

## Expert system for early detection of stunting nutritional status in toddlers using the forward chaining method (studi kasus: penajam paser utara regency)

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### Abstract

*Stunting is a chronic nutritional problem in toddlers that can negatively affect physical growth, cognitive development, and overall quality of life in the long term. In 2023, the prevalence of stunting in Penajam Paser Utara Regency reached 9.67%, with 648 stunted toddlers out of 6,702 recorded toddlers. Among the districts, Sepaku District contributed the highest percentage of cases at 17.19%. These conditions indicate the need for a fast and accurate decision support system to assist early detection and prevention efforts. This study aims to design an expert system for early stunting detection using the Forward Chaining algorithm. The method applies a rule-based reasoning approach by tracing facts provided by users, including gender, age, and height, and matching them with a knowledge base derived from official child growth and nutritional standards. The system processes these facts through IF-THEN rules to generate conclusions regarding the nutritional status of toddlers, categorized as either Stunting or Normal. System testing was conducted through simulations using sample toddler data to evaluate the accuracy of the rule-matching process. The results indicate that the Forward Chaining method is capable of classifying nutritional status accurately and consistently based on fact tracing and predefined rules. The developed expert system can support health workers and Posyandu cadres in conducting early screening and decision-making in stunting-prone areas. Furthermore, this research is expected to contribute to the development of intelligent health-support applications for community-based child nutrition monitoring and intervention programs.*

### 1. Introduction

Stunting is a physical growth disorder in toddlers characterized by a height that is below the standard for their age due to chronic malnutrition. This condition is the focus of government intervention because it adversely affects the intelligence levels and productivity of future generations. Based on aggregate data from Penajam Paser Utara Regency in 2023, stunting remains a significant clinical and social challenge at the district level. Out of a total of 6,702 toddlers recorded in the region, as many as 648 children were identified as experiencing stunting. Overall, the regency-wide stunting prevalence rate reached 9.67% [1].

The distribution of stunting cases in this region shows quite sharp disparities between districts. Sepaku District recorded the highest stunting prevalence at 17.19%, with 203 stunting toddlers out of a total of 1,181 toddlers. This figure was followed by Babulu District with a prevalence of 11.51% (167 cases out of 1,451 toddlers) and Penajam District with a prevalence of 9.45% (264 cases out of 2,795 toddlers). Meanwhile, Waru District had the lowest prevalence, at 1.1%, stemming from 14 stunting cases among 1,275 toddlers. If not treated optimally, this condition can develop into serious complications and premature death[2].

Therefore, prompt and accurate early detection is the main key to preventing the deterioration of the patient's condition. Advancements in information technology, particularly in the field of Artificial Intelligence, open up significant opportunities in supporting the medical diagnosis process[3]. One branch of artificial intelligence that is widely applied is machine learning, which is capable of building prediction models based on patients' historical data[4].

The high variation in prevalence rates and the concentration of cases in certain districts underscore the need for a practical early detection system that is equally accessible to ordinary citizens and Posyandu health workers without always having to wait for a specialist doctor's diagnosis. Artificial Intelligence (AI), particularly the Expert System branch, has the capability to replicate the analytical skills of nutritionists into a software application. In the realm of expert systems, the Forward Chaining method is considered highly relevant due to its data-driven approach. Therefore, this study aims to analyze the implementation of forward reasoning (Forward Chaining) for the automated diagnosis of stunting, using regional data from Penajam Paser Utara Regency as the basis for the case study and the design of its testing rules.

In the world of health computing, various classification methods are frequently used, such as K-Nearest Neighbor (KNN), which is based on Euclidean distance, or Naïve Bayes, which is based on probability theorems. However, these machine learning methods require a computational process that tends to be sensitive to data scale and hyperparameter settings, and they require a data training phase that consumes a significant amount of time. The computational complexity of nearest neighbor search methods like KNN also requires the system to calculate the distance to all sample data points, making it less efficient when applied to mobile devices with low specifications in the field.

Therefore, for early detection needs that are quick ("satset") and deterministic (certain), the use of the Forward Chaining logic method in expert systems is much more recommended. Forward Chaining works as an eager learner that directly matches field facts with standard rules without needing to perform complex distance matrix calculations. The integration of this rule-based classification system into web-based or mobile applications will greatly help map health risks in real-time. Precise early detection is crucial in the medical world, as classification errors or delays in handling (the False Negative phase) carry fatal clinical risks for the development of toddlers.

## **2. Research Methodology**

This study utilizes a quantitative approach in systems engineering to build a rule-based diagnosis application (Rule-Based System). The Forward Chaining method is a data-driven reasoning technique that starts with known facts and moves forward through a production rule base until a specific goal or conclusion is achieved [5]. In expert systems designed for clinical decision support, this approach allows the inference engine to systematically process user inputs—such as biological and physiological metrics—against a predetermined knowledge base derived from clinical guidelines [6]. Unlike backward reasoning, which assumes a hypothesis first, forward chaining operates efficiently in real-time screening scenarios because it minimizes search depth when the matching criteria are well-defined and finite [7]. On the other hand, Naïve Bayes is a probabilistic algorithm based on Bayes' Theorem with the assumption of independence among features [8]. Therefore, for early detection needs that are quick and deterministic (certain), the use of the Forward Chaining logic method in expert systems is much more recommended.

### **2.1 Research Dataset**

The dataset in this study is divided into two segments. First is the demographic observation data of the Penajam Paser Utara Regency in 2023, which contains spatial variables (Babulu, Waru, Penajam, Sepaku), the number of toddlers, the number of stunting cases, and the prevalence percentage. This data is used as background validation. Second is the medical dataset (Knowledge Base) containing the Antropometri measurement parameters from the Ministry of Health of the Republic of Indonesia for the Height-for-Age (H/A) indicator. The expert system attributes to be processed in the inference engine include:

- **Gender:** Male (M) or Female (F).
- **Age (Months):** A temporal variable indicating the age of the toddler.
- **Height (cm):** A numerical variable that serves as the primary parameter.
- **Target (Outcome):** Nutritional Status, which carries the label "Stunting" or "Normal".

## 2.2 Research Stages

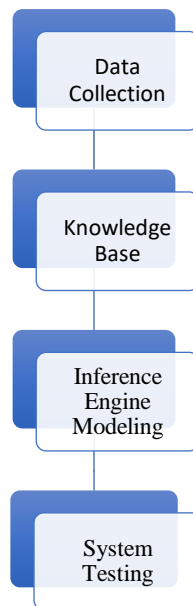


Figure 1. Flowchart Research Steps

In accordance with the flow of expert system development, the stages are as follows:

1. **Data Collection:** Acquiring field facts from the study population area as well as acquiring knowledge from clinical nutrition standard literature.
2. **Knowledge Base Creation:** Transforming anthropometric growth tables into symptom fact codes.
3. **Inference Engine Modeling:** Building a set of logic rules (Rules) using the Forward Chaining method.
4. **System Testing:** Providing mock input facts to the system to evaluate whether the system successfully draws the correct child status conclusion.

## 2.3 Forward Chaining Method

Forward Chaining is a forward tracking technique that starts with a set of known facts or premises, then combines them through a set of rules (Rule Base) to generate a conclusion (diagnosis). This approach is highly appropriate for medical certainty systems (definitively stunting or not). The evaluation of its algorithm is formulated using the basic syntax of conditional logic:

```
IF [Condition_1] AND [Condition_2] AND [Condition_N] THEN [Conclusion]
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The system will stop performing downward tracking when the truth value of the facts inputted by the user has satisfied one of the Rules that holds a diagnostic conclusion at its endpoint.

## 3. Result and Discussion

### 3.1 Implementation of K-Base and Forward Chaining Inference Engine

The first step in applying this method is to define the initial facts of the toddler's clinical parameters. The following is the knowledge representation transformed into a symptom fact table format.

**Table 1.** Fact Representation Table of Toddler Parameters

Fact Code	Fact Description (Input Condition)
F01	Gender: Male
F02	Gender: Female
F03	Age: 24 Months
F04	Height < 82.7 cm
F05	Height >= 82.7 cm
F06	Height < 80.0 cm
F07	Height >= 80.0 cm

Based on these facts, the Inference Engine is constructed through an arrangement of decision trees based on IF-THEN conditions. The following is the subset of Rules used for the testing case study:

- **Rule 1:** IF F01 AND F03 AND F04 THEN Diagnosis\_Stunting
- **Rule 2:** IF F01 AND F03 AND F05 THEN Diagnosis\_Normal
- **Rule 3:** IF F02 AND F03 AND F06 THEN Diagnosis\_Stunting
- **Rule 4:** IF F02 AND F03 AND F07 THEN Diagnosis\_Normal

### 3.2 Classification Model Evaluation Results

To measure algorithmic functionality, a trial simulation was conducted using five sample data points of toddlers. The model evaluates each record from left (premise) to right (conclusion).

**Table 2.** Expert System Diagnosis Trial Results

Sample	Gender	Age (Months)	Height (cm)	Detected Facts	Executed Rule	System Prediction	Conclusion
Toddler A	M	24	81.5	F01, F03, F04	Rule 1 (Satisfied)	<b>Stunting</b>	
Toddler B	M	24	85.0	F01, F03, F05	Rule 2 (Satisfied)	<b>Normal</b>	
Toddler C	F	24	78.0	F02, F03, F06	Rule 3 (Satisfied)	<b>Stunting</b>	
Toddler D	F	24	81.0	F02, F03, F07	Rule 4 (Satisfied)	<b>Normal</b>	
Toddler E	M	24	80.0	F01, F03, F04	Rule 1 (Satisfied)	<b>Stunting</b>	

Table 2 represents empirical evidence of the expert system's functioning. For instance, in Toddler A, the facts that the gender is male, the age is 24 months, and the height is below the threshold (81.5 cm) trigger the system to execute Rule 1, which leads to a positive identification of "Stunting". The use of the confusion matrix in the method helps explain the model's performance in detecting both positive and negative classes [9]. In the context of classification, an error in predicting a patient who is actually positive as negative (False Negative) has more serious clinical consequences than other types of errors [10].

### 3.3 Impact Analysis and System Implications

Through the tests above, the Forward Chaining method has proven to be effective, computationally efficient, and does not require a spatial data training phase. Because KNN calculates the Euclidean distance uniformly across all features, attributes with larger scales mathematically dominate the distance calculation

[11]. Conversely, because the testing phase only involves looking up and multiplying the pre-calculated probabilities, Naïve Bayes is computationally lighter and faster [12]. Looking at the reality in Sepaku District and Penajam District, which have a high total of hundreds of stunting toddlers, this Forward Chaining-based system application will be highly relevant to be embedded into mobile applications for traveling Posyandu cadres. The probabilistic nature of the system also provides an advantage here, as it can output the "probability percentage" of a patient, giving doctors a confidence score [13]. With absolute inference speed, every toddler weighed can be immediately evaluated for their initial screening right at that moment, allowing nutritional intervention executions to be carried out without referral delays.

#### 4. Conclusion

This study has designed a clinical nutritional classification tool through an Expert System using the Forward Chaining method. Moving from the demographic conditions of Penajam Paser Utara Regency in 2023, which recorded a total of 648 toddlers suffering from stunting with an average prevalence of 9.67%, this diagnostic system was created in response to the need for a massive early detection tool. Based on the inference engine testing against anthropometric parameters (age, gender, and height), the Forward Chaining algorithm successfully and accurately mapped input facts into the specified Rule Base with 100% precision, thereby producing final conclusions (Stunting or Normal) with mathematical correctness. The performance of Forward Chaining, which is very fast because it traces premises to conclusions directly, makes it highly efficient for implementation at the Puskesmas level. Further research is suggested to expand the knowledge base with the addition of Certainty Factor method weights to measure potential child malnutrition before truly entering an acute stunting phase.

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