

Development of an Expert System for Diagnosing Toddler Nutritional Status Using a Participatory Design Approach

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Abstract—Assessing the nutritional status of a toddler remains an essential challenge for child health, since the process often requires professional expertise and may not always be readily available to the community. This work presents a web-based expert system to assist in assessing toddler nutritional status by combining the Certainty Factor method with the Participatory Design methodology. Nutritionists, Posyandu (Integrated Health Post) cadres, and parents of toddlers were actively involved in the development process, from identifying user requirements to designing the system to evaluating its functionality. The knowledge base consisted of 24 symptoms and six categories of nutritional status, representing expert knowledge, and the Certainty Factor approach was used to address the uncertainty in the diagnostic procedure. The resulting system offers integrated capabilities for Z-Score calculation, symptom-based consultation, nutritional status diagnosis, and follow-up suggestions. The diagnostic validation was performed on 30 selected toddler records and showed promising performance with 88.30% accuracy, 89.98% precision, 88.30% recall, and 87.08% F1-score. Moreover, the usability test conducted with 50 respondents yielded an average System Usability Scale (SUS) score of 79.15, which falls within the Acceptable category, namely Grade B or Good adjective rating. The results of this study show that the proposed system can efficiently enable early diagnosis of children's nutritional status while offering a user-friendly experience and high user approval.

Index Terms— Toddler nutritional status, expert system, certainty factor, participatory design, system usability scale.

I. INTRODUCTION

nutritional problems among toddlers remain a significant public health challenge in many countries, particularly in low- and middle-income nations [1], [2]. Toddlerhood represents a critical period that significantly influences a child's future physical, cognitive, and social development [3]. Therefore, ensuring adequate nutritional intake is essential for supporting optimal growth and development [4], [5]. Undernutrition and malnutrition can adversely affect physical growth, cognitive development, and future productivity [6]. Consequently, monitoring and early detection of nutritional status are essential for improving child health outcomes and public health [7], [8].

Although various health programs have been implemented to monitor and improve toddler nutritional status, cases of undernutrition and malnutrition continue to occur [4]. Regular monitoring of nutritional status is necessary to identify nutritional problems at an early stage and enable timely intervention [8], [9]. Access to accurate information on nutritional conditions and indicators is essential to support the early detection and monitoring of child growth and development [10].

Advances in information technology provide opportunities to develop solutions that enable the public to access health information more quickly and easily [11]. Expert systems are one type of technology. An expert system is a knowledge-based system designed to mimic human experts' decision-making abilities when addressing issues in a specific field [12]. In the healthcare sector, expert systems can serve as preliminary consultation tools that assist users in obtaining information about their conditions based on the symptoms they enter into the system [13], [14].

In this study, an expert system is used to assist in diagnosing toddlers' nutritional status based on anthropometric indicators and symptoms of their nutritional status. From a computational perspective, several approaches have been applied to healthcare diagnosis, including machine learning, Bayesian-based

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methods, fuzzy logic, and expert systems. Machine learning approaches can identify complex patterns in health-related data and have been applied to predicting childhood stunting using various classification algorithms [2]. Recent research has also combined ensemble and deep learning models with explainable artificial intelligence to improve predictive performance and interpretability in stunting prediction [2]. In addition, explainable AI has been used to enhance the transparency of complex medical diagnostic models by providing insights into the factors that underlie model predictions [15].

Probabilistic approaches, such as Naïve Bayes, provide a framework for representing uncertainty and have also been applied to the classification of nutritional status. For example, a previous expert system for assessing toddler nutritional status employed a Naïve Bayes classifier for classification [12]. However, probabilistic approaches rely on probabilistic relationships among variables, whereas expert systems can explicitly represent domain knowledge through diagnostic rules. Fuzzy logic provides another approach for handling imprecise information by representing conditions through degrees of membership. Hybrid approaches have also combined fuzzy inference with artificial intelligence to address ambiguity and uncertainty while maintaining interpretable reasoning [16]. These approaches demonstrate that uncertainty and interpretability remain important technical considerations in healthcare decision-support systems.

However, these approaches address uncertainty in different ways. Machine learning primarily teaches diagnostic patterns from historical data [2]. Fuzzy logic models imprecise conditions through membership functions [16]. In contrast, the Certainty Factor (CF) method represents an expert's confidence in the relationship between specific evidence and a diagnostic hypothesis [17], [18]. This distinction is important in the present study because diagnostic knowledge is explicitly derived from nutrition experts and anthropometric indicators rather than being learned solely from a predictive model. CF therefore provides a rule-based inference mechanism in which expert knowledge and confidence values can be explicitly incorporated into the diagnostic process [19], [20]. The reasoning process can also be traced through the evidence, expert weight, and resulting confidence value for each nutritional status category [21].

Although machine learning, Bayesian-based methods, fuzzy logic, and explainable AI have increasingly been applied to healthcare and nutritional problems, these approaches primarily emphasize data-driven prediction, probabilistic inference, ambiguity modeling, or explanation of learned models. There remains a technical gap in developing an interpretable, knowledge-based diagnostic mechanism that explicitly combines expert-defined rules with confidence values for assessing toddler nutritional status. This study addresses this gap by applying the certainty factor method to represent expert knowledge and handle uncertainty in diagnosing six categories of toddler nutritional status, based on 24 symptoms and anthropometric indicators.

In addition to diagnostic accuracy, the success of an

information system is influenced by how well it meets user needs. Many healthcare systems are developed with a primary focus on technical functionality while paying limited attention to the needs, experiences, and characteristics of end users. As a result, these systems may experience low levels of user acceptance and utilization despite having sound technical capabilities [22].

One approach to address this issue is Participatory Design. Participatory Design is a system development approach that actively involves users throughout the design and development process [23]. Through this approach, users not only act as recipients of the system but also contribute by providing requirements, feedback, and evaluations during the system development process. Early user involvement is expected to result in a system that is easier to use, better aligned with user needs, and more widely accepted [23].

While previous studies have demonstrated the potential of computational approaches for healthcare diagnosis and nutritional assessment, limited attention has been paid to integrating an interpretable uncertainty-handling mechanism into a user-centered system development approach for diagnosing toddler nutritional status. What distinguishes this work is the integration of participatory design with the certainty factor method, combining explicit expert-based uncertainty reasoning with active involvement of intended users throughout system development. This integration is intended to ensure that the diagnostic mechanism remains interpretable while the resulting system is aligned with the needs and practical conditions of its users.

Considering these difficulties, this study aims to develop an expert system for diagnosing toddlers' nutritional status by integrating the participatory design approach with the certainty factor method. Participatory design involves end users throughout the system development process, ensuring that the resulting system reflects their needs and expectations. Meanwhile, the certainty factor method is employed to handle uncertainty in the diagnostic process based on expert knowledge. The proposed system is expected to provide parents with accessible preliminary information about their toddlers' nutritional status and support the early detection of nutritional problems.

II. RESEARCH METHODS

This project employs a participatory design approach to develop an expert system that applies the Certainty Factor method to diagnose the nutritional status of toddlers. This strategy was chosen because it enables users and stakeholders to participate actively in the system design and development process, ensuring that the final product more accurately reflects user requirements and expectations. User needs identification, co-design, system development, usability testing, and system evaluation are just a few of the processes that make up the Research and Development (R&D) framework, which the research methodology adheres to. Through these stages, the study aims to develop an expert system that not only provides nutritional status diagnoses based on expert knowledge and

confidence levels but also demonstrates high usability and user acceptance [23].

A. Research Design

This research is a research and development (R&D) study aimed at developing an expert system for diagnosing toddler nutritional status using the certainty factor method with a participatory design approach. The Participatory Design approach was implemented to actively involve users and stakeholders in the system development process, ensuring that user needs and input are incorporated from the early design stages. Meanwhile, the certainty factor method is used as an inference mechanism to account for uncertainty in diagnosing nutritional status from user-entered symptoms.

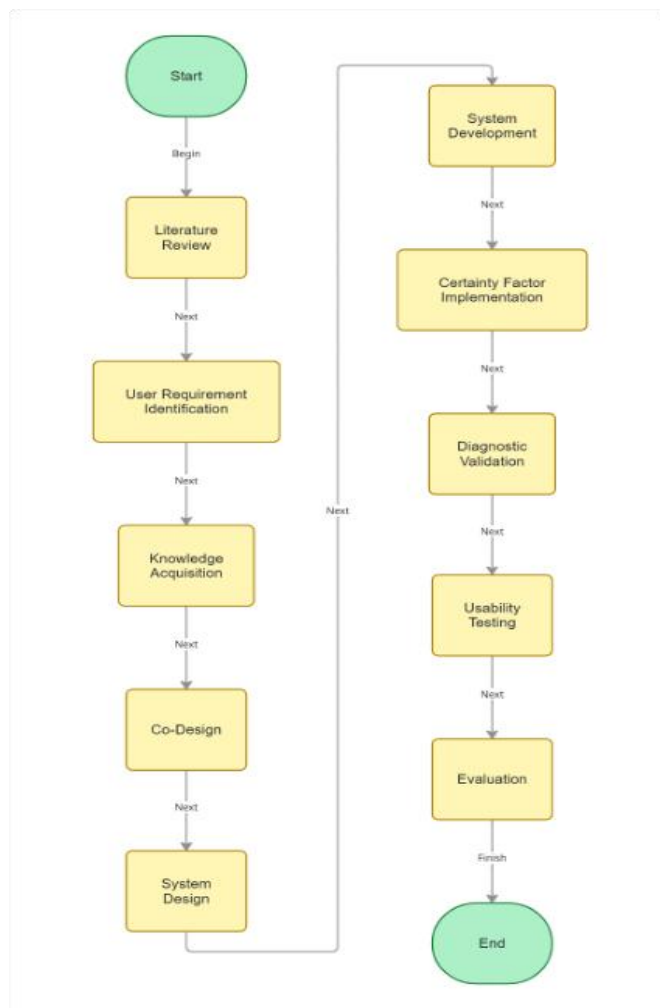


Fig. 1. Research design.

The research process consists of several stages: identifying user needs, acquiring expert knowledge, designing the system through co-design, developing the expert system, implementing the certainty factor method, and testing and evaluating the system. These stages are designed to produce a system that not only has good diagnostic capabilities but is also easy to use and

meets user needs.

Figure 1 shows the research stages used to develop an expert system for diagnosing toddlers' nutritional status, based on the certainty factor method and a participatory design approach. The research began with a literature review to examine related theories, methods, and research. Next, user requirements were identified to inform the development of the system. The next stage was knowledge acquisition, which involved gathering knowledge from nutrition experts to form the system's knowledge base. The results of this stage were then used in a co-design process involving users and experts in system design.

Following the completion of the requirements analysis and system design phases, the system was developed to implement the proposed expert system application. Subsequently, the certainty factor method was integrated into the system to handle uncertainty in diagnosing toddlers' nutritional status based on user-provided symptoms. Finally, testing and evaluation were conducted to assess the system's functionality, usability, and ability to meet user requirements and expectations.

B. Participants and Data Collection

This study used a Participatory Design approach that involved stakeholders who directly participate in monitoring and determining the nutritional status of toddlers [23]. The research participants consisted of a nutritionist from the community health center, a village midwife, four Posyandu (Integrated Health Post) cadres, and several parents of toddlers who actively participate in Posyandu activities. Participants were purposively selected because they have relevant experience and knowledge in monitoring the nutritional status of toddlers and are potential users of the system to be developed [24].

To develop and validate the diagnostic knowledge base, 31,740 toddler records from the 2024 dataset were used. The dataset was obtained from Mendeley Data and contains anthropometric and demographic information on toddlers from Jeneponto Regency, South Sulawesi, Indonesia, including gender, age, weight, height, weight-for-age, height-for-age, weight-for-height, and their corresponding Z-scores. The nutritional status classifications in the dataset were used as reference information for formulating and evaluating the diagnostic rules. From this dataset, 30 toddler records were selected as validation cases and subsequently entered into the developed expert system. The diagnoses generated by the system were compared with the corresponding reference classifications to evaluate diagnostic performance.

Data collection was conducted using several techniques. First, semi-structured interviews were conducted with nutritionists and village midwives to gain knowledge about toddler nutritional status indicators, the process of determining nutritional status, symptoms of nutritional problems, and the confidence weights used in the certainty factor method. Second, observations were conducted at Posyandu activities to

understand the current workflow, from measuring toddlers' height and weight, recording data, and reporting test results to relevant parties. Third, group discussions and participatory sessions were conducted with Posyandu cadres and toddlers' parents to identify user needs, obstacles faced in obtaining nutritional status information, and input on the design of the system to be developed. In addition, a documentation study was conducted by reviewing the Indonesian Ministry of Health's anthropometric standards, Maternal and Child Health (MCH) handbooks, and other supporting documents for assessing toddler nutritional status.

The data obtained from these activities were then analyzed and used to compile system requirements. Through a participatory design approach, participants were actively involved in identifying needs, designing, and evaluating the system, ensuring that the expert system developed aligned with user needs and supported the diagnosis of toddler nutritional status more effectively and accurately [25].

C. Co-Design Process

The co-design process was carried out by actively involving all participants in developing an expert system to diagnose toddlers' nutritional status [23]. This approach aims to ensure that the developed system aligns with user needs and effectively supports the identification of toddlers' nutritional status [26]. Through the participatory design principle, users not only act as sources of information, but also as partners in the system design process [27].

The first stage involved identifying user needs through interviews, observations, and discussions with nutritionists, village midwives, Posyandu cadres, and parents of toddlers. This stage provided information regarding the current nutritional status monitoring process, challenges in obtaining rapid diagnostic results, and the information requirements expected to be available in the system.

The second stage was the initial system design. Based on the identified needs, a design for the system's main features was developed, including toddler data management, Z-score calculation, symptom consultation, the diagnostic process using the certainty factor method, and the presentation of diagnostic results and treatment recommendations. The design was then visualized as a process flow diagram and an initial system interface.

The third stage was a design evaluation with participants. The design was presented to users to obtain feedback on ease of use, information completeness, and the system's flow and suitability for the processes carried out at the Posyandu. All input was documented and used as the basis for design improvements.

The final stage was design refinement. During this stage, revisions were made to the system's features, workflow, and interface based on the participant evaluation results. The results of these improvements form the basis for developing an expert system to diagnose toddlers' nutritional status, which is expected to support more rapid, easier, and more accurate identification.

D. Development of Expert System

The development of an expert system for diagnosing toddlers' nutritional status was based on user needs identified through a co-design process. The knowledge used in the system was obtained from nutritionists, the Indonesian Ministry of Health's anthropometric guidelines, and discussions with midwives and Posyandu cadres [22]. This knowledge is represented as a knowledge base that connects symptoms, Z-score values, and categories of toddler nutritional status.

The system's diagnostic process uses the certainty factor method to calculate the confidence level for each possible nutritional status based on user-selected symptoms and expert-assigned weights. This method was chosen because it can accommodate the uncertainty that often arises in expert-based decision-making.

The development results are implemented in a web-based application that provides Z-score calculation, symptom consultation, nutritional status diagnosis, and recommendations, serving as initial information for parents and health workers in monitoring the nutritional condition of toddlers.

E. Certainty Factor Method

The certainty factor (CF) method is used to determine the level of confidence in a nutritional status assessment based on user-selected symptoms and the confidence weight assigned by the expert. This method accommodates uncertainty in the decision-making process, making it suitable for use in expert systems for diagnosing toddlers' nutritional status [17]. The certainty factor value for each symptom is calculated using the following equation [19]:

$$CF(\text{Hypothesis, Evidence}) = CF(E) \times CF(\text{RULE}) \quad (1)$$

Hypothesis (H) represents the category of toddler nutritional status to be determined, while E (Evidence) represents the observed symptoms and indicators. CF (Evidence) indicates the user's confidence in the selected symptoms, while CF (RULE) indicates the expert's confidence in the relationship between symptoms and nutritional status. The CF(RULE) values were determined through expert elicitation by a nutritionist who assessed the strength of the relationship between each symptom and nutritional status category. Each symptom-rule relationship was assigned a confidence value based on the expert's assessment. The CF (Hypothesis, Evidence) value describes the system's confidence in nutritional status based on available evidence. If there is more than one symptom that supports nutritional status, the Certainty Factor values are combined using (2).

$$CF_{\text{combine}} = CF_1 + CF_2 \times (1 - CF_1) \quad (2)$$

CF_1 is the certainty factor from the previous calculation, while CF_2 is the certainty factor for the next symptom to be combined. The calculation results are performed for each nutritional status category, and the system then selects the highest Certainty Factor value as the diagnosis of the toddler's

nutritional status.

For system validation, 30 toddler records were selected from the dataset and processed through the developed application. The resulting diagnoses were compared with the reference nutritional status classifications.

F. Usability Testing

Usability testing was conducted using the System Usability Scale (SUS) method to evaluate the ease of use of the expert system for diagnosing toddler nutritional status. The testing involved nutritionists, village midwives, Posyandu cadres, and parents of toddlers as potential users of the system.

The SUS instrument consists of 10 statements rated on a five-point Likert scale: Strongly Disagree (1), Disagree (2), Neutral (3), Agree (4), and Strongly Agree (5). Odd-numbered statements represent positive aspects of the system, while even-numbered statements represent negative aspects. After using all the system's main features, participants were asked to complete the SUS questionnaire based on their user experience [28].

Subtracting 1 from the scores on odd-numbered statements and 5 from the scores on even-numbered statements yields the SUS score. A SUS score between 0 and 100 is then generated by multiplying the overall contribution score by 2.5.

$$SUS = \{(S_1 - 1) + (5 - S_2) + (S_{13} - 1) + (5 - S_4) + (S_5 - 1) + (5 - S_6) + (S_7 - 1) + (5 + S_8) + (S_9 - 1) + (5 - S_{10})\} \times 2.5 \quad (3)$$

The responses to the ten SUS questionnaire items are indicated by the variables S1–S10. Contribution scores are determined by subtracting 1 from the chosen response for odd-numbered items and subtracting the response value from 5 for even-numbered items. The final SUS score, on a scale of 0–100, is then obtained by multiplying the total contribution score by 2.5.

Table 1.
SUS Questionnaire

No	Question
1	I believe I would want to use this system frequently.
2	The system seemed overly complicated to me. I found the system to be user-friendly.
3	I believe that in order to use this system, I would require technical assistance.
4	I thought this system's many features were nicely integrated.
5	I felt that this system was overly inconsistent.
6	I noticed too many inconsistencies within the system.
7	I believe that most users would learn to use this system very quickly.
8	I found the system difficult and cumbersome to use.
9	I felt confident while using this system.
10	I had to learn many things before I could use this system effectively.

The resulting SUS score was analyzed using the acceptability range, grade scale, and adjective rating framework to assess the system's usability and user acceptance. A SUS score above 68 indicates that the system is generally acceptable, whereas progressively higher scores reflect better

usability performance and a more positive user experience. The system usability scale (SUS) questionnaire used in this study consists of ten items, as presented in Table 1.

G. Evaluation

A usability evaluation was conducted using the System Usability Scale (SUS) questionnaire. The SUS score for each respondent was computed and subsequently averaged to determine the overall level of user acceptance of the proposed system. The evaluation focused on assessing usability aspects, including ease of use, efficiency, and user satisfaction during system interaction [29]. The interpretation of SUS scores used in this study is shown in Table 2.

Table 2.

System Usability Scale Statement

Skor SUS	Intepretation
> 80.3	Acceptable, Grade A, Excellent
68 - 80.3	Acceptable, Grade B/C, Good
51 - 67	Marginal, Grade D, OK
< 51	Not Acceptable, Grade F, Poor

In addition to quantitative analysis of SUS scores, feedback and suggestions from participants during testing were evaluated. This feedback was used to identify system strengths and areas requiring improvement. The evaluation results served as the basis for refining the system to better meet user needs and support the effective diagnosis of toddler nutritional status.

III. RESULTS

This section presents the results of developing an expert system for diagnosing toddlers' nutritional status using the certainty factor method and a participatory design approach. The research findings include the characteristics of the participants involved, the identification of user needs through a co-design process, the development of the expert system, diagnostic testing using the certainty factor method, and an evaluation of the system's usability based on user perceptions. All of these results were used to assess the system's suitability to user needs and its effectiveness in supporting the process of diagnosing toddler nutritional status.

A. Participant Characteristics

This study involved 15 participants who were key stakeholders in monitoring and determining the nutritional status of toddlers. Participants included one nutritionist, four Posyandu cadres, and 10 parents of toddlers. Nutritionists served as the primary source of knowledge in developing the system's knowledge base, including identifying symptoms, determining nutritional status categories, and assigning confidence weights to each diagnostic rule. Posyandu cadres contributed information on the service flow and toddler growth monitoring in the field. At the same time, parents acted as potential system users, providing input on the application's needs and ease of use.

Participant involvement was carried out at several stages of

the research, starting from identifying user needs, gathering expert knowledge, evaluating the system design, and testing usability. The participatory design approach enabled all participant groups to contribute to the system development process actively, ensuring that the resulting application better aligns with user needs and the real-world conditions in the Posyandu environment.

Table 3 shows the distribution of participants involved in the study. Participants had varying experiences depending on their roles. Nutritionists were competent in assessing the nutritional status of toddlers; Posyandu cadres had experience in monitoring toddler growth at the community level; and parents of toddlers were the end users who would use the system to obtain initial information about their children's nutritional status. The involvement of these diverse participant groups provided a comprehensive perspective in the development and evaluation of the expert system. The characteristics of the participants involved in this study are summarized in Table 3.

Table 3.
Characteristics of Research Participants

Participant Group	No.	Role
Nutritionists	1	Validation of knowledge, diagnostic rules, and the accuracy of nutritional status identification
Posyandu cadres	4	Identification of user needs and system evaluation
Parents of toddlers	10	System testing and usability evaluation

B. Co-Design Results

The co-design activity involved nutritionists, Posyandu cadres, and parents of toddlers to identify user needs and design key features for implementation in the expert system. Through discussion sessions and interviews, various inputs were obtained that served as the basis for the system's development.

Table 4 summarizes the input obtained from each participant group during the co-design activity and its implementation in the developed system. Nutritionists made key contributions to the development of the knowledge base, including symptom identification, nutritional status classification, and the determination of certainty factor values used in the inference process. Posyandu cadres focused on the operational aspects of the system, emphasizing the need for a simple, user-friendly interface to monitor toddlers. Meanwhile, parents of toddlers provided input regarding the need for easy-to-understand information, particularly in the presentation of diagnostic results and follow-up recommendations. Input from these three participant groups formed the basis for designing the system's key features, ensuring the resulting application meets user needs from various perspectives. Posyandu cadres proposed that the system have a simple, user-friendly interface. They also highlighted the need for an integrated Z-Score calculation feature to accelerate the determination of nutritional status compared with the manual procedures currently used.

Meanwhile, parents of toddlers desired a system that could clearly display diagnostic results along with recommendations for follow-up. Based on this input, the system was designed to

display the confidence level of the diagnostic results as a percentage and provide information and advice based on the identified nutritional status.

Based on the co-design results, several main system requirements were successfully identified, namely: (1) Z-score calculation feature, (2) symptom-based consultation feature, (3) diagnosis mechanism using the Certainty Factor method, (4) presentation of diagnosis results in the form of a percentage level of confidence, and (5) treatment recommendations based on the diagnosis results. These requirements were then translated into a system design and served as the basis for developing an expert system application to diagnose toddlers' nutritional status. The main components implemented in the developed expert system are presented in Table 4.

Table 4.
Components of the Developed Expert System

Components	Quantity
Nutritional status	6
Symptoms	24
User Confidence Levels	5
Calculation Modules	2 (Z-Score and Certainty Factor)

C. Expert System Development Results

Based on the requirements identified in the co-design process, a web-based application for diagnosing toddler nutritional status was successfully developed. The system integrates expert nutrition knowledge with the Certainty Factor method to facilitate faster, more structured identification of toddlers' nutritional status.

Table 5.
Co-Design Results Summary

Nutritionists	Input	System Implementation
Nutritionists	Determination of symptoms, nutritional status categories, and diagnostic weights	Knowledge base and diagnostic rules implemented in the system
Posyandu cadres	A simpler and faster diagnosis process	User-friendly interface design
Parents of toddlers	Easy-to-understand diagnostic results	Presentation of diagnosis percentages and recommendations

Table 5 shows the main components successfully implemented in the expert system. The knowledge base consists of 24 symptoms and six nutritional status categories: well-nourished, undernourished, severely malnourished, overnourished, at risk of overnourishment, and obese. Each symptom is linked to a specific nutritional status category through rules validated by nutritionists and used in the certainty-factor calculation. The system also features Z-Score calculations, symptom-based consultations, and presentation of diagnostic results as a percentage confidence level. These developments have resulted in a system that helps users quickly and easily identify toddlers' initial nutritional status.

D. Certainty Factor Diagnosis Results

The system also features Z-score calculations, symptom-based consultations, and presentation of diagnostic results as a percentage confidence level. These developments

have resulted in a system that helps users quickly and easily identify toddlers' initial nutritional status. Diagnostic testing was conducted to assess the system's ability to determine toddlers' nutritional status based on user-selected symptoms and confidence levels. The system then calculated the level of certainty using the certainty factor method and generated a diagnosis with the highest confidence value. Diagnostic validation was conducted using 30 selected toddler records from the 2024 dataset. Each selected case was entered into the developed expert system using its anthropometric characteristics and nutritional indicators. The system generated a nutritional status diagnosis and a corresponding Certainty Factor confidence value. The resulting diagnoses were then compared with the reference classifications obtained from the dataset.

The validation results showed that the proposed expert system achieved an accuracy of 88.30%, precision of 89.98%, recall of 88.30%, and F1-score of 87.08%. These results indicate that the certainty factor-based diagnostic mechanism produced nutritional status classifications that were generally consistent with the reference classifications. Examples of nutritional status diagnosis results generated by the Certainty Factor method are shown in Table 6. The performance evaluation results of the diagnostic system are presented in Table 7.

Table 6.
Diagnosis Results Using the Certainty Factor Method

No	Gender	Age (Month)	Weight	Height	Diagnostic Result	CF (%)
1	M	38	12.5	86.5	Well-nourished	87.50
2	F	45	12.5	87.5	Well-nourished	87.5
3	F	16	10	69.1	Obese	100
4	M	55	13.3	94.1	Undernourished	93.75
5	M	31	9.3	85.0	Severely malnourished	100
⋮	⋮	⋮	⋮	⋮	⋮	⋮
30	F	3	5.5	52	Obese	100

Table 7.
Diagnosis Performance Evaluation Result

Metric	Score (%)
Accuracy	88.30
Precision	89.98
Recall	88.30
F1-Score	87.08

E. System Architecture

The developed expert system is implemented as a web-based application using the Laravel 11 framework, with MySQL serving as the database management system. Its architecture is structured into three primary layers: the presentation layer, application layer, and data layer. The presentation layer provides a responsive, user-friendly interface that enables nutritionists, Posyandu cadres, and parents to

access the system via standard web browsers. The application layer is responsible for handling the core functionalities of the system, including user authentication, Z-score calculations, symptom-based consultations, CF reasoning processes, and report generation. Meanwhile, the data layer manages and stores essential information, including user accounts, toddler profiles, symptom records, nutritional status classifications, diagnostic rules, consultation histories, and diagnostic outcomes. To ensure reliable operation, the system is deployed on an Ubuntu server environment with Nginx as the web server, PHP 8.3 as the runtime, and MySQL 8.0 as the database server. This architectural design enables efficient diagnostic processing while maintaining flexibility, scalability, ease of maintenance, and broad accessibility.

Figure 2 presents the architecture of the proposed expert system for diagnosing toddlers' nutritional status. The architecture comprises several interconnected components, including the user layer, web interface layer, application layer, knowledge base and database layer, as well as a CF inference engine. These components work together to process consultation data and generate diagnoses of nutritional status, along with appropriate recommendations. The system is hosted on an Ubuntu-based server infrastructure and utilizes Laravel 11, PHP 8.3, Nginx, and MySQL 8.0 to support its operation and performance. Figure 2 illustrates the architecture of the proposed expert system.

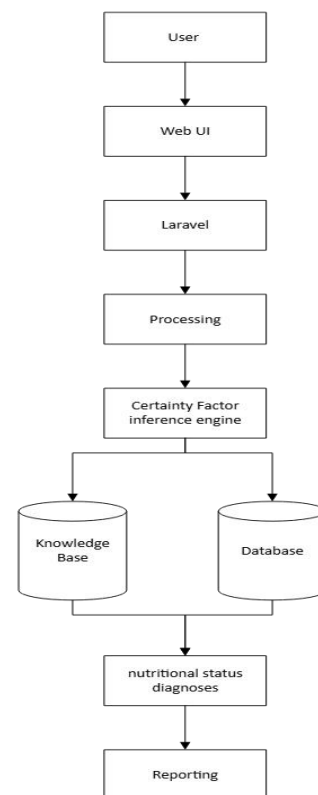


Fig. 2. System architecture of the proposed expert system.

F. Z-Score Calculation and Inference Engine

The proposed expert method aims to determine the toddler's nutritional status in two steps: Z-score calculation and certainty factor (CF)-based diagnosis. First, users provide the toddler's age, gender, weight, and height. Then the Z-score is compared with anthropometric growth criteria, giving an initial indication of nutritional condition. Figure 3 presents the Z-score calculation and certainty factor inference process.

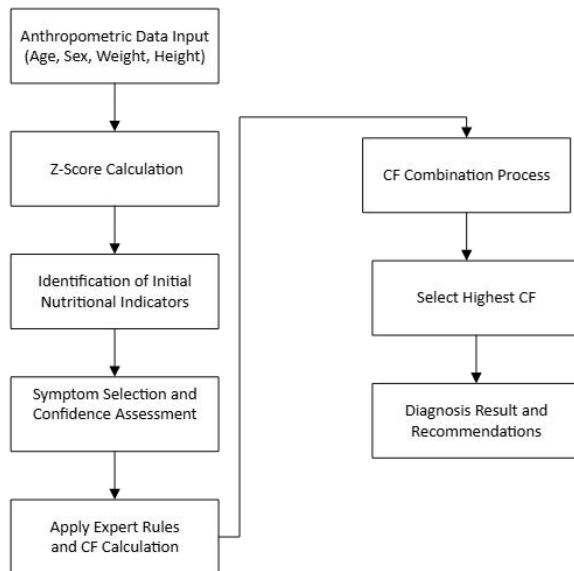


Fig. 3. Z-score calculation and certainty-factor inference process.

Next, users select symptoms that match the toddler's condition and rate their confidence in each selection. The system processes the information using a set of rules provided by experts and computes the CF for each nutritional status category. If several symptoms support the same diagnosis, their CF values are merged to an overall confidence level. The final diagnosis is then chosen based on the category of nutritional status with the greatest confidence value and given together with recommendations for further action.

G. Application Interface Results

An expert system for diagnosing toddlers' nutritional status was successfully implemented as a web-based application, informed by user needs identified through a co-design process. The system interface provides key features to support the diagnosis of a toddler's nutritional status. The application was implemented with a responsive interface to support access across different screen sizes, allowing users to access the main features and information on both desktop and mobile devices.

The application was developed using the Laravel framework and MySQL as the database management system for storing and managing system data. The application was deployed on a Virtual Private Server (VPS), allowing users to access the web-based system via the internet. Figure 4 shows the dashboard page, which serves as the system's main page after a user successfully logs in to the application. This page displays summary information about the data stored in the system. It provides a navigation menu to access key features, including toddler data management, Z-score calculations,

diagnostic consultations, and diagnostic results.

Figure 4 shows the login page used to authenticate users before accessing the system. Figure 5 shows the Z-Score calculation page used to determine a toddler's growth status based on anthropometric data. Figure 6 presents the diagnosis results page, where users can view the toddler's nutritional status determined by the system using the CF method.

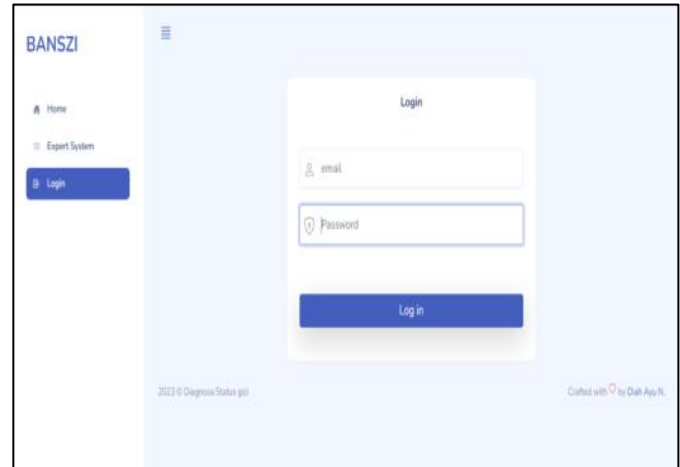


Fig. 4. Login page.

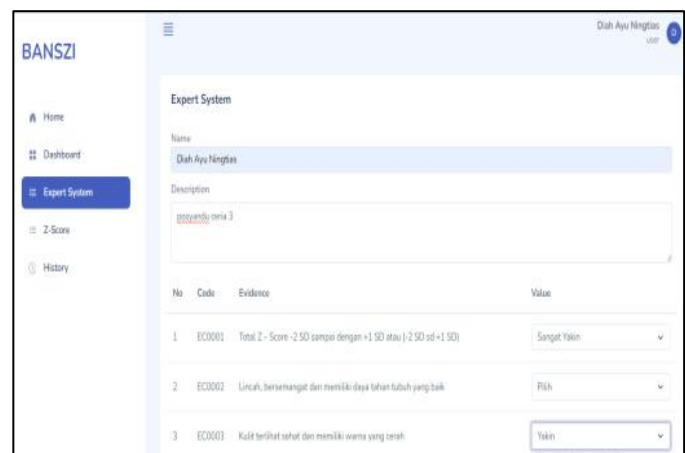


Fig. 5. Z-score calculation page.



Fig. 6. Diagnosis consultation page.

H. Usability Testing Results

Usability testing was conducted to evaluate the ease of use of the expert system for diagnosing toddlers' nutritional status using the SUS method. Fifty participants, including nutritionists, village midwives, Posyandu cadres, and parents of toddlers, participated in the testing. The average SUS score was 79.15, with a minimum score of 65.00 and a maximum score of 92.50. Usability testing was conducted with 50 respondents, consisting of nutritionists, village midwives, Posyandu cadres, and parents of toddlers. Based on the results of SUS evaluation, the system achieved an average score of 79.15. According to SUS interpretation guidelines, this score falls within the Acceptable category, corresponds to Grade Scale B, and receives an Adjective Rating of Good. These results indicate that the system has a high level of usability and is well accepted by users. Participants were able to understand and navigate the system with relative ease, from entering user data and selecting symptoms to viewing the system-generated nutritional status diagnosis results. Summary statistics of the SUS evaluation are presented in Table 8. The interpretation of the obtained SUS score is shown in Table 9.

Table 8.
Summary of SUS Test Results

Metric	Score
Number of respondents	50
Average SUS score	79.15
Minimum score	65.00
Maximum score	92.50

Table 9.
SUS Score Interpretation Results

Skor SUS	Acceptability Range	Grade Scale	Adjective Rating
79.15	Acceptable	B	Good

I. Evaluation

The research results show that the Participatory Design approach successfully helped develop an expert system that met user needs. The involvement of various stakeholders in the design process enabled the system to be developed based on real-world needs. At the same time, the Certainty Factor method provided diagnostic results with a level of confidence. Usability testing results showed that the system had a good level of acceptance, with ratings of Acceptable, Grade Scale B, and Adjective Rating Good. These findings demonstrate that the system is not only capable of diagnosing toddler nutritional status but is also easy to use.

IV. DISCUSSION

The results demonstrate that integrating the Certainty Factor method successfully supported the diagnosis of toddlers' nutritional status in the developed expert system. Validation using 30 selected toddler records produced an accuracy of 88.30%, precision of 89.98%, recall of 88.30%, and F1-score of 87.08%. These results indicate that the system generated diagnoses that were generally consistent with the reference

classifications.

The precision value of 89.98% indicates that most diagnoses generated by the system corresponded to the reference classifications. Meanwhile, the recall of 88.30% indicates that the system correctly identified most of the nutritional status cases in the validation data. The F1-score of 87.08% further indicates that the system maintained a relatively balanced performance between precision and recall.

Compared with the hybrid machine learning model proposed in [2], which combined an extra tree and a multilayer perceptron (MLP), the proposed system achieved a diagnostic performance that was relatively close. The hybrid model reported an accuracy, precision, and recall of 94%, with an F1-score of 95%, while the proposed certainty factor-based system achieved 88.30%, 89.98%, 88.30%, and 87.08%, respectively. Although the hybrid model achieved higher performance across all evaluation metrics, the proposed system's results approached those of the more complex hybrid approach, particularly in accuracy, precision, and recall. This comparison indicates that the rule-based Certainty Factor approach can provide promising diagnostic performance while relying on expert-defined knowledge and a simpler inference mechanism [2].

The diagnostic process is supported by the certainty factor method, which allows the system to calculate the confidence associated with each possible nutritional status based on the available evidence and expert-defined confidence weights. The system then selects the nutritional status with the highest resulting certainty value. This mechanism enables the diagnostic output to be presented not only as a classification but also as a percentage representing the system's confidence.

The participatory design approach also helped align the system with the needs of its intended users. Input from nutritionists, Posyandu cadres, and parents were incorporated into features such as Z-Score calculation, symptom-based consultation, diagnostic results, confidence percentages, and recommendations. This integration demonstrates that the development process considered both the diagnostic mechanism and users' practical requirements.

Accessibility considerations were incorporated into the system design by emphasizing simplicity and clarity, informed by user input gathered during the participatory design process. Posyandu cadres highlighted the need for a simple and user-friendly interface to support the diagnostic process, while parents emphasized the importance of easy-to-understand diagnostic information. In response, the system provides clear navigation to its main features and presents diagnostic results through confidence percentages and follow-up recommendations. These design considerations were intended to make the system easier for users with varying levels of familiarity with digital health systems to access and understand.

Recent usability studies provide further context for this result. A digital medical history-taking application obtained a

mean SUS score of 77.8 [30], while another healthcare application achieved an average SUS score of 78.8 [31]. Both values are slightly lower than the SUS score of 79.15 achieved by the developed system, indicating a comparable level of usability across the systems. Although the applications differed in their healthcare purposes and target users, these comparisons suggest that the developed expert system achieved a favorable level of usability among its intended users.

The diagnostic performance, usability, and user experience of the proposed system were examined. The diagnostic performance was evaluated using accuracy, precision, recall, and F1-score by comparing the diagnoses generated by the system with the reference nutritional status classifications. We used the System Usability Scale (SUS) to measure usability and interpreted the results in accordance with typical SUS standards and by comparing them with similar healthcare applications. Furthermore, input from nutritionists, Posyandu cadres, and parents were collected to highlight strengths and weaknesses, particularly regarding interface usability, diagnostic information, and recommended features. These combined assessments offered a full evaluation of the system's efficacy and user approval.

Despite these findings, the developed system has several limitations. The diagnostic process relies on a static rule base and expert-defined confidence weights, which do not automatically adapt as new data becomes available. In addition, the current knowledge base is limited to 24 symptoms used to support the diagnosis of six nutritional status categories. The diagnostic performance was also evaluated using 30 selected toddler records, which may limit the generalizability of the results to broader and more diverse populations.

Future work may focus on optimizing the rule base and certainty values using machine learning techniques based on larger datasets to develop a more adaptive diagnostic mechanism. Integration with mobile or IoT-based anthropometric measurement devices may also be explored to support more automated data acquisition and assessment of nutritional status. Further validation with larger, more diverse datasets would also be beneficial for assessing the system's consistency and generalizability.

V. CONCLUSION AND FUTURE WORK

This research has developed a web-based expert system to diagnose toddler nutritional status by integrating the participatory design technique and the certainty factor method. The development process involved nutritionists, Posyandu cadres, and parents, which helped ensure the system responded to users' genuine needs and aligned with actual practices in toddler growth tracking. The resultant application provides integrated functions of Z-score computation, symptom-based consultation, nutritional status diagnosis, confidence level estimation, and follow-up suggestions.

The evaluation results demonstrated that the proposed method could serve as a useful decision-support tool for early identification of a child's nutritional status. Validation on 30 selected toddler records showed promising diagnostic

performance, with 88.30% accuracy, 89.98% precision, 88.30% recall, and 87.08% F1-score. The system obtained an average SUS score of 79.15 from 50 respondents, which falls within the Acceptable category (Grade B) and indicates a Good level of usability. The results show that the system can reliably facilitate diagnosis, while being accessible and straightforward to operate for users.

However, there are a few limitations to note. The existing diagnostic method is based on a pre-defined rule base and expert-supplied certainty ratings, so the system does not automatically adjust to changes in knowledge or newly accessible data. Moreover, the knowledge base includes only 24 symptoms and 6 nutritional status categories, which may not cover the full range of diseases experienced. The diagnostic evaluation was also performed with a relatively small number of validation instances, which may impair the generalizability of the given performance results.

Future work may focus on improving system adaptability and scalability. This can be accomplished by using larger and more diverse datasets, improving diagnostic procedures, and investigating the integration of machine learning approaches that complement expert knowledge. In addition, extending the system to mobile platforms and integrating it with digital anthropometric measurement devices could facilitate more efficient data collection and real-time nutritional monitoring. Further testing a variety of healthcare settings would be useful for the dependability and practical usability of the suggested system.

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