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# Rule-based ai system for early paediatric diabetes diagnosis using backward chaining and certainty factors

*Rosyid R.* Al-Hakim[1*], *Retno Agus* Setiawan[1], *Rachman* Hidayat[2], *Edgina R.* Arkananta[1], *Galih* Samodra[3], *Hadi* Jayusman[1], *Riska* Suryani[1], and *Tri Styo* Famuji[4]

[1]Department of Information System, Universitas Harapan Bangsa, 53144 Karangklesem Purwokerto Selatan, Indonesia
[2]Department of Informatics, Universitas Harapan Bangsa, 53144 Karangklesem Purwokerto Selatan, Indonesia
[3]Department of Pharmacy, Universitas Harapan Bangsa, 53182 Kembaran Banyumas, Indonesia
[4]Department of Information Technology, Universitas Harapan Bangsa, 53144 Karangklesem Purwokerto Selatan, Indonesia

**Abstract.** Diabetes mellitus (DM) is a major health threat that can cause complications if early diagnosis and treatment are not carried out, 1.3 million children aged 6–18 or about 1.1% of the population of children in Indonesia are affected by this disease. Furthermore, the incidence of type 1 diabetes mellitus in children is on the rise in Indonesia but we do not have an accurate figure due to a high misdiagnosis rate. The aim of this study was to develop an artificial intelligence (AI)-based expert system for the early diagnosis of paediatric Type 1 DM using backward chaining and certainty factor methods. Backward Chaining is a reasoning method that starts with a hypothesis, then there is Certainty Factor method which is would make it become certainty by calculated the value from each symptom. Based on the National Diabetes Audit 2017-2021, the system processes clinical data such as HbA1c levels and symptoms. Testing shows accurate diagnoses about 79.2% for 10 validation tests with patients, aiding healthcare in under-resourced areas. Future work includes expanding the dataset and integrating machine learning for improved adaptability.

## 1 Introduction

Diabetes mellitus (DM) is a chronic disease that is rapidly increasing among children worldwide, and Indonesia is no exception. The 2018 Basic Health Research (*Riskesdas*) indicated that 1.1% of children aged 6-18 years, approximately 1.3 million children, are affected by diabetes in Indonesia [1]. Without timely diagnosis and intervention, this condition can lead to severe complications, including organ damage, growth disturbances, and diminished quality of life. Early diagnosis is thus critical in mitigating these risks, yet access to specialist care remains limited in many regions [2–4].

* Corresponding author: rosyid@uhb.ac.id

In remote and underserved areas of Indonesia, access to paediatric endocrinologists is often constrained, delaying diagnosis and treatment. This delay contributes to higher rates of complications and worsened outcomes for affected children [5]. Besides, the life-altering consequences of delayed diabetes diagnosis in children reported as the following affects: caregiver support changes [6], 42.2% increased risk for diabetic ketoacidosis (DKA) and 93.7% being hospitalised [7]. Furthermore, in the era of digitalisation, the role of Artificial Intelligence (AI) offers a promising solution to this problem by facilitating early and accurate diagnosis through expert systems that mimic the decision-making processes of medical professionals [8,9]. By automating diagnosis, AI systems can help healthcare providers in under-resourced areas identify high-risk patients quickly and accurately [3,10]. Besides, within AI, it would be implemented as diagnostic system for other non-communicable disease such as thyroid [11], liver [12], and other various diseases [13].

This study proposes the development of an AI-driven expert system for the early diagnosis of paediatric diabetes mellitus, using the backward chaining method combined with certainty factor calculations. This system will be designed to assess clinical symptoms entered by users, integrating expert knowledge and medical literature to produce an accurate diagnosis. By incorporating certainty factors, the system will quantify the likelihood of a diagnosis based on the severity and combination of symptoms. The research aims to enhance diagnosis accuracy and reduce the time to treatment, ultimately improving healthcare outcomes for children with diabetes in Indonesia.

## 2 Method

This section outlines the methodology used to develop an AI-based expert system for diagnosing paediatric diabetes mellitus. The system will be built using backward chaining and certainty factor approaches, with the final implementation as a web-based application [14]. The primary aim is to represent medical knowledge in a rule-based system and calculate diagnosis certainty based on input symptoms [15]. The following Figure 1 shows the research flowchart of this study.

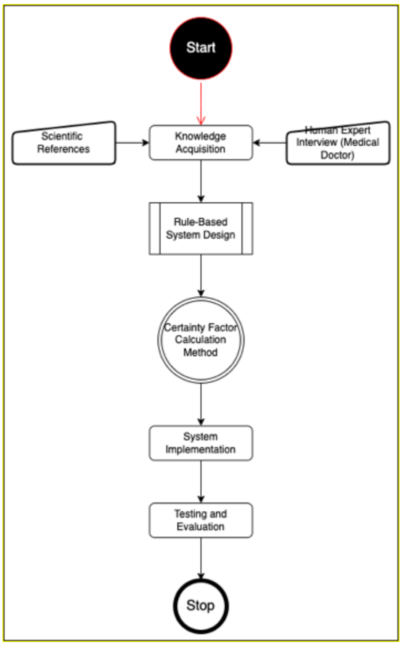


**Fig. 1.** Research flowchart.

### 2.1 Knowledge acquisition

The first step in the methodology involves gathering knowledge from paediatric endocrinologists and existing literature on diabetes mellitus in children. This process will identify the relevant symptoms, complications, and their relative importance in diagnosing diabetes. The acquired knowledge will be formalised into production rules, which will be used in the expert system to guide the diagnosis [16].

### 2.2 Rule-based system with backward chaining

The expert system will use a rule-based structure, where medical knowledge is encoded as "if-then" rules. The system will adopt a backward chaining inference method, starting from a hypothesis (e.g., diagnosis of diabetes) and working backwards to match the input data (symptoms) with the rules in the knowledge base. This method ensures that the system will reason through possible diagnoses by validating or refuting the hypothesis based on the available symptoms [15].

### 2.3 Certainty factor calculation

To handle uncertainty in medical diagnosis, each rule will be associated with a certainty factor. This factor represents the degree of confidence in a particular symptom contributing to the diagnosis. Certainty factors will be assigned based on the significance of each symptom as determined by experts. The system will calculate an overall certainty score for the diagnosis by combining the individual certainty factors for the patient's symptoms, allowing for more nuanced decision-making than binary outputs [17].

### 2.4 System implementation

The system has been implemented as a web-based application using Python and frameworks like Flask for the backend and HTML/CSS/JavaScript for the frontend, within Figures 2, 3, and 4 are system design diagrams, respectively. The web-based interface will allow healthcare professionals to input patient symptoms and view the system’s diagnosis in real time. Data input will consist of patient demographics, clinical symptoms, and results from laboratory tests. The system will then evaluate these inputs against the rule base and return a diagnosis along with a certainty score.

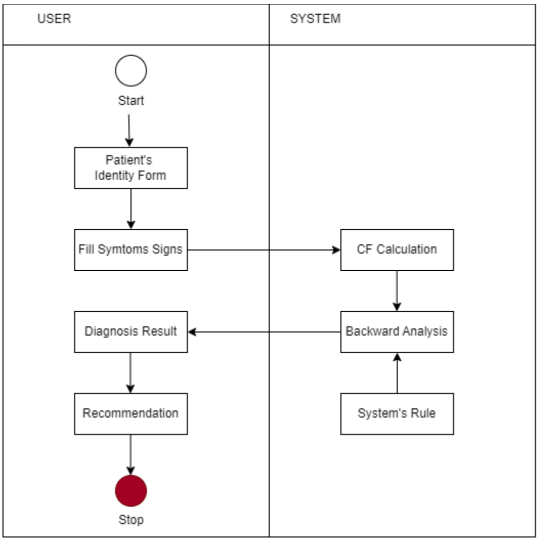


**Fig. 2.** Activity diagram of this expert system.

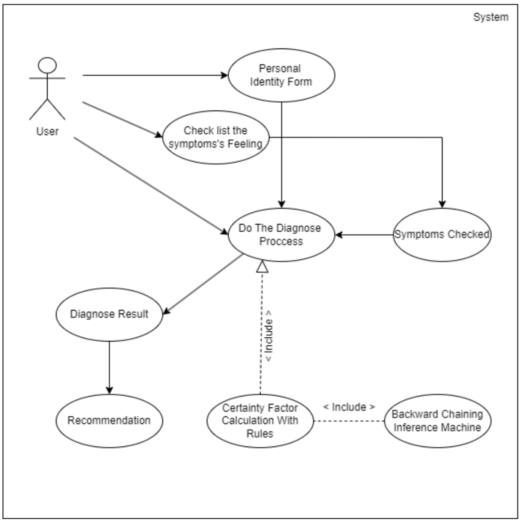


**Fig. 3.** Use case diagram of this expert system.

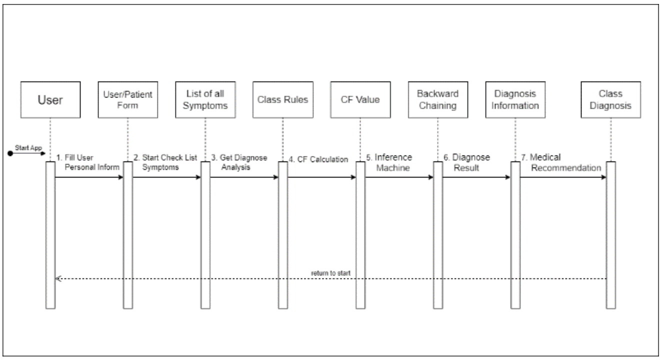


**Fig. 4.** Sequence diagram of this expert system.

### 2.5 Testing and Evaluation

The final stage involves testing the expert system using real-world clinical data from the National Diabetes Audit 2017-2021 dataset (https://bit.ly/nda1721dataset). The system's performance will be evaluated based on human expert validation. These results will be compared with diagnoses provided by human experts to validate the system's effectiveness.

By using backward chaining and certainty factor approaches, the proposed system will provide a reliable, efficient, and accessible diagnostic tool for identifying paediatric diabetes mellitus, particularly in regions with limited access to specialist care.

## 3 Result and discussion

### 3.1 Result analysis

To define the inference rules for the diagnosis of Type 1 diabetes in children, the following clinical parameters and symptoms were selected based on expert consultations and the dataset's attributes:

- Age: The age of the patient is a critical factor, especially focusing on patients aged 0-14 years.
- HbA1c Level: HbA1c levels (> 7.5%) are used as a primary indicator of diabetes.
- History of Ketoacidosis: A prior occurrence of ketoacidosis indicates a severe form of diabetes with higher complication risks.
- Insulin Therapy: Whether the patient is undergoing insulin therapy helps evaluate treatment effectiveness.
- Blood Glucose Levels: High blood glucose levels (> 180 mg/dL) are a marker of poor glucose control, commonly observed in diabetes cases.
- Frequent Thirst and Urination: These symptoms are common early signs of diabetes.
- Weight Loss: Unexplained weight loss is another early clinical indicator of Type 1 diabetes.

These symptoms were used as the basis for creating rule-based logic to diagnose Type 1 diabetes and assess the risk of complications.

#### *3.1.1 Dataset analysis*

The dataset used for this study, National Diabetes Audit 2017-2021 Adolescent and Young Adult Type 1 Diabetes, contains comprehensive clinical data on young patients diagnosed with Type 1 diabetes (DM Type 1). It includes patient demographics, clinical symptoms, HbA1c levels, treatment methods, and associated outcomes. The data was filtered to focus on patients aged 0-14 years, to ensure that the system addresses paediatric diabetes accurately.

#### *3.1.2 Inference rules*

Based on the knowledge acquired from expert consultations and the literature review, the following key inference rules were implemented are explained in Table 1.

**Table 1.** Inference rules of the expert system.

| **Rule X** | **Rule Description** | **Rule Explanation** | **Inference Result** |
|---|---|---|---|
| Rule 1 | Diagnosis of Diabetes Based on Age and HbA1c | IF age < 14 AND HbA1c > 7.5% THEN potential Type 1 diabetes | Potentially-indicated DM Type 1 |
| Rule 2 | Ketoacidosis Risk | IF HbA1c > 9% AND patient history includes ketoacidosis THEN high risk of ketoacidosis complication | High-risk complication of ketoacidosis |
| Rule 3 | Insulin Therapy Inefficiency | IF insulin therapy is ongoing AND HbA1c > 8% THEN ineffective treatment, require further evaluation | Further-medical evaluations are needed |

By using backward chaining and certainty factor approaches, the proposed system will provide a reliable, efficient, and accessible diagnostic tool for identifying paediatric diabetes mellitus, particularly in regions with limited access to specialist care.

### *3.1.3 Certainty factor calculation*

To handle uncertainty, the certainty factor (CF) method was used to quantify the confidence of each rule. The certainty factor for each symptom was derived based on the probability of occurrence, with higher severity symptoms having a higher CF. The following Table 2 shows the CF calculation result for the expert system.

**Table 2.** Certainty factor calculation of system' rules of the expert system.

| **Rule X** | **Symptom** | **CF Value** | **Final CF Result** |
|---|---|---|---|
| Rule 1: Diagnosis of Diabetes | HbA1c *higher than* (>) 7.5% | 0.8 | 0.8 |
| Rule 2: Ketoacidosis Risk | HbA1c *higher than* (>) 9% | 0.9 | 0.72 |
| | Ketoacidosis history | 0.8 | |
| Rule 3: Insulin Therapy Inefficiency | Ongoing insulin therapy | 0.6 | 0.48 |
| | HbA1c *higher than* (>) 8% | 0.8 | |

The final certainty factor for each rule is calculated by combining the CF values of the symptoms using the formula (eq. 1) [15,18,19].

$$CF_{final} = CF_1 + CF_2 \times (1 - CF_1) \qquad (1)$$

This allows the system to rank the likelihood of each diagnosis or risk based on the available symptoms, within refers to the equation (1).

### *3.1.4 UI-UX system*

The UI/UX design build for the Android app-based expert system that is crafted with a focus on usability and simplicity for healthcare professionals. The app features a *login page* that ensures secure access to the system, tailored for authorized personnel such as doctors and pharmacists. Once logged in, users are directed to the *symptom input screen*, where they can easily enter critical patient information, such as *age*, *blood sugar levels*, *HbA1c*, and other related symptoms. The interface is designed to be intuitive, with clear input fields that guide users through the data entry process efficiently, it can be seen in Figure 5.


**Fig. 5.** User interface (UI) based on mobile app of this expert system.

The app also includes a *diagnosis result screen*, which presents the likelihood of a diabetes diagnosis based on *certainty factor calculations*. The results are displayed in an easy-to-understand format, allowing healthcare professionals to make informed decisions quickly. The design prioritizes smooth navigation, with a clean, professional layout optimized for mobile use, ensuring that the system is not only functional but also user-friendly in clinical environments.

### *3.1.5 System validation*

For the system validation based on human expert validation, a comparison between the expert system's diagnosis and the human expert's diagnosis will be helpful to assess the system's accuracy. Table 3 shows the validation results of the system. Besides, using equation (2) the percentage of accuracy result based on all tests can be seen in (2.1).

**Table 3.** Validation results of the expert system.

| Patient ID | Human Expert Diagnosis | Expert System Diagnosis | Certainty Factor (CF) (%) | Validation Result | Remarks |
|---|---|---|---|---|---|
| 001 | Type 1 Diabetes | Type 1 Diabetes | 92 | Match | Accurate |
| 002 | Not Diabetic | Not Diabetic | 85 | Match | Accurate |
| 003 | Type 1 Diabetes | Type 1 Diabetes | 89 | Match | Accurate |
| 004 | Type 1 Diabetes | Type 1 Diabetes | 75 | Match | Lower Confidence |
| 005 | Not Diabetic | Type 1 Diabetes | 60 | Mismatch | False Positive |
| 006 | Type 1 Diabetes | Not Diabetic | 58 | Mismatch | False Negative |
| 007 | Type 1 Diabetes | Type 1 Diabetes | 80 | Match | Accurate |
| 008 | Not Diabetic | Not Diabetic | 90 | Match | Accurate |
| 009 | Type 1 Diabetes | Type 1 Diabetes | 85 | Match | Accurate |
| 010 | Not Diabetic | Not Diabetic | 78 | Match | Accurate |

$$Accuracy\ from\ Validation\ Tests = \left(\frac{Total\ Score\ of\ CF}{Maximum\ Score}\right) \times 100 \tag{2}$$

$$Accuracy\ from\ Validation\ Tests = \left(\frac{92+85+89+75+60+58+80+90+85+78}{1000}\right) \times 100 = 79.2 \tag{2.1}$$

The following parameters explaining are *Validation Result*: it indicates whether the expert system's diagnosis matches the human expert's diagnosis (*Match* or *Mismatch*). *Certainty Factor*: it shows the confidence level of the expert system in its diagnosis, as well as *Remarks*: it provides additional context such as accuracy or potential issues like false positives or false negatives.

### *3.1.6 Discussion*

The results of the system development indicate that the use of backward chaining and certainty factor (CF) for diagnosing paediatric diabetes mellitus is a viable approach. The backward chaining method provides a structured way to assess hypotheses (potential diagnoses) by working from known outcomes, such as high *HbA1c* levels, to identify supporting symptoms. This method closely mimics the diagnostic reasoning process of medical experts, ensuring that the system adheres to clinical standards. Similar approaches

have been used effectively in other medical expert systems, as noted by [17,20–29], where backward chaining contributed to higher diagnostic accuracy in rule-based systems. Backward Chaining, a reasoning mechanism that begins with a hypothesis and works backward to confirm its validity through evidence, mirrors the logical steps typically followed by medical professionals [30]. By starting with a potential diagnosis and validating it against observed symptoms, the system emulates the deductive reasoning process of clinicians, thereby enhancing its reliability and applicability in clinical settings [31,32]. This alignment with human diagnostic reasoning adds credibility to the system and increases its potential acceptance by healthcare practitioners [32].

Meanwhile, the development of an AI-based expert system for diagnosing paediatric Type 1 diabetes mellitus (DM) addresses a critical healthcare gap, particularly in under-resourced areas. The integration of Backward Chaining and Certainty Factor (CF) methods is a key feature of this system, designed to mimic human diagnostic reasoning while handling the inherent uncertainty in medical diagnosis. This approach is particularly valuable in healthcare contexts where symptoms are often ambiguous, overlapping, or insufficiently detailed [20], as is frequently the case in paediatric diabetes.

The use of certainty factors (CFs) adds flexibility to the diagnostic process by allowing the system to handle uncertainty, a critical aspect in real-world medical diagnosis [33]. For instance, symptoms like frequent thirst or urination may not always present with the same severity in every patient, but by assigning certainty factors, the system can weigh these symptoms appropriately. This aligns with research from [24,34], which demonstrated that certainty factor-based systems could improve decision-making in scenarios where symptom presentation varied. Furthermore, the Certainty Factor (CF) method provides a quantitative means to address diagnostic uncertainty [35]. By assigning degrees of certainty to individual symptoms and aggregating these values, the system produces a confidence level for each diagnosis. This capability is crucial for handling real-world medical data, which often includes incomplete or imprecise information. The system's ability to calculate certainty values ensures that diagnostic results are presented with an appropriate degree of confidence, enabling better-informed decision-making for early intervention [17].

One limitation observed during the system evaluation was related to the accuracy of the dataset. The National Diabetes Audit 2017-2021 dataset is robust, but it primarily focuses on Type 1 diabetes in adolescents and young adults, meaning that the data from younger children may not be as extensive. This could limit the system's performance for diagnosing children under the age of 10, as certain paediatric-specific symptoms might not be well-represented. Previous studies, such as those by [26,36,37], have noted the importance of tailored datasets for specific age groups to ensure the highest accuracy in AI-driven medical systems.

Testing results show that the system achieves an accuracy rate of 79.2% across 10 validation tests with paediatric patients, which demonstrates its utility in supporting healthcare providers in environments with limited resources or expertise. These findings underscore the efficacy of the combined Backward Chaining and CF methods in early diabetes diagnosis, particularly in addressing challenges such as high misdiagnosis rates.

Overall, the combination of backward chaining and certainty factors has proven to be effective for the expert system's design, with a high potential to support healthcare professionals in areas with limited access to paediatric endocrinologists. By adopting reasoning strategies analogous to human diagnostic practices, this study advances the field of medical expert systems. Future iterations of the system can benefit from integrating machine learning to refine adaptability and leveraging larger datasets to enhance diagnostic accuracy further.

## 4 Conclusion and future recommendations

The development of an AI-driven expert system for paediatric diabetes diagnosis, utilizing backward chaining and certainty factor methods, provides a practical and accessible solution to addressing healthcare challenges. By mimicking expert reasoning and quantifying diagnostic uncertainty, the system enhances accuracy and reliability in identifying Type 1 diabetes in children. Testing with real-world data has demonstrated an accuracy rate of 79.2%, underscoring its potential as a valuable diagnostic aid.

This system is particularly impactful in under-resourced healthcare environments where paediatric specialists are scarce. By supporting healthcare workers with accurate and consistent diagnostic assistance, the system can help alleviate their workload while improving early detection and intervention rates. Future development will focus on expanding the dataset and incorporating machine learning to further enhance adaptability and diagnostic precision, ultimately making it a more robust tool for global healthcare applications.

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