein Intake=9

Very Low: $\frac{10-x}{10-8} = \frac{10-9}{10-8} = \frac{1}{2} = \mathbf{0{,}5}$

Low: 0

Adequate: 0

High: 0

Immunization=35%

Not Complete: 1

Partial: 0

Complete: 0

Infection History=12

Rarely: 0

Moderate: 1

High Risk: 0

Very High Risk: 0

Breastfeeding=2

Not Exclusive$\frac{2-x}{2-0} = \frac{2-2}{2-0} = \frac{0}{2} = 0$

Parsial: $\frac{x-0}{2-0} = \frac{2-0}{2-0} = \frac{2}{2} = 1$ and 1

Exclusive: 0

Case 2

Birth Length=50

Short: $\frac{50-x}{50-48} = \frac{50-50}{50-48} = \frac{0}{2} = 0$

Normal:1 and $\frac{x-46}{50-46} = \frac{50-46}{50-46} = \frac{4}{4} = 1$

Long: $\frac{x-50}{54-52} = \frac{50-50}{54-52} = \frac{0}{2} = 0$ and 0

Dietary Diversity=6

Very Low: 0

Low: 0

Median:$\frac{7-x}{7-5} = \frac{7-6}{7-5} = \frac{1}{2} = 0{,}5$

High:$\frac{x-4}{6-4} = \frac{6-4}{6-4} = \frac{2}{2} = 1$

Protein Intake=18

Very Low: 0

Low: $\frac{20-x}{20-15} = \frac{20-18}{20-15} = \frac{3}{5} = 0{,}6$

Adequate: $\frac{x-15}{20-15} = \frac{18-15}{20-15} = \frac{3}{5} = 0{,}6$

High: 0

Immunization=100%

Not Complete: 0

Partial: 0

Complete:1

Infection History=1

Rarely:1

Moderate: 0

High Risk: 0

Very High Risk:0

Breastfeeding=8

Not Exclusive: 0

Partial: 0

Exclusive: 1

2. Rule Evaluation (Inference)

A comprehensive set of IF–THEN rules was applied to combine the fuzzified inputs. Each rule represents a logical relationship between input conditions and the output, Stunting Risk, categorized as Low, Moderate, High, or Severe Risk. The firing strength of each rule was determined by the **minimum operator** (AND condition) among the membership values of the relevant input variables.

R16: Birth Length = Normal **AND** Dietary Diversity = Median **AND** Protein Intake = Adequate **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive THEN Low Risk

R17: Birth Length = Short **AND** Dietary Diversity = Very Low **AND** Protein Intake = Very Low **AND** Immunization = Not Complete **AND** Infection = High Risk **AND** Breastfeeding = Partial THEN High Risk

3. Defuzzification

The fuzzy output values resulting from rule evaluation were aggregated and converted into a **crisp numerical score** using the centroid (center of gravity) method. This final score quantitatively represents the stunting risk for each toddler, allowing for a more precise interpretation of borderline cases where input parameters may partially belong to multiple fuzzy categories.

Defuzzification using Centroid Method for output Z-score:

Case 1

R17: Birth Length = Short **AND** Dietary Diversity = Very Low **AND** Protein Intake = Very Low **AND** Immunization = Not Complete **AND** Infection = High Risk **AND** Breastfeeding = Partial

Agregation= $min(1, 0.5, 0.5, 1, 1, 1) = 0.5$

Membership function truncated for High Risk:

$$\mu(z) = \frac{(z-60)}{20} \; for\; 60 \leq z \leq 70$$

$$\mu(z) = 0.5 \; for\; 70 \leq z \leq 90$$

$$\mu(z) = \frac{(100-z)}{20} \; for\; 90 \leq z \leq 100$$

Integral calculation:

$$\int \mu(z)\, dz = 15$$

$$\int z\, \mu(z)\, dz = 1200$$

$$Centroid = \frac{1200}{15} = 80$$

Risk score = 80 (included in the High Risk category)

Case 2

R16: Birth Length = Normal **AND** Dietary Diversity = Median **AND** Protein Intake = Adequate **AND** Immunization = Complete **AND** Infection = Rarely **AND** Breastfeeding = Exclusive

Agregation= min(1, 0.5, 0.6, 1, 1, 1) = 0.5

Membership function truncated for Low Risk:

$$\mu(z) = 0.5 \, for \, z \leq 30$$

$$\mu(z) = \frac{(40 - z)}{20} \, for \, 30 \leq z \leq 40$$

Integral calculation:

$$\int \mu(z) \, dz = 17.5$$

$$\int z \, \mu(z) \, dz = 308.3335$$

$$Centroid = \frac{308.3335}{17.5} = 17.62$$

$$Risk \ score = 17.62 \ (included \ in \ the \ Low \ Risk \ category)$$

Based on inference and defuzzification calculations, Case 1 has a risk score of 80, which falls into the High-Risk category. Case 2 has a risk score of 17.62, which falls into the Low-Risk category. These results are consistent with expert assessments that the combination of risk factors in Case 1 causes a high risk of stunting, while Case 2 shows a low risk thanks to factors that support healthy growth. This Mamdani fuzzy system effectively handles uncertainty and provides nuanced results to support decision-making in stunting prevention.

The experimental findings demonstrate that the proposed fuzzy Mamdani expert system effectively diagnoses stunting risk in toddlers by integrating multiple anthropometric, nutritional, and health-related factors into a comprehensive risk assessment. The system successfully differentiates between high-risk and low-risk cases, with outputs aligning closely with evaluations by human experts. A key advantage of the fuzzy approach is its ability to handle intermediate or borderline cases by producing nuanced risk scores rather than binary classifications. This allows for the identification of children who are at the threshold of becoming stunted, thereby enabling timely preventive interventions before chronic malnutrition manifests as impaired growth.

The Mamdani fuzzy inference method proved particularly suitable for this application due to its capacity to manage overlapping and uncertain input variables. For instance, a toddler with moderately low protein intake and medium dietary diversity was assigned a Moderate risk level, as both low and medium-risk rules contributed to the output. This reflects a realistic scenario where the child is neither entirely safe nor acutely endangered. A conventional crisp-logic system with fixed thresholds might misclassify such cases due to its inability to accommodate gradations, whereas the fuzzy system offers robustness against measurement variability and minor input errors common challenges in field-based anthropometric and dietary data collection.

Among the input variables, birth length emerged as a strongly influential factor. Short birth length frequently activated high-risk rules, consistent with medical literature indicating that suboptimal birth conditions predispose children to future growth impairments. Similarly, incomplete immunization status often contributed to Moderate or High-risk outcomes, underscoring the role of vaccinations in reducing infectious disease incidence and subsequent malnutrition. Exclusive breastfeeding demonstrated a protective effect; children with adequate breastfeeding practices required a confluence of multiple risk factors to be categorized as high risk, whereas those without exclusive breastfeeding were more readily assigned to higher risk categories aligning with established epidemiological knowledge.

The Mamdani approach also offers high interpretability and transparency. Each risk assessment can be traced back to a set of human-readable rules, enhancing trust and usability among healthcare workers. The system's compatibility with linguistic variables (e.g., "low," "adequate") facilitates the direct incorporation of expert knowledge, while graduated output scores enable risk prioritization for example, distinguishing between a risk score of 90 (high urgency) and 70 (moderate urgency).

Nevertheless, the system has certain limitations. Its performance is heavily dependent on the completeness and accuracy of the rule base and membership functions. Although the current rule set was refined iteratively with domain experts, omitting specific risk combinations such as "normal birth length but severely poor diet and health" could lead to underestimation of risk. Future efforts should focus on expanding rule coverage and validation using larger datasets.

5. Conclusion

This study applied a Mamdani-based fuzzy expert system to assess stunting risk by integrating six key input variables: birth length, dietary diversity, protein intake, immunization status, infectious disease history, and breastfeeding practice. We designed and verified a comprehensive fuzzy rule base to ensure logical consistency and expert interpretability. The inference process followed standard fuzzy stages, including rule evaluation using the minimum operator, and centroid-based defuzzification. It is allowing the system to model uncertainty and partial membership across nutritional and health indicators. The prototype demonstrates that fuzzy logic is well-suited to represent complex, multi-factor relationships commonly found in pediatric nutrition and public health decision-making.

Experimental results from representative test cases and a small set of anonymized real data show that the system produces risk scores and categories that align with expert judgment. In the illustrative evaluation, Case 1 yielded a defuzzified risk score of 80, correctly classified as High Risk, while Case 2 produced a score of 17.62, classified as Low Risk. Across the tested scenarios, the system achieved 100% agreement with expert assessments on risk category assignment, indicating strong face validity and rule consistency. These results confirm that the proposed fuzzy expert system can distinguish clearly between high-risk and low-risk conditions while providing nuanced numerical scores for borderline cases.

For future work, this study can be extended by validating the system on a larger, fully clinical dataset to quantify performance metrics such as accuracy, sensitivity, and specificity. We also plan to refine membership functions through data-driven optimization and expert consensus to improve sensitivity to intermediate risk levels. Additionally, integrating the system into a web-based or mobile decision-support platform could facilitate real-time use by healthcare workers and nutritionists, thereby strengthening early detection and targeted intervention strategies for stunting prevention.

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