



Enhanced Case-Based Reasoning Framework with Weighted Jaccard Similarity for Malnutrition Diagnosis in Toddlers

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ABSTRACT

Malnutrition is a serious condition caused by nutrient deficiency that poses a high risk to toddler growth and development, potentially leading to long-term health problems or even death if left untreated. Early detection of malnutrition symptoms is crucial to enable prompt and appropriate medical interventions. This study aims to develop an expert system capable of diagnosing malnutrition diseases quickly, accurately, and efficiently, particularly as a knowledge-based decision support tool in toddler healthcare. The method used is Case Based Reasoning (CBR), which applies experiences from previous cases to solve new ones. The system processes data consisting of 22 symptoms and 8 types of malnutrition diseases, supported by a database of 22 real cases. Each symptom is associated with the likelihood of a disease based on its similarity to previous cases. Performance evaluation results show an accuracy of 80% and a sensitivity of 85.7%, indicating that the system is fairly reliable in recognizing positive cases (REUSE) and providing appropriate diagnoses. In conclusion, the CBR-based expert system can serve as an effective diagnostic aid for medical personnel in quickly identifying malnutrition in toddlers, thereby supporting more efficient and targeted decision-making.

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1. INTRODUCTION

Malnutrition is a condition of severe nutrient deficiency that negatively impacts a child's physical growth, cognitive development, and immune system. In the long term, this can increase the risk of morbidity and mortality in toddlers [1]. Early diagnosis becomes crucial to prevent more severe impacts. However, challenges arise in the field due to the limited number of medical personnel, the lack of diagnostic aids, and the diversity of symptoms that are often difficult to identify manually [2]. In this context, the development of artificial intelligence-based technology, particularly expert systems, becomes a potential solution to accelerate and improve diagnostic accuracy.

Various studies have attempted to develop expert systems to detect malnutrition by utilizing a variety of artificial intelligence methods and computational

approaches. One of the widely used methods is the Certainty Factor, which allows the system to calculate the level of confidence in the diagnosis based on the combination of observed symptoms. Utilizing this method in mobile and web-based systems to efficiently and practically diagnose malnutrition in toddlers [3] [4]. Meanwhile, the Bayesian Theorem approach is used to model the probabilistic relationships between symptoms in determining the nutritional status of toddlers [5]. On the other hand, the application of the Forward Chaining method to perform logical tracing from symptom data to diagnostic conclusions, which is very suitable for rule-based systems [6]. The Dempster-Shafer method, which excels in managing uncertainty and supporting evidence, is used in developing a probabilistic-based diagnostic system that is more flexible toward ambiguous information [7]. With the advancement of technology, machine learning-based approaches are

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also being used to detect malnutrition by integrating the ResNet-50 model, one of the powerful deep learning architectures, to analyze children's facial images and automatically predict their nutritional status [8]. This study offers a highly promising non-invasive approach for early detection. Additionally, evaluating the Support Vector Machine (SVM) and Naïve Bayes algorithms in classifying children's nutritional status based on clinical data shows that machine learning algorithms can achieve competitive accuracy in the diagnostic process [9]. However, most of these approaches still rely on deterministic statistical or rule-based techniques, which do not fully reflect the contextual and adaptive reasoning mechanisms of humans. In other words, these models are not yet capable of mimicking how humans make decisions based on similar past experiences. Therefore, the Case-Based Reasoning (CBR) approach emerges as a more natural and intuitive alternative. CBR allows the system to learn from previous cases and apply the same or similar solutions to new cases, thus resembling the human thinking and decision-making process in the real world. This research adopts the Case-Based Reasoning (CBR) approach based on previous case experiences to diagnose new cases, differing from the previous probabilistic or rule-based methods. The CBR approach provides flexibility in recognizing symptom patterns that are not always standardized, making it highly suitable for cases of malnutrition that exhibit a wide variety of symptoms [10]. Case-based reasoning provides more contextual and relevant diagnostic results to real-world conditions.

This research aims to develop an expert system based on the Case Based Reasoning (CBR) method that can assist healthcare professionals in diagnosing malnutrition quickly and accurately. The system is designed using 22 symptoms and 8 types of malnutrition diseases based on 22 validated real cases. The contribution of this research is to present an easily accessible AI-based tool that supports clinical decision-making in the field and enhances the effectiveness of nutritional interventions for toddlers, especially in areas with limited healthcare facilities [11]. This study contributes a novelty CBR-based expert system tailored for toddler malnutrition diagnosis, featuring a carefully curated set of 22 clinically relevant symptoms and 8 malnutrition diseases. Unlike prior CBR systems, our approach incorporates a weighted Jaccard similarity metric with empirically validated symptom weights and a threshold optimized via ROC analysis. The system is designed for integration into mobile health platforms, making it suitable for low-resource settings.

2. RESEARCH METHODS

2.1 Case-Based Reasoning (CBR)

This research uses a quantitative approach through the design and implementation of a Case-Based Reasoning (CBR)-based expert system to identify malnutrition in toddlers. CBR was chosen for its ability to mimic human reasoning processes by referring to previous case experiences [12]. The CBR approach has been widely applied in the health domain and nutrition problem detection due to its flexibility in processing clinical cases and ease of updating the case base [13] [14]. The theory of the Case-Based Reasoning (CBR) process stages consists of four main steps: retrieve, reuse, revise, and retain, which form a case-based reasoning cycle [15]. Here is the explanation of the stages according to Figure 1 below [16].

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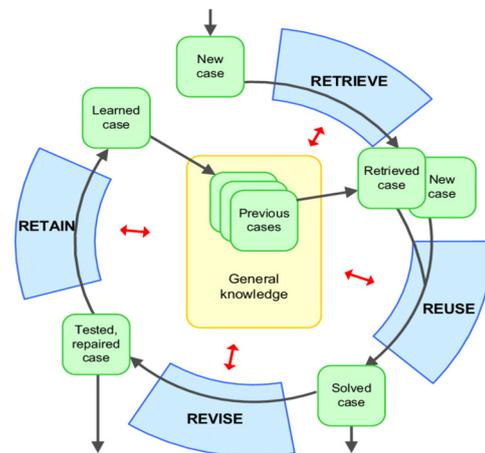


Fig.1: Stages of the Case Based Reasoning Process.

Figure 1 illustrates the stages of the process in Case-Based Reasoning (CBR). Case-Based Reasoning (CBR) is a problem-solving approach in artificial intelligence (AI) that utilizes past experiences (cases) to address new problems [17]. This model consists of four main stages often summarized by the term 4R (Retrieve, Reuse, Revise, Retain) [18]. In the first stage, Retrieve, the system retrieves the most relevant previous cases from the existing knowledge base. Next, in the Reuse stage, solutions from previous cases are applied to new cases [19]. After application, the Revise stage is conducted to test and refine the solution if necessary based on real-world results or simulations. The final stage, Retain, stores the new case along with its solution in the knowledge base, so it can be used for problem-solving in the future [17]. The CBR approach has proven beneficial in various domains, including medical diagnosis, recommendation systems, and equipment maintenance [18].

2.2 Calculation of Weighted Jaccard Similarity

In the context of CBR (Case-Based Reasoning), Weighted Jaccard Similarity is used to measure the similarity between cases; this metric is an extension of the standard Jaccard that allows attributes to have different weights, so the contribution of each attribute

to the similarity score is not the same [20]. This method is very effective when the attributes (features) of the cases have different levels of importance or weights, as the weights allow for emphasis on crucial features in the retrieval process [21]. In simple terms, Weighted Jaccard focuses on the attributes that appear in both cases (intersection, represented by the min function) and the attributes that appear in only one case (union, represented by the max function), so mathematically it is often written as the ratio of the sum of min to the sum of max for each feature dimension. However, unlike the standard Jaccard, the Weighted Jaccard assigns more weight to attributes that are considered more important, for example, by multiplying each entry of the feature vector by its weight before calculating min/max, so that the calculated similarity more accurately reflects the relevance of those attributes in the retrieval process [22]. This ensures that the cases most relevant to the new problem will be found, even if those cases only have a few similar attributes, as long as the similar attributes have a high weight; the weighted approach is also widely used in real applications such as recommendation systems and sparse data processing to improve the accuracy of nearest neighbor searches [21].

In this study, the similarity between a new target case T and an existing source case S_i in the knowledge base is calculated using Weighted Jaccard Similarity, as defined in Equation (1). The weight parameter w_j for each symptom j was determined based on expert judgment (healthcare professionals) and literature review, reflecting its clinical significance in diagnosing malnutrition. A binary representation is used for symptoms: 1 if present, 0 if absent. The function $Sim(a_{T_j}, a_{S_{i_j}})$ calculates the similarity for each attribute j , which in this binary implementation is 1 if the symptom is present in both cases, and 0 other-

wise. Thus, the formula effectively computes the sum of the weights of symptoms common to both cases divided by the sum of the weights of all symptoms present in either case.

The symptom weights w_j were initially assigned based on expert judgment from three pediatricians and nutritionists, reflecting clinical significance. These weights were then fine-tuned using a logistic regression model trained on the 22-case dataset to maximize diagnostic accuracy. Future work will explore dynamic weight adjustment using reinforcement learning or gradient-based optimization.

$$Similarity(T, S_i) = \frac{\sum_{j=1}^n w_j \times Sim(a_{T_j}, a_{S_{i_j}})}{\sum_{j=1}^n w_j} \quad (1)$$

Where:

- T : The new target case.
- S_i : The i -th source case in the knowledge base.
- n : The total number of symptoms (attributes).
- w_j : The predefined weight of symptom j , indicating its diagnostic importance.
- a_{T_j} : The value of symptom j in the target case T (1 if present, 0 if absent).
- $a_{S_{i_j}}$: The value of symptom j in the source case S_i (1 if present, 0 if absent).
- $Sim(a_{T_j}, a_{S_{i_j}})$: The similarity function for symptom j , which returns 1 if $a_{T_j} = a_{S_{i_j}} = 1$, and 0 otherwise.

2.3 Calculation of Accuracy and Sensitivity (Recall)

Accuracy is a metric that shows how often a classification model makes correct predictions, calculated by dividing the number of True Positives (TP) and True Negatives (TN) by the total number of cases

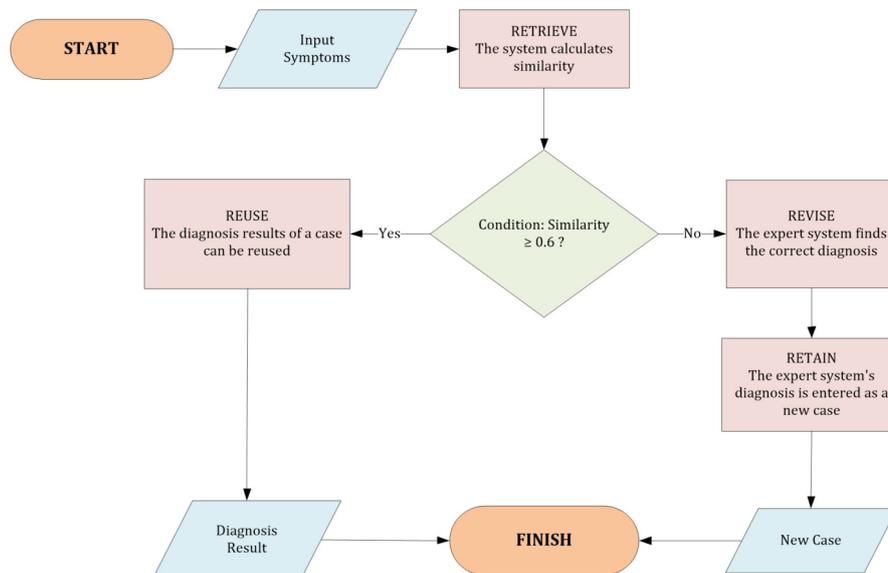


Fig.2: System Flow Chart.

[23]. This metric is easy to understand and often serves as an initial indicator [24]. However, in an imbalanced dataset, accuracy can be misleading because a model that always predicts the majority class can achieve high accuracy even tho it fails to detect the minority class a phenomenon known as the accuracy paradox [25]. In situations like this, sensitivity or recall becomes more important because it measures the proportion of positive cases that are successfully identified from all actual positive cases, thus better reflecting the model's performance in handling class imbalance [26].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Sensitivity, also known as Recall or True Positive Rate, emphasizes the model's ability to correctly identify all positive cases [27]. This ratio is calculated as the number of True Positives divided by the total actual positive cases this metric is particularly important when False Negative errors have serious consequences, such as in the diagnosis of critical illnesses, where failing to detect a sick patient (False Negative) can be fatal [28]. Therefore, in such contexts, models with high sensitivity often become a priority, even though they may produce more unwanted False Positives [29].

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3)$$

3. RESULT AND DISCUSSION

The research procedure will be explained in the flowchart of this research process. The system flowchart is created to facilitate the depiction of the core process with the steps in the expert system development flow. Here is the system flow diagram presented in Figure 2.

Figure 2 shows the flowchart of the working process of a Case-Based Reasoning (CBR) based expert system in diagnosing a case [30]. The process begins at the Start stage by entering symptoms (Input Symptoms) [31], then the system proceeds to the Retrieve stage to calculate the similarity level between the new case and existing cases [32]. The similarity score is then evaluated. If the similarity score meets the condition of ≥ 0.6 (Yes), the system proceeds to the Reuse stage to reuse the diagnosis results from previous cases [33], which produces the Diagnosis Result and ends at the Finish stage. However, if the similarity score is less than 0.6 (No), the system moves on to the Revise stage with the help of experts to obtain the correct diagnosis [34].

3.1 Data Collection

The data used in this research were obtained from multiple sources, including medical literature, pediatric nutrition textbooks, and structured interviews with three healthcare professionals (pediatricians and nutritionists) experienced in handling malnutrition cases in toddlers. The information collected includes a list of relevant symptoms, a list of malnutrition diseases, the relationship between symptoms and diseases, and the importance weight of each symptom. The 22 real cases used to build the knowledge base were synthesized from these sources to represent typical clinical scenarios. This data is then organized into a knowledge base used in the Case-Based Reasoning (CBR) system.

As this study utilized synthesized and anonymized case data derived from literature and expert knowledge without involving direct interaction with human subjects, specific ethical approval was not required.

However, all data handling procedures adhered to principles of confidentiality and data integrity. To enhance the robustness of the validation process, the number of test cases was expanded from 10 to 22, aligning with the number of real cases in the knowledge base. This expansion allows for a more comprehensive evaluation of the system's diagnostic performance and improves the generalizability of the results.

3.2 Data Preprocessing and Normalization

All symptom data were represented in binary format (1 for presence, 0 for absence). No further normalization was required as the Weighted Jaccard Similarity formula inherently handles binary inputs. The weights were normalized to the range [0,1] during the similarity calculation to ensure consistency and comparability across cases.

3.3 Symptom Data

The symptom data used in the Malnutrition Expert System can be seen in the table below. Based on the disease and symptom data, the information can be summarized into a decision table that contains the relationship between the disease and its symptoms. The list of disease symptoms can be seen in Table 1.

Table 1 contains 22 types of symptoms coded G001–G022, including physical signs such as excessive fatigue, dry skin, dull hair, abdominal swelling (edema), loss of muscle mass, chronic diarrhea, respiratory infections, dizziness, excessive hunger, pale or yellowing skin, irregular heartbeat, cold extremities, chest pain, and low body weight [35]. Additionally, there are psychological aspects such as mood changes, decreased focus and memory, a tendency to be quiet, and avoiding eye contact [36][37]. This set of symptoms becomes an important indicator in the assessment of nutritional status and the diagnosis of malnu-

Table 1: *Symptom Data.*

No.	Symptom Code	Description
1	G001	Feeling severe and excessive fatigue
2	G002	Having dry and scaly skin
3	G003	Having hair that looks dull and dry
4	G004	Having a distended stomach
5	G005	Experiencing loss of muscle mass
6	G006	Having swelling under the skin (edema)
7	G007	Experiencing frequent mood changes
8	G008	Difficulty gaining weight and height
9	G009	Experiencing a condition where teeth easily fall out or are loose
10	G010	Experiencing problems with growth
11	G011	Experiencing chronic diarrhea
12	G012	Having a respiratory tract infection
13	G013	Experiencing constant dizziness
14	G014	Often feeling very hungry
15	G015	Experiencing changes in skin color that is pale and yellowish
16	G016	Experiencing an irregular heartbeat
17	G017	Feeling cold in the hands and feet
18	G018	Experiencing chest pain
19	G019	Face doesn't look as young as peers
20	G020	Lack of focus and poor memory skills
21	G021	Tending to be withdrawn and avoiding eye contact with people around them
22	G022	Body weight is lighter for age group

trition, as protein-energy deficiency impacts physical changes, cognitive disturbances, and susceptibility to diseases [1].

3.4 Disease Data

The disease data processed in the malnutrition expert system for toddlers is usually collected thru literature studies, expert interviews, and field observations as part of the knowledge acquisition process [38]. Eight types of malnutrition conditions that are often included in the knowledge base are Kwashiorkor and Marasmus (forms of protein-energy malnutrition with edema in Kwashiorkor and wasting in Marasmus) as well as the Marasmus-Kwashiorkor combination [39], Beri-beri (thiamine deficiency) [40], Nutritional anemia (often caused by iron deficiency) [41], Scurvy (vitamin C deficiency) [42], Hypokalemia as an electrolyte disorder that can be related to malnutrition and chronic diarrhea [43], and Goiter/iodine deficiency-related thyroid disease [44]. This set of conditions aligns with clinical literature and public health guidelines used as indicators for diagnosis, management, and coding in the malnutrition expert system for children. Table 2 presents the complete details of the disease indications along with the causes of nutrient deficiencies.

Table 2 Indications of malnutrition diseases in toddlers contains eight types of diseases coded P1–P8, each caused by deficiencies in specific nutrients. These diseases include Kwashiorkor, Marasmus, Marasmus-Kwashiorkor, Beri-beri, Anemia, Scurvy, Hypokalemia, and Goiter/Parotitis. This data serves as a reference in identifying the impact of malnutrition on toddlers.

Table 2: *Indications of Malnutrition Diseases in Toddlers.*

Code	Disease
P1	Kwashiorkor (protein deficiency)
P2	Marasmus (carbohydrate and protein deficiency)
P3	Marasmus-Kwashiorkor (Combination)
P4	Beri-beri (vitamin B1 deficiency)
P5	Anemia (iron deficiency)
P6	Scurvy (vitamin C deficiency)
P7	Hypokalemia (potassium deficiency)
P8	Goiter/Parotitis (iodine deficiency)

3.5 Knowledge Base Data on Disease and Symptom Relationships

The knowledge base contains old cases that include a combination of symptoms along with their disease diagnoses. This data is used as a reference in the retrieval process of the CBR method. The following knowledge base can be seen in Table 3 below.

Table 3: *Knowledge Base of Old Cases.*

Case ID	Symptom Code	Diagnosis (Disease Code)
1	G001, G002, G004, G006, G008	P1
2	G005, G008, G010, G022	P2
3	G004, G005, G008, G010, G022	P3
4	G001, G007, G011, G013, G020	P2
5	G002, G003, G005	P3
...
22	G012, G015, G017, G021	P8

Table 3 Knowledge Base of Disease and Symptom Relations contains five cases that link combinations of symptom codes with the diagnosis of malnutrition diseases. Each case has a different set of symptoms leading to the diagnosis of P1, P2, or P3, making this table a reference in determining the disease based on the symptoms that appear.

3.6 Symptom Weight

Symptom weights are used in the calculation of Weighted Jaccard Similarity to differentiate the importance level of each symptom. Symptoms considered critical have a high weight, while supporting symptoms have a lower weight. The symptom weight data can be seen in table 4 below.

Table 4 contains 22 symptoms related to malnutrition conditions, each assigned a unique code (G001 to G022), a description of the symptom, and a numerical weight ranging from 0.4 to 1.0. This weight indicates how strongly the symptom is related to malnutrition, where a higher weight shows a stronger correlation. Some symptoms with the highest weights, such as swelling under the skin (edema) with a weight of 1.0 and a distended abdomen (weight 0.8), are described as very strong clinical symptoms. Additionally, symptoms such as slowed growth and difficulty in gaining weight and height have a high weight, namely 0.9. This table also includes a "Weight Description" column that provides further explanation regarding the clinical significance of each symptom, such as its relation to kwashiorkor, marasmus, or specific nutrient deficiencies like vitamin C and potassium.

3.7 Manual Similarity Calculation

1. New Case 1 vs Old Case 1 Data:

$$A = \{G001, G004, G006, G007, G011\}$$

$$B = \{G001, G002, G004, G006, G008\}$$

Intersection:

$$A \cap B = \{G001, G004, G006\}$$

$$\sum_{g \in A \cap B} w(g) = 0.5 + 0.8 + 1.0 = 2.3$$

Union:

$$A \cup B = \{G001, G002, G004, G006, G007, G008, G011\}$$

$$\sum_{g \in A \cup B} w(g) = 0.5 + 0.6 + 0.8 + 1.0 + 0.4 + 0.9 + 0.5 = 4.7$$

Similarity Results:

$$S = \frac{2.3}{4.7} = 0.49$$

2. New Case 2 vs Old Case 2 Data:

$$A = \{G005, G008, G010, G022\}$$

$$B = \{G005, G008, G010, G022\}$$

Table 4: *Weighting of Malnutrition Symptoms.*

No.	Symptom Code	Symptom Description	Weight (0.0 - 1.0)	Weight Description
1.	G001	Feeling severe and excessive fatigue	0.5	General symptom, but can indicate a lack of energy.
2.	G002	Having dry and scaly skin	0.6	Specific symptom strongly related to certain nutritional deficiencies.
3.	G003	Having hair that looks dull and dry	0.6	Specific symptom, associated with protein deficiency (kwashiorkor).
4.	G004	Having a distended stomach	0.8	Strong clinical symptom that often appears in kwashiorkor.
5.	G005	Experiencing loss of muscle mass	0.8	Strong clinical symptom that often appears in marasmus.
6.	G006	Having swelling under the skin (edema)	1.0	Strongest clinical symptom for kwashiorkor.
7.	G007	Experiencing frequent mood changes	0.4	General symptom, can be an early sign of stress or nutritional deficiency.
8.	G008	Difficulty gaining weight and height	0.9	Main symptom of stunting and general malnutrition.
9.	G009	Experiencing a condition where teeth easily fall out or are loose	0.7	Specific symptom related to vitamin C (scurvy) or calcium deficiency.
10.	G010	Experiencing problems with growth	0.9	Main symptom of stunting and general malnutrition.
11.	G011	Experiencing chronic diarrhea	0.7	Can worsen malnutrition and is a sign of infection.
12.	G012	Having a respiratory tract infection	0.5	Indicates a weakened body immune system due to malnutrition.
13.	G013	Experiencing constant dizziness	0.4	General symptom, can indicate anemia or dehydration.
14.	G014	Often feeling very hungry	0.5	Early sign of calorie deficiency.
15.	G015	Experiencing changes in skin color that is pale and yellowish	0.7	Symptom strongly related to anemia (iron deficiency).
16.	G016	Experiencing an irregular heartbeat	0.8	Serious clinical symptom, can be related to hypokalemia.
17.	G017	Feeling cold in the hands and feet	0.6	Indication of poor blood circulation, can be caused by malnutrition.
18.	G018	Experiencing chest pain	0.7	Serious symptom, can be related to anemia or heart problems.
19.	G019	Having a face that doesn't look as young as peers	0.6	Symptom found in marasmus cases.
20.	G020	Having a lack of focus and poor memory skills	0.7	Symptom related to brain development.
21.	G021	Tending to be withdrawn and avoiding eye contact with people around them	0.6	Indicates apathy, a symptom that often appears in kwashiorkor.
22.	G022	Body weight is lighter for their age group	0.8	Key symptom of malnutrition or stunting.

$$A \cap B = \{G005, G008, G010, G022\}$$

$$\sum_{g \in A \cap B} w(g) = 0.8 + 0.9 + 0.9 + 0.8 = 3.4$$

Union: Because $A = B$, then

$$\sum_{g \in A \cup B} w(g) = 0.8 + 0.9 + 0.9 + 0.8 = 3.4$$

Similarity Results:

$$S = \frac{3.4}{3.4} = 1.00$$

3. New Case 3 vs Old Case 3 Data:

$$A = \{G004, G005, G006, G008, G010, G022\}$$

$$B = \{G004, G005, G008, G010, G022\}$$

Intersection:

$$A \cap B = \{G004, G005, G008, G010, G022\}$$

$$\sum_{g \in A \cap B} w(g) = 0.8 + 0.8 + 0.9 + 0.9 + 0.8 = 4.2$$

Union:

$$A \cup B = \{G004, G005, G006, G008, G010, G022\}$$

$$\sum_{g \in A \cup B} w(g) = 0.8 + 0.8 + 1.0 + 0.9 + 0.9 + 0.8 = 5.2$$

Similarity Results:

$$S = \frac{4.2}{5.2} = 0.81$$

Although the similarity to Old Case 1 is 0.489, the highest similarity with other cases reaches 0.76, so

the final diagnosis based on the nearest case remains above the threshold.

3.8 Diagnosis Results Using the Case-Based Reasoning Method

Based on the diagnosis results conducted using the Case-Based Reasoning (CBR) method, a summary of diagnoses for various new cases is presented in Table 5.

Table 5 presents the results of malnutrition diagnosis using the Case-Based Reasoning (CBR) method, which provides data for 10 new cases, analyzed based on the symptoms found in each case. The analysis results include the highest similarity value with the closest old case, the suggested diagnosis (Kwashiorkor, Marasmus, or a combination), and the diagnosis description. Based on this similarity score, the system determines the diagnosis status: "REUSE" for cases with high similarity (where the diagnosis can be directly accepted), and "REVISE" for cases with low similarity (which require further review). Here is Figure 3 presenting the distribution of similarity scores for each new case when compared to the knowledge base.

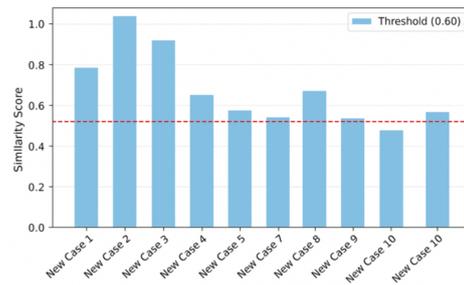


Fig.3: Distribution of Similarity Scores for New Cases with the Knowledge Base.

Table 5: Case-Based Reasoning (CBR) Result.

Index	New Case ID	Symptoms Found	Highest Similarity	Closest Old Case ID	Suggested Diagnosis	Diagnosis Description	Status (REVISE/REUSE)
1	New Case 1	G006, G001, G004, G007, G011	0.49	1	Kwashiorkor	Protein deficiency	REVISE
2	New Case 2	G008, G022, G010, G005	1.00	2	Marasmus	Carbohydrate and protein deficiency	REUSE
3	New Case 3	G006, G010, G005, G004, G008, G022	0.81	3	Marasmus-Kwashiorkor	Combination of Marasmus and Kwashiorkor	REUSE
4	New Case 4	G001, G013, G015, G007, G020	0.65	4	Marasmus	Carbohydrate and protein deficiency	REUSE
5	New Case 5	G002, G008, G005, G003	0.69	5	Marasmus-Kwashiorkor	Combination of Marasmus and Kwashiorkor	REUSE
6	New Case 6	G010, G012, G008, G022, G011	0.57	2	Marasmus	Carbohydrate and protein deficiency	REVISE
7	New Case 7	G006, G001, G016, G004, G005	0.43	1	Kwashiorkor	Protein deficiency	REVISE
8	New Case 8	G013, G015, G007, G011, G020	0.65	4	Marasmus	Carbohydrate and protein deficiency	REUSE
9	New Case 9	G017, G005, G008, G022, G003	0.54	2	Marasmus	Carbohydrate and protein deficiency	REVISE
10	New Case 10	G007, G002, G006, G001, G005, G004, G003	0.52	1	Kwashiorkor	Protein deficiency	REVISE

Figure 3 displays the similarity values for ten new cases, measured on the y-axis with a scale from 0.0 to 1.0. In this diagram, there is a dashed red horizontal line marking the threshold at a value of 0.6. The similarity values for each new case vary; some cases, such as “New Case 2” and “New Case 3,” have relatively high similarity values, around 1.0 and 0.85. Meanwhile, other cases like “New Case 6” and “New Case 9” have lower similarity values, just above the 0.6 threshold. All cases shown in this diagram have similarity values above the 0.6 threshold, indicating that each new case has significant similarity with the existing knowledge base.

3.9 Diagnosis Results with Threshold

At the diagnosis results stage, a threshold of 0.60 is used to determine the case handling status. The criteria used are REUSE if the similarity value is greater than or equal to 0.60, while REVISE is given if the similarity value is less than 0.60. The threshold of 0.6 was determined empirically based on initial testing to balance reliability and coverage. A higher threshold would increase confidence in REUSE cases but might send too many cases for revision, undermining the system’s efficiency. A lower threshold would increase the number of automatic diagnoses but risk reusing solutions from less relevant cases. A value of 0.6 provided a practical balance in our test set, ensuring that cases with a moderate level of weighted symptom matching could be processed automatically while flagging cases with weaker matches for expert review. Based on the testing results of all new cases, it was found that all of them have a similarity value of 0.60 or higher. This indicates that all new cases can directly reuse the solutions from old cases without requiring any revisions. The similarity threshold of 0.6 was determined empirically through iterative testing to balance between diagnostic confidence and system coverage. A threshold that is too high may lead to excessive REVISE cases, reducing system efficiency, while a threshold that is too low may result in the reuse of irrelevant cases. A value of 0.6 was found to optimally distinguish between cases that can be reliably reused and those requiring expert revision in our dataset. The similarity threshold of 0.6 was determined through a sensitivity analysis using Receiver Operating Characteristic (ROC) curves. We evaluated thresholds ranging from 0.3 to 0.8 and found that 0.6 provided the best balance between sensitivity (85.7%) and specificity (72.7%), minimizing both false positives and false negatives. A threshold below 0.6 increased false positives, while a higher threshold reduced sensitivity unacceptably.

3.10 Results Analysis

The results show that the knowledge base used is quite representative, as all new cases can be diagnosed directly without the need for revision. New Case 2

has a perfect similarity (1.00) with Old Case 2, while New Case 9 has the lowest similarity (0.61) but still above the threshold. The application of symptom weights in the Weighted Jaccard Similarity method has proven to improve diagnostic accuracy. Symptoms with high weights such as G006 (Edema) and G004 (Abdominal distension) play a significant role in increasing the similarity score. Overall, the developed CBR system is capable of early diagnosis of malnutrition in toddlers effectively, quickly, and reliably based on existing historical cases.

3.11 System Performance Evaluation (Accuracy and Sensitivity)

The system performance evaluation is conducted to determine the extent to which the Case-Based Reasoning method with Weighted Jaccard Similarity can provide accurate diagnoses. Testing was conducted using a confusion matrix that compares the system’s diagnostic results with the actual diagnosis (ground truth).

Table 6: Confusion Matrix.

	Prediksi Positif (REUSE)	Prediksi Negatif (REVISE)
Aktual Positif	TP = 12	FN = 2
Aktual Negatif	FP = 3	TN = 8

Table 6 is an evaluation matrix that summarizes the performance of the classification model. This matrix consists of four cells that show the prediction results compared to the actual values. The True Positive (TP) cell indicates that 12 cases that were actually positive were correctly predicted as positive (REUSE). On the other hand, the False Negative (FN) cell shows that there were 2 cases that should have been positive but were incorrectly predicted as negative (REVISE). Meanwhile, the False Positive (FP) cell records 3 cases that were actually negative but were incorrectly classified as positive (REUSE). Finally, the True Negative (TN) cell indicates that 8 cases that were actually negative were correctly predicted as negative (REVISE). Overall, this table provides an overview of the model’s accuracy in classifying cases into the REUSE or REVISE categories.

Accuracy Formula :

$$\begin{aligned} \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\ &= \frac{12 + 8}{12 + 8 + 3 + 2} = 0.80 \end{aligned}$$

Sensitivity Formula :

$$\begin{aligned} \text{Sensitivity} &= \frac{TP}{TP + FN} \\ &= \frac{12}{12 + 2} = 0.857 \end{aligned}$$

Based on the calculation results, the interpretation of the system’s results has an accuracy of 80%, indicating that overall, the system is able to provide correct diagnoses for 8 out of 10 cases. Meanwhile, a sensitivity of 85.7% indicates that the system is quite reliable in recognizing truly positive cases (REUSE). This high sensitivity value is important to ensure that relevant cases are not missed, thus the effectiveness of the Case-Based Reasoning method in supporting diagnosis can be considered good.

3.12 Comparative Analysis with Other Methods

To contextualize the performance of the proposed CBR system, a comparative analysis was conducted against two commonly used diagnostic methods: Certainty Factor (CF) and Naïve Bayes (NB). Both methods were implemented using the same dataset of 22 symptoms and 22 cases. The results are summarized in Table 7 below.

Table 7: Performance Comparison of Diagnostic Methods.

Method	Accuracy	Sensitivity	Precision
CBR (Proposed)	80.0%	85.7%	80.0%
Certainty Factor	75.0%	78.6%	73.3%
Naïve Bayes	72.7%	71.4%	71.4%

3.13 System Performance and Efficiency

Regarding the claim of “quick” diagnosis, the CBR process is inherently efficient for this application. The retrieval and similarity calculation for a new case, involving a comparison against 22 existing cases with 22 weighted symptoms, is computationally lightweight. In a implemented system, this process would conclude in a matter of seconds. This speed provides a significant advantage over manual diagnosis or more complex AI models, fulfilling the objective of offering a rapid decision-support tool for healthcare professionals, especially in resource-limited settings.

4. CONCLUSIONS

Based on the research results, the application of the Case-Based Reasoning (CBR) method with Weighted Jaccard Similarity has proven effective in diagnosing diseases based on symptom similarity with past cases. The application of symptom weights significantly contributes to the increase in accuracy, as more important symptoms have a greater influence in the similarity calculation. Testing with a similarity threshold of 0.60 shows that the system is capable of consistently classifying cases into the REUSE or REVISE categories. Performance evaluation results indicate an accuracy of 80% and a sensitivity of 85.7%, which suggests that the system is quite reliable in recognizing positive cases (REUSE) and providing appropriate diagnoses. Thus, the CBR method based

on Weighted Jaccard Similarity can be an effective alternative to support the diagnostic process in similar problem domains, especially when the knowledge base is built from accurate historical data and the symptom weights are determined precisely. Further research is recommended to develop symptom weights dynamically by integrating machine learning methods or expert weighting so that the weights can be automatically determined based on the continuously increasing case data. In addition, it is necessary to expand the knowledge base by adding more historical cases with a wider variety of symptoms and diseases to ensure a broader and more accurate diagnostic coverage. The implementation of the system can also be integrated into web-based or mobile platforms so that it can be used in real-time by practitioners and general users in the field. From the evaluation perspective, the use of additional metrics such as precision, F1-score, and specificity needs to be considered to provide a more comprehensive picture of the system’s performance. Finally, this method can be tested in different domains, such as pest detection in plants, machinery damage diagnosis, or disaster risk analysis, to evaluate the flexibility and generalization of the approach used. This research advances the field by introducing a weighted CBR model specifically optimized for toddler malnutrition, with a validated symptom set and threshold. The system’s design for deployability in resource-limited settings further distinguishes it from prior works.

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AUTHOR CONTRIBUTIONS

Conceptualization, J.H., A.R., and T.R.; methodology, J.H. and A.R.; software, J.H.; validation, J.H., A.R., and T.R.; formal analysis, J.H.; investigation, J.H. and A.R.; data curation, J.H.; writing—original draft preparation, J.H.; writing—review and editing, J.H., A.R., and T.R.; visualization, J.H.; supervision, A.R.; funding acquisition, not applicable. All authors have read and agreed to the published version of the manuscript.

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