Stunting Risk Detection and Food Recommendation via Maternal Diagnosis Using the CF Method

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ABSTRACT

Stunting in children often stems from maternal health conditions during pregnancy. This study aims to develop an intelligent rule-based IF–THEN system using the Certainty Factor method as a decision-support tool for the early detection of stunting risk factors. The detection is performed indirectly by diagnosing maternal health conditions during pregnancy. The knowledge base was constructed through interviews with obstetricians and nutritionists, encompassing 20 symptoms categorized into three primary conditions namely Chronic Energy Deficiency (CED), anemia, and preeclampsia. A total of 119 pregnant women from 11 villages in Muara Satu District participated as respondents. Implementation results revealed that among the respondents, 20 were identified with CED, 96 had anemia, and 3 exhibited signs of preeclampsia. Based on Certainty Factor (CF) calculations, the confidence distribution for CED included 2 respondents with CF <50%, 5 respondents within the 50–80% range, and 13 respondents with CF >80%. For anemia, 1 respondent had a CF value <50%, 4 fell within the 50–80% range, and 91 respondents had CF values above 80%. Meanwhile, for preeclampsia, all respondents exceeded the 50% CF threshold, with 1 respondent in the 50–80% range and 2 respondents >80%. In addition to diagnosis, the system provides tailored meal recommendations (breakfast, lunch, and dinner) based on the identified health conditions. Expert validation indicated a 90% agreement rate. However, results still require confirmation through clinical examinations and consultations to ensure medical accuracy.

I. INTRODUCTION

Stunting remains a critical public health concern in Indonesia. According to the most recent data from 2023, the national stunting prevalence stands at 21.5% [1]. The government has set a target to reduce the national stunting rate to 14% by 2024. However, as of now, this goal has yet to be fully and effectively achieved [2]. According to the World Health Organization (WHO), Indonesia ranks as the third-highest country in terms of stunting prevalence across Southeast Asia [3]. This condition highlights a substantial gap between the ideal targets and the current reality. Stunting, resulting from prolonged nutritional deficiencies, adversely affects both the physical development and cognitive potential of children in the long term [4]. Pregnant women are among the high-risk groups in the chain of stunting causation, particularly when affected by anemia, chronic energy deficiency, or inadequate nutritional intake that fails to meet physiological needs [5]. According to Indonesia's Minister of Health, Budi Gunadi Sadikin, stunting is most effectively prevented during pregnancy through targeted interventions, rather than through treatment after birth. Therefore, ensuring focused and adequate nutrition for pregnant women is a key strategy that must be prioritized [6].

While many stunting prevention programs emphasize postnatal monitoring, there remains a critical gap in prenatal risk detection using computational tools. The system proposed in this study is not intended to diagnose stunting in infants directly, as such assessments require postnatal anthropometric measurements. Instead, the system identifies indirect risk indicators by analyzing maternal health conditions particularly those linked to anemia, chronic energy deficiency, and other nutritional risk factors during pregnancy. By focusing on key prenatal health conditions such as anemia, chronic energy deficiency, and preeclampsia, the system functions as an early-warning tool that provides targeted nutritional menu recommendations aligned with each condition. This preventive approach is intended to improve maternal health and thereby reduce the risk of stunting in newborns.

To date, there has been no intelligent system truly capable of identifying maternal health risks associated with stunting while effectively recommending individualized nutritious food plans. Leveraging Artificial Intelligence (AI) through expert systems offers a promising solution to address this gap. These systems are designed to emulate expert reasoning in analyzing problems and delivering knowledge-based food recommendations [7]. The system operates by asking a series of questions related to the health condition of pregnant women to identify potential stunting risk factors, and subsequently provides dietary menu recommendations tailored to the results of the analysis [8]. The absence of a comparable system in Indonesia positions this study as an innovative contribution to support government initiatives in preventing stunting at birth through more targeted monitoring of maternal nutrition and health conditions.

II. METHOD

To address the research objectives, this study employed a knowledge-based approach rooted in expert system principles. The methodology encompasses the design, development, and validation of an intelligent system that integrates expert knowledge with the Certainty Factor algorithm to diagnose maternal health conditions and recommend personalized food interventions. The following subsections detail the research design, system architecture, knowledge acquisition process, inference mechanism, and validation strategy..

A. Research Design and Setting

This research was conducted in January 2025 in the Muara Satu Subdistrict, Lhokseumawe City, Aceh Province. The study involved 11 villages: Batuphat Barat, Batuphat Timur, Blang Naleung Mameh, Blang Panyang, Blang Pulo, Cot Trieng, Meunasah Dayah, Meuria Paloh, Padang Sakti, Paloh Punti, and Ujong Pacu. A total of 119 pregnant women participated in the field validation process. Data collection was carried out through integrated health post (posyandu) activities in collaboration with local midwives. Two domain experts a certified obstetrician and a professional nutritionist from Arun Hospital participated directly in the knowledge acquisition process to construct the system's diagnostic rules and menu recommendations.

B. System Architecture and Workflow

The intelligent system is structured to simulate expert reasoning in identifying maternal health conditions that may contribute to the risk of stunting in newborns [9]. Expert systems are increasingly employed in medical contexts to replicate the decision-making capabilities of human experts under uncertainty [10] [11]. The core stages include user input of symptoms, diagnosis using the Certainty Factor (CF) method, and delivery of personalized food recommendations. A flowchart diagram was developed to visualize the entire process from data input to output generation. This schematic enhances both conceptual clarity and traceability of the decision-making process embedded within the system.

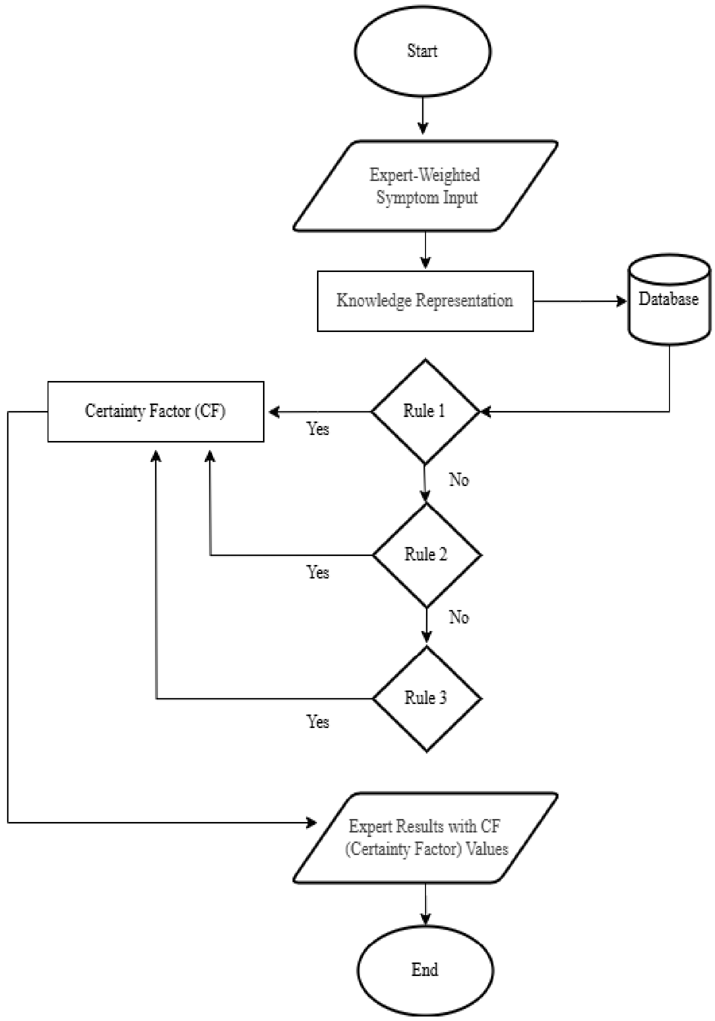

Figure 1. System Framework

C. Knowledge Base Construction

The knowledge base was constructed from symptom patterns and associated health conditions derived through direct interviews with domain experts. Symptom data and maternal health indicators were obtained through consultations with an obstetrician, while nutritional foods recommendations were formulated based on structured interviews with a certified clinical nutritionist. The system diagnoses three major prenatal conditions: Chronic Energy Deficiency (CED), anemia, and preeclampsia. Each condition is represented by a set of symptoms organized into 3 inference rules using a standard IF–THEN format. For example, the anemia rule is triggered when a combination of symptoms such as pallor, fatigue, low hemoglobin, and shortness of breath is identified. These rule-based representations are commonly applied in medical expert systems to enhance transparency and maintain domain knowledge consistency. The system adopts a sequential IF–THEN evaluation approach, wherein each rule is examined individually by the inference engine to determine the most probable diagnosis based on the presented symptoms [12]. It is important to emphasize that the system does not directly detect stunting rather, it identifies maternal health conditions that are recognized risk factors contributing to stunting outcomes.

D. Certainty Factor Method

The Certainty Factor is a method used to quantify the degree of confidence or certainty in a given fact or hypothesis, based on expert knowledge [13]. This concept was first introduced by Shortliffe and Buchanan during the development of the MYCIN expert system, which was designed to express the strength of belief in information under uncertain conditions [14]. The calculation process in the Certainty Factor method involves multiplying the user's confidence value with the certainty value provided by the expert. The result of this multiplication generates a combined CF value, which is then used to determine the overall level of certainty [15]. In this method, the final decision is made based on the highest combined CF score among the available hypotheses [16]. The Certainty Factor formula is defined as follows:

$$CF_{symptom} = CF_{expert}\,[H] * \ CF_{user}[E] \quad (1)$$

$$CF_{combine} = CF_{old} + \ CF_{symptom} * (1 - CF_{old}\ ) \quad (2)$$

$$CF_{precentage} = CF_{combine} * 100\% \quad (3)$$

A classification threshold was established to interpret the CF values:

- Less than 50%: Not Indicated
- 50–80%: Possibly Indicated
- Greater than 80%: Strongly Indicated

III. Result And Discussion

This section provides a comprehensive overview of the research findings, covering the data collection process, diagnostic results, and evaluation of the system's overall performance. The discussion highlights how the system contributes to early identification of maternal health issues and supports the formulation of appropriate nutritional menu recommendations aimed at reducing potential risks during pregnancy.

A. Field Data Collection Location and Process

This research was carried out in the Muara Satu Subdistrict, encompassing 11 villages as observation sites: Batuphat Barat, Batuphat Timur, Blang Naleung Mameh, Blang Panyang, Blang Pulo, Cot Trieng, Meunasah Dayah, Meuria Paloh, Padang Sakti, Paloh Punti, and Ujong Pacu. Research took place over a two-month period through local community health posts (*posyandu*), with the active involvement of village midwives. A total of 119 pregnant women participated in this phase of the study. Specifically, 9 respondents were from Blang Pulo, 14 from Batuphat Barat, 11 from Batuphat Timur, 6 from Blang Naleung Mameh, 9 each from Padang Sakti, Meuria Paloh, and Cot Trieng, 7 from Meunasah Dayah, 12 from Blang Panyang, 10 from Ujong Pacu, and the highest number, 23, were from Paloh Punti.

B. Expert System Knowledge Base

The construction of the expert system's knowledge base was grounded in a series of in-depth interviews conducted with a practicing obstetrician experienced in maternal health. These consultations served as the foundation for identifying key symptoms and conditions commonly observed during pregnancy that are known to contribute to stunting risk factors. Based on the insights obtained from this expert engagement, the system integrates 20 distinct symptoms, which are systematically classified into three primary prenatal conditions Chronic Energy Deficiency (CED), anemia, and preeclampsia.

These conditions were selected due to their documented impact on maternal and fetal health, as supported by national clinical guidelines and public health recommendations. Each condition is defined by a specific combination of symptoms, which are formalized into structured rule-based representations to support diagnostic reasoning. This rule formulation is implemented using a standard IF–THEN format, enabling consistent interpretation by the system's inference engine.

Importantly, the expert system developed in this study is explicitly rule-based. All diagnostic decisions are driven by predefined logical rules derived from medical expert knowledge, rather than by probabilistic models, machine learning algorithms, or data mining approaches.

TABLE I
SYMPTOM AND HEALTH CONDITION

Symptom Code	Symptom	Health Condition
G001	Upper arm circumference less than 23.5 cm	Chronic Energy Deficiency (CED)
G002	Severely underweight (Body Mass Index below 18.5)	

G003	Inadequate weight gain relative to gestational age	
G004	Persistent fatigue	
G005	Body aches	
G006	Difficulty concentrating or remembering things	
G007	Numbness or tingling sensations	
G008	General weakness, exhaustion, sluggishness, fatigu, and lack of energy	Anemia
G009	Hemoglobin (Hb) level below 11 g/dL	
G010	Pale face, lips, or nail beds	
G011	Headache or dizziness	
G012	Shortness of breath	
G013	Rapid and irregular heartbeat	
G014	Chest pain	
G015	Blood pressure above 140/90 mmHg	Preeclampsia
G016	Visual disturbances (e.g., blurry vision or light sensitivity)	
G017	Severe and persistent headache	
G018	Pain in the upper abdomen or epigastric region	
G019	Swelling in the legs or face	
G020	Foamy or bubbly urine	

C. Rule

Rule formulation represents a core component of the expert system, as it forms the foundation for the diagnostic inference process [7] . In this study, the rules were derived through structured interviews with a practicing obstetrician, ensuring that each condition is defined according to clinical expertise. Based on the previously identified symptom data and maternal health conditions described in Table 1, a total of 3 diagnostic rules were constructed. Each rule corresponds to one of the three targeted prenatal conditions, namely Chronic Energy Deficiency (CED), anemia, and preeclampsia. The rules are developed using combinations of specific symptoms seven symptoms are used to define CED and anemia, while six symptoms are associated with preeclampsia. These rules are formalized in an IF–THEN structure, which enables the system to map symptom patterns to likely diagnoses. The complete rule set is presented in Table II.

TABLE II
RULE BASED

No	Rule Based (IF-THEN)
1	**IF** Upper arm circumference less than 23.5 cm **AND** Severely underweight (Body Mass Index below 18.5) **AND** Inadequate weight gain relative to gestational age **AND** Persistent fatigue **AND** Body aches **AND** Difficulty concentrating or remembering things **AND** Numbness or tingling sensations **THEN** Chronic Energy Deficiency (CED)
2	**IF** General weakness, exhaustion, sluggishness, fatigue, and lack of energy **AND** Hemoglobin (Hb) level below 11 g/dl **AND** Pale face, lips, or nail beds **AND** Headache or dizziness **AND** Shortness of breath **AND** Rapid and irregular heartbeat **AND** Chest pain **THEN** Anemia
3	**IF** Blood pressure above 140/90 mmHg **AND** Visual disturbances (e.g., blurry vision or light sensitivity) **AND** Severe and persistent headache **AND** Pain in the upper abdomen or epigastric region **AND** Swelling in the legs or face **AND** Foamy or bubbly urine **THEN** Preeclampsia

D. Food Menu Recommendations

Food menu recommendations are provided after the system completes the diagnostic process of the pregnant woman's health condition. These recommendations were obtained through direct interviews with a professional nutritionist experienced in maternal nutrition. The suggested menus are aligned with the diagnosed health condition namely Chronic Energy Deficiency (CED), anemia, or preeclampsia and are not based on individual symptoms. Instead, the nutritionist selected the menus by considering the appropriate balance of nutrients required to support recovery from each specific condition. Nutritional components such as energy, protein, iron, folic acid, and other essential micronutrients were taken into account to help reduce potential complications and to promote optimal fetal development. The complete food menu recommendations are presented in the table below:

TABLE III
FOOD MENU RECOMMENDATION

Health Condition	Food Recommendation
Chronic Energy Deficiency (CED)	**07:00 AM**: 250 grams of white rice or potatoes, 100 grams of vegetables such as sautéed Japanese pumpkin, 100 grams of animal protein such as chicken egg, 100 grams of plant-based protein such as fried tempeh, one large piece of fruit, a glass of milk, and mung bean porridge as a snack. **12:00 PM**: 270 grams of white rice or potatoes, 100 grams of spinach soup, 100 grams of animal protein such as pickled fish, 100 grams of plant-based protein such as fried tofu, one orange, and biscuits as a snack. **08:00 PM**: 250 grams of white rice or potatoes, 100 grams of mixed vegetables (capcay), 100 grams of braised chicken, 100 grams of tempeh cooked in sweet soy sauce (*tempe bacem*), one orange, and a glass of milk
Anemia	**07:00 AM**: 250 grams of white rice or potatoes, 100 grams of sautéed broccoli, 100 grams of animal protein such as chicken egg, 100 grams of plant-based protein such as fried tempeh, one large piece of fruit, a glass of milk, and mung bean porridge as a snack. **12:00 PM**: 270 grams of white rice or potatoes, 100 grams of spinach soup, 100 grams of animal protein such as skipjack tuna, 100 grams of plant-based protein such as fried tofu, one orange, and beetroot juice. **08:00 PM**: 250 grams of white rice or potatoes, 100 grams of mixed vegetables (capcay), 100 grams of braised chicken, 100 grams of *tempe bacem*, one orange, and a glass of milk **Note**: Drinking tea during or shortly after meals is not recommended, as it may inhibit the absorption of essential nutrients
Preeclampsia	**07:00 AM**: 250 grams of white rice or potatoes, 100 grams of sautéed Japanese pumpkin, 100 grams of animal protein such as chicken egg, 100 grams of plant-based protein such as fried tempeh, one large portion of fruit, a glass of milk, and mung bean porridge as a snack. **12:00 PM**: 270 grams of white rice or potatoes, 100 grams of clear spinach soup, 100 grams of animal protein such as pickled fish, 100 grams of plant-based protein such as fried tofu, one orange, and a glass of avocado juice. **08:00 PM**: 250 grams of white rice or potatoes, 100 grams of stir-fried mixed vegetables (*capcay*), 100 grams of braised chicken, 100 grams of sweet-simmered tempeh (*tempe bacem*), one pomegranate, and a glass of milk. **Note**: It is advised to limit the intake of salt and processed or instant foods

As presented in Table III, the meal recommendations developed in collaboration with a nutritionist are designed to be consumed at three main times morning, afternoon, and evening based on the daily nutritional needs of pregnant women according to their health conditions. Each meal plan considers a balanced intake of both macronutrients and micronutrients needed to support maternal recovery and promote optimal fetal development. Additionally, certain health conditions include relevant advisories. For example, in cases of preeclampsia, it is recommended to limit salt consumption and avoid processed or instant foods in order to prevent worsening symptoms and to help maintain stable blood pressure. Meanwhile, pregnant women at risk of anemia are advised not to drink tea during or shortly after meals, as the tannins in tea may interfere with iron absorption, which is essential for hemoglobin production.

E. Weight Assignment of CF Values by Experts

The assignment of confidence weights to each symptom serves as a critical component in designing a precise and academically accountable expert system. This phase establishes the foundational logic behind the system's decision-making process and directly impacts the accuracy of the diagnoses it generates in relation to users' actual conditions. In this study, the weighting process was carried out methodically through structured consultations with an obstetrics specialist possessing both clinical expertise and extensive professional experience. The certainty factor values were not arbitrarily assigned but rather reflect valid medical considerations grounded in evidence-based practice. This approach ensures that the system delivers recommendations that are logically sound, theoretically consistent, and contextually relevant to real-world medical scenarios. To calculate the certainty factor values, it is necessary to use the Measure of Belief (MB) and Measure of Disbelief (MD), as outlined below.

TABLE IV
WEIGHT VALUES FOR MEASURE OF BELIEF (MB) AND MEASURE OF DISBELIEF (MD)

No	Description	MB	MD
1	Very Certain	1.0	0.0
2	Certain	0.8	0.2
3	Fairly Certain	0.6	0.4
4	Slightly Certain	0.4	0.6
5	Don't Know	0.2	0.8
6	No	0.0	1.0

Based on Table IV, the confidence levels for each symptom were determined through direct interviews with an obstetrician, who evaluated each symptom using their clinical expertise and professional judgment. This confidence assignment was not conducted arbitrarily but was entirely grounded in the expert's medical knowledge and interpretation of how each symptom correlates with the suspected condition (hypothesis). In this context, the obstetrician assessed the degree of relevance between each symptom and a given condition using a six-point confidence scale. This scale reflects the expert's level of belief that a particular symptom contributes to supporting a specific hypothesis. The expert-defined confidence levels can be seen as follows:

TABLE V
EXPERT CONFIDENCE VALUES

Health Condition	Symptom Code	Confidence Value (MB)
CED	G001	1.0
	G002	1.0
	G003	0.8
	G004	0.4
	G005	0.4
	G006	0.4
	G007	0.4
Anemia	G008	1.0
	G009	1.0
	G010	0.8
	G011	0.8
	G012	0.4
	G013	0.4
	G014	0.4
Preeclampsia	G015	0.8
	G016	1.0
	G017	0.8
	G018	0.8
	G019	0.4
	G020	0.4

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F. Manual Calculation of Certainty Factor

To generate a diagnosis that closely aligns with the user's actual condition, the system applies the Certainty Factor (CF) method, which calculates the degree of confidence by combining expert certainty values with the user's belief level regarding the selected symptoms. This calculation is carried out in several steps.

TABLE VI
COMBINED CF VALUES FROM EXPERT AND USER INPUTS

Symptom	CF Expert	CF User	CF[H,E] = Expert * User
G001	1.0	1.0	1.0
G002	1.0	1.0	1.0
G003	0.8	1.0	0.8
G004	0.4	0.6	0.24
G005	0.4	0.8	0.32
G006	0.4	0.0	0.0
G007	0.4	0.0	0.0

Calculate the CF Combine value where $CF_{combine} = CF_{old} + CF_{Symptom} * (1 - CF_{old})$

Combine G001 and G002 : $CF_{1,2} = 1.0 + 1.0 * (1 - 1.0) = 1.0$
Combine result with G003 : $CF = 1.0 + 0.8 * (1 - 1.0) = 1.0$
Combine result with G004 : $CF = 1.0 + 0.24 * (1 - 1.0) = 1.0$
Combine result with G005 : $CF = 1.0 + 0.32 * (1 - 1.0) = 1.0$
Combine result with G006 : $CF = 1.0 + 0.0 * (1 - 1.0) = 1.0$
Combine result with G007 : $CF = 1.0 + 0.0 * (1 - 1.0) = 1.0$

Once all CF values are sequentially combined across the relevant symptoms, the confidence percentage is derived using the formula: $CF_{percentage} = CF_{combine} * 100\%$. Given the final CF_combine is 1.0, the resulting confidence score is 100%. This computation is performed for each hypothesis, and the system identifies the most likely diagnosis based on the highest resulting percentage [17]. For example, if the final result of this calculation yields 100%, this value will be displayed as the diagnosis result and classified as Strongly Indicated based on the established interpretation scale.

G. System Design

System design is a critical stage that defines the flow and structure of the application based on its functional requirements. These components are further illustrated through diagrams to reflect the interactions between actors and system features, as described below:

1) *Use Case Diagram for Admin*: System design represents a critical stage in the development of intelligent applications, serving to define and formalize the functional structure, logical flow, and interaction mechanisms between users and system components. This structure is commonly depicted using Unified Modeling Language (UML) diagrams to provide a clear visual overview of the roles, actions, and system boundaries. In the proposed system, the administrative role is held by the domain expert, typically a healthcare professional, who is responsible for managing the knowledge base and inference parameters.

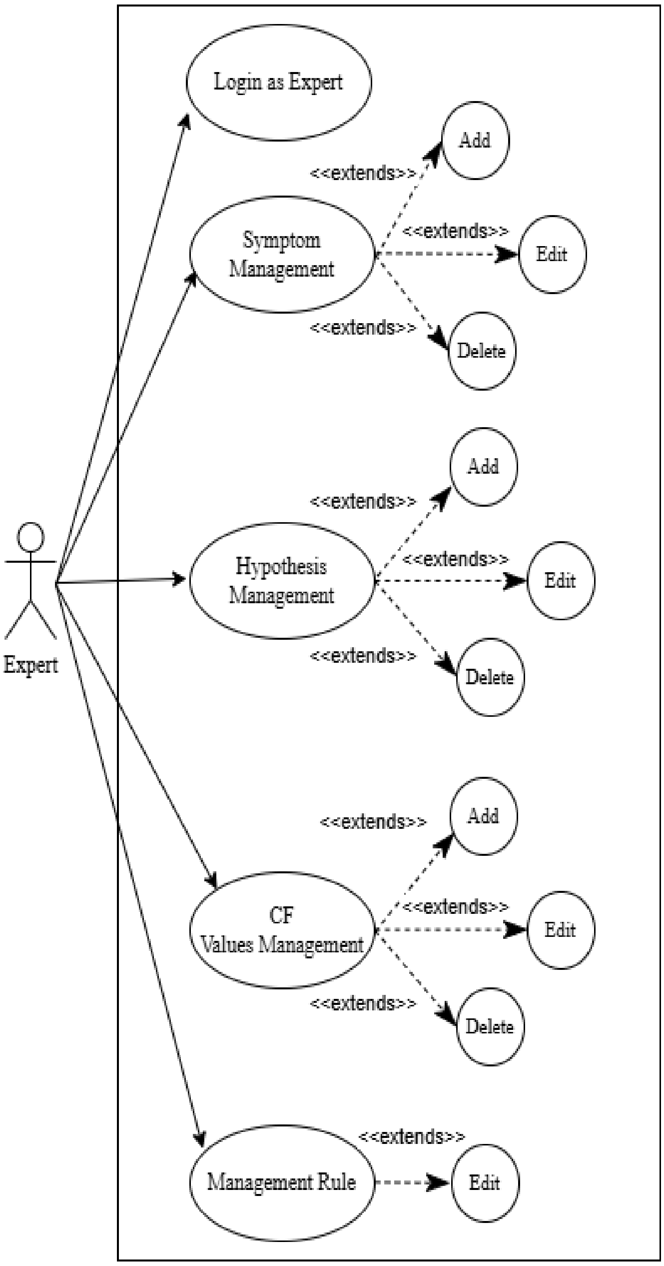

Figure 2. Use Case Diagram for Admin

As illustrated in the use case diagram, the process begins with the expert logging into the system through a secure authentication module. This step ensures that access to sensitive functionalities is restricted to authorized individuals only. Once authenticated, the expert is granted comprehensive control over the system's core knowledge entities. The first set of actions includes Symptom Management, allowing the expert to add new symptoms, edit existing ones, or delete obsolete entries. These actions are crucial in keeping the symptom database aligned with current medical observations and diagnostic trends. The expert also manages Hypothesis Management, where diagnostic conditions such as Chronic Energy Deficiency (CED), anemia, and preeclampsia are maintained. This feature supports the creation, revision, and removal of diagnostic hypotheses based on validated medical criteria and field evidence. In addition, the system enables CF Values Management, a critical component for calculating the Certainty Factor. Experts input confidence values representing the Measure of Belief (MB) and Measure of Disbelief (MD) for each symptom-hypothesis pair. These values are essential for performing accurate inference, and must reflect the expert's professional judgment rooted in clinical knowledge. The final key function is Management Rule, which allows the expert to construct and edit rule-based logic that connects symptoms to diagnostic outcomes. These rules follow a standard IF–THEN format and form the backbone of the expert system's decision-making process. The expert is responsible for ensuring that these rules remain consistent with domain knowledge, evidence-based practices, and updated diagnostic guidelines. Overall, this use case diagram reflects a modular and expert-driven approach to knowledge management within the system. It underscores the pivotal role of the expert not only as a data administrator but also as a knowledge engineer whose insights directly shape the accuracy, reliability, and scientific integrity of the application.

2) *Use Case Diagram for User*: This diagram outlines the user interaction flow within the system, which can be accessed without authentication. Users are granted direct access to the homepage, where they can explore essential information regarding the system's objectives and operational framework. From there, the user initiates the consultation process by selecting the "Get Recommendations" feature. The subsequent steps involve entering personal data, selecting symptoms that match their current condition, and assigning a level of confidence to each selected symptom. The system then processes the input using the Certainty Factor (CF) method to estimate the likelihood of specific health conditions. Based on this analysis, the system generates a diagnostic result represented as a percentage of certainty. In parallel, a tailored nutritional menu is recommended to address the identified condition, aiming to support maternal nutritional improvements in a precise and targeted manner.

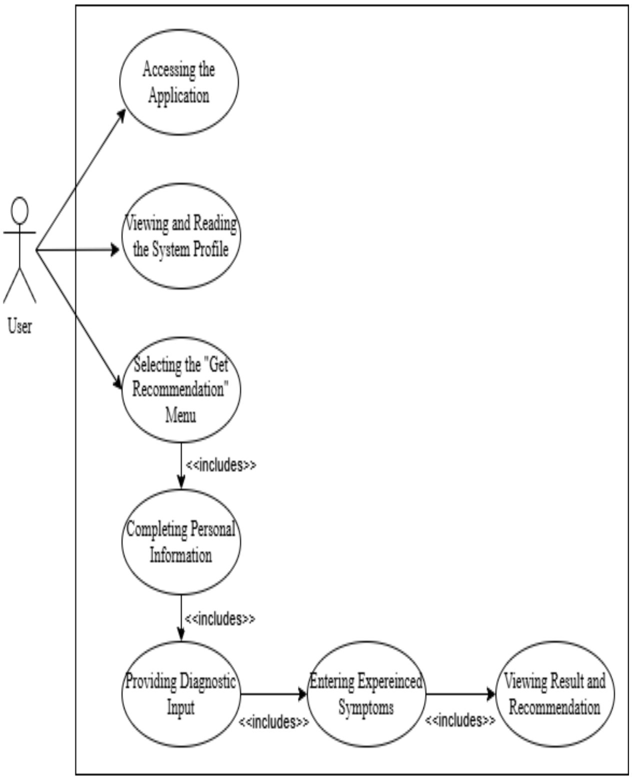

Figure 3. Use Case Diagram for User

H. System Performance

The system's performance reflects its ability to process actual user input, combining it with expert confidence levels to generate a primary diagnosis along with relevant nutritional recommendations. This section illustrates the distribution of diagnostic outcomes, categorized by hypothesis type and degree of certainty. A bar chart is used to facilitate a comprehensive interpretation of the system's outputs. Further details are presented in the following graphical visualization.

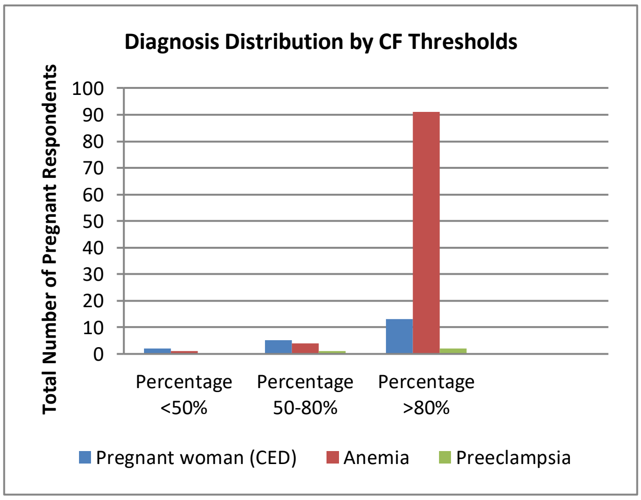

Figure 4. *Diagnostic Chart Based on Highest CF Value*

Figure 4 illustrates the distribution of diagnoses among the 119 pregnant women who participated in the study. Of these, 20 were identified as experiencing Chronic Energy Deficiency (CED), 96 were diagnosed with anemia, and 3 exhibited signs of preeclampsia. These classifications were derived from the highest certainty factor (CF) value calculated by the system for each user. The distribution is visualized through a graph to highlight the health conditions most frequently detected. The system generates a final diagnosis solely based on the highest CF value. This approach is justifiable from a logical and mathematical standpoint, as the system is designed to determine the most probable condition by comparing probabilistic values among hypotheses, rather than relying on a fixed absolute threshold. Each pregnant woman diagnosed with CED, anemia, or preeclampsia receives tailored food recommendations covering three daily meals breakfast, lunch, and dinner. These recommendations, detailed in Tables III, aim to improve intake of essential nutrients such as energy, protein, iron, and other micronutrients in a balanced manner, allowing for gradual improvement in the identified condition. Through this approach, the system contributes to stunting prevention efforts via targeted nutritional interventions that align with the clinical needs of each individual. Additionally, the system's confidence levels for each diagnosis are categorized into three distinct certainty thresholds below 50% (Not Indicated), between 50% - 80% (Possibly Indicated), and above 80% (Strongly Indicated). These categories are presented through a dedicated graphical visualization, which illustrates the distribution of certainty values across all evaluated hypotheses. This representation aims to provide a clearer understanding of how the system distinguishes varying degrees of diagnostic confidence based on the Certainty Factor calculation.

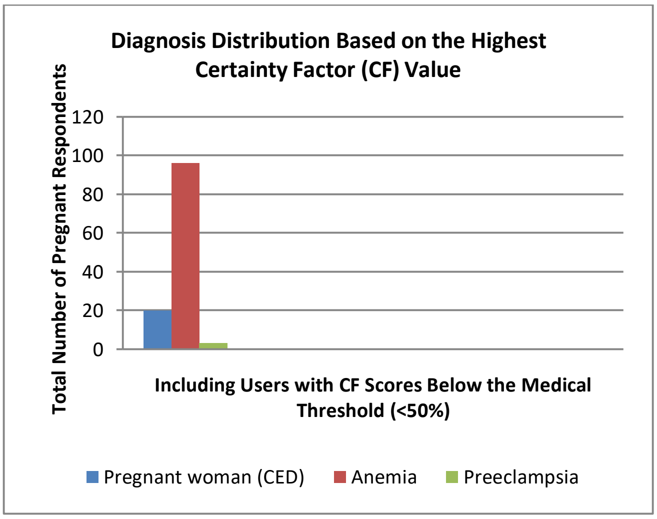

Figure 5. *Diagnosis by CF Value Range*

Figure 5 illustrates the distribution of expert system diagnoses based on Certainty Factor (CF) values for three maternal health conditions namely Chronic Energy Deficiency (CED), anemia, and preeclampsia. Among the 20 pregnant women identified with CED, 2 had CF values below 50%, 5 were within the 50–80% range, and 13 exceeded 80%. For anemia, of the 96 diagnosed cases, only 1 fell below 50%, 4 were in the 50–80% category, and 91 recorded CF values above 80%. In the case of preeclampsia, no respondents were found below the 50% threshold, 1 was between 50–80%, and 2 were above 80%. CF values between 50% and 80% suggest the possible presence of a health condition that warrants attention, preventive measures, and continued monitoring. CF values above 80% indicate a strong likelihood of the condition being present and therefore necessitate more serious medical consideration. It is important to emphasize that this expert system is intended as a decision-support tool rather than a replacement for professional clinical judgment. While the system demonstrates internally consistent logic and has been validated by medical experts with a 90% alignment rate compared to physicians' diagnoses, all diagnostic outcomes must still be confirmed through clinical consultation and physical examination. This is because the expert system evaluates conditions strictly through predefined formulas and expert-assigned confidence weights tied to specific symptoms. For instance, user-reported symptoms such as fatigue or dizziness may arise from causes unrelated to anemia, underscoring the necessity of comprehensive clinical assessment by qualified healthcare professionals before finalizing any diagnosis.

Follow-up evaluations involving participants who utilized the system indicated a positive impact on maternal health conditions. Respondents who were initially identified with a high degree of symptom certainty, as determined by the system's diagnostic process, later exhibited a noticeable decline in symptom certainty after following the recommended dietary menus. In several cases, symptoms that were previously prominent became significantly reduced or were no longer experienced following the adoption of the suggested dietary pattern. This suggests that, although the system does not offer a direct medical diagnosis, it may indirectly support improvements in maternal health through more appropriate nutritional intake. Accordingly, the system functions as an early-stage assistive tool that contributes to the prevention of conditions associated with the risk of stunting, while underscoring the importance of ongoing clinical evaluations and professional consultations to ensure medical accuracy.

IV. Conclusion

This study was conducted across 11 villages within the Muara Satu District of Lhokseumawe City, involving a total of 119 pregnant women as respondents identified through local posyandu (community-based health services). The intelligent system developed in this research was designed to analyze user-input symptoms and determine the likelihood of one of three maternal health conditions namely Chronic Energy Deficiency (CED), anemia, or preeclampsia. In addition to diagnosis, the system also delivered condition-specific nutritional meal recommendations for breakfast, lunch, and dinner to support maternal health outcomes.

Importantly, the system does not detect stunting directly. Instead, it focuses on identifying maternal health conditions that are clinically recognized as significant risk factors contributing to stunted growth in children. By intervening early and providing targeted food recommendation guidance, the system aims to indirectly support stunting prevention efforts through improved maternal care. The implementation results indicated that 20 pregnant women were diagnosed with CED, 96 with anemia, and 3 with preeclampsia. Among those identified with CED, 2 respondents recorded Certainty Factor (CF) values below 50%, 5 fell within the 50–80% range, and 13 exceeded 80%. For anemia, only 1 case had a CF value below 50%, 4 were within the 50–80% range, and 91 were strongly indicated with CF values above 80%. In the case of preeclampsia, none of the diagnoses were below the 50% threshold, 1 was within 50–80%, and 2 were above 80%.

These findings indicate that the system developed in this study is fundamentally rule-based, relying on predefined IF–THEN rules constructed from expert consultations to support its decision-making process. By adopting this rule-driven structure, the system is able to replicate expert reasoning systematically and ensure that each diagnostic outcome is grounded in medically validated logic. The integration of the Certainty Factor method further strengthens this framework by quantifying the level of diagnostic confidence based on both expert-derived weights and user-reported symptoms.

Validation conducted by a team of domain experts including obstetricians and nutritionists resulted in a 90% alignment rate between the system's diagnostic outputs and clinical evaluations. Nonetheless, the system is intended to function as a decision-support tool rather than a substitute for professional medical judgment. Therefore, all diagnostic outcomes should be clinically verified through direct examination and medical consultation to ensure accuracy and patient safety.

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