



## OPTIMIZING PREDIABETES DIAGNOSIS THROUGH KNOWLEDGE-BASED SYSTEMS

Siti Rohajawati<sup>1\*</sup>

<sup>1</sup>Information Systems, Universitas Bakrie, Indonesia

Email: [siti.rohajawati@bakrie.ac.id](mailto:siti.rohajawati@bakrie.ac.id)<sup>1\*</sup>

### ABSTRACT

The escalating global prevalence of prediabetes highlights the urgency of preventive measures, particularly given its association with increased age, obesity, and additional risk factors. Addressing this concern, the explainability component of Artificial Intelligence (AI) emerges as a valuable asset in diabetes prevention strategies. AI used to manage diabetes encompasses all facets of the condition, including screening, diagnosis, treatment, prevention, and prediction. By incorporating AI into clinical practice, diabetes care could become more personalized, precise, pervasive, and predictive. This study aims to apply a concept of knowledge-based systems and utilizing the knowledge engineering method to analysis and design a web-based health tool for prediabetes diagnosis. The process encompasses acquisition, representation, validation, inferencing, and explanation phases. The online diagnostic tool not only facilitates self-diagnosis but also delivers conclusive findings and enables user registration. Practical solutions and preventive recommendations are offered, aligning with the overarching goal of diabetes prevention. The study identifies three operational phases – self-diagnosis, presentation of final findings, and member registration. To enhance the application's efficacy, the analysis provides constructive suggestions for future refinements and advancements. This research underscores the potential of AI-driven, explainable systems in contributing to the global effort to combat the rising prevalence of diabetes.

**Keywords:** Knowledge Based Systems, Prediabet Diagnosis, Naïve Bayes

### INTRODUCTION

The global prevalence of prediabetes is substantial and increasing (Baek et al., 2022)(Lawal et al., 2020)(S. Roriz-Filho et al., 2009). In 2021, the age-adjusted prevalence of impaired glucose tolerance (IGT) and impaired fasting glucose (IFG) was 9.1% (464 million) and 5.8% (298 million) among adults aged 20–79 years worldwide. By 2045, the prevalence is anticipated to increase to 10.0% for IGT and 6.5% for IFG (Rooney et al., 2023). The International Diabetes Federation (IDF) estimated the global prevalence of IGT at 7.3% of the adult population in 2017, equivalent to 352.1 million individuals, and projected it to increase to 8.3% by 2045, equivalent to an estimated 587 million individuals (Hostalek, 2019). The Centers for Disease Control and Prevention (CDC) reported that an estimated 97.6 million adults aged 18 years or older had prediabetes in 2021,

which is approximately 34.5% of the adult population in the United States. The prevalence of prediabetes is increasing rapidly in all parts of the world, and action is required to halt this increase and avoid the future diabetes epidemic (Rooney et al., 2023)(Mahat et al., 2019).

Diabetes leads to both small and large blood vessel complications, significantly impacting economic resources. The American Diabetes Association reported in 2017 that diabetes-related expenses in the U.S. amounted to \$237 billion. Addressing these costs requires proactive measures to prevent diabetes, focusing on its risk factors. Type 2 Diabetes (T2D) is more common among older adults, certain ethnic groups, and those who are overweight, inactive, have a family history of diabetes, or have had gestational diabetes (Mahat et al., 2019). Obesity, a condition characterized by excessive body fat leading to potential health risks and decreased lifespan, is a crucial factor influencing the development of both prediabetes and diabetes (Baek et al., 2022).

Numerous health organizations, such as the American Diabetes Association (ADA), the National Institute for Health and Care Excellence (NICE), the World Health Organization (WHO), and the International Diabetes Federation (IDF), have created criteria for diagnosing prediabetes and diabetes. To lower the incidence of Type 2 Diabetes (T2D) and its long-term consequences, prediabetes must be recognized and managed. There are two primary categories of long-term problems associated with diabetes: microvascular complications and macrovascular complications (Magalhães et al., 2023).

Impaired glucose tolerance, often known as prediabetes (Tabák et al., 2012), is a serious health condition that raises the risk of type 2 diabetic mellitus (T2DM). Elevated blood sugar levels that fall short of the diabetic threshold characterize this illness. Around 10.7 million people worldwide had diabetes in 2019. The 2018 Indonesian Basic Health Research found that West Kalimantan Province, Indonesia, had a 1.6% prevalence of type 2 diabetes, which was somewhat lower than the country as a whole. Nonetheless, 42% of adults over 40 in Pontianak City, West Kalimantan, had type 2 diabetes in 2019. Between 2007 and 2018, the prevalence of T2DM and prediabetes increased dramatically, from 5.7% to 10.9% (Budiastutik et al., 2022). Particularly in those with atherosclerosis, prediabetes raises the risk of cardiovascular illnesses and all-cause mortality. In addition to age, obesity, sedentary lifestyle, low HDL cholesterol, gestational diabetes, and polycystic ovarian syndrome, other risk factors include hypertension, low HDL cholesterol, a history of elevated blood sugar, and ethnic minority status (Budiastutik et al., 2022).

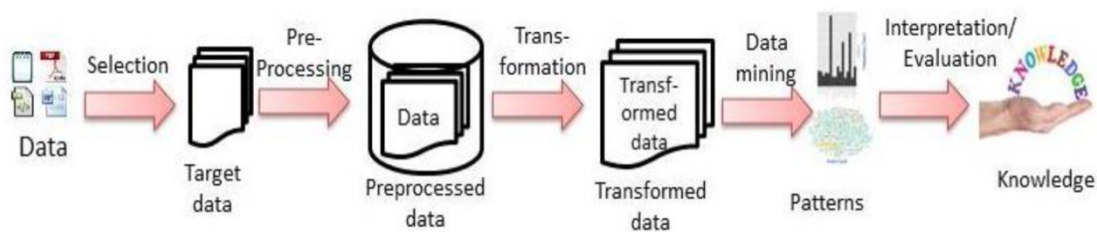
According to research (Marzukhi et al., 2018; Nguyen et al., 2020), diabetes is a serious and persistent health issue that affects people all over the world along with their families and communities (Hostalek, 2019). 463 million individuals, or 9.3% of the world's population, suffered from this illness as of 2019. By 2030, there is expected to be a 10.2% increase (578 million) and by 2045, a 10.9% increase (700 million) (Cromer et al., 2022). In addition, the global senior population is growing significantly, particularly in developing nations, placing pressure on the social security and healthcare systems (Anggrawan & Mayadi, 2023).

About 5.76 million people in a certain Southeast Asian nation presently suffer from diabetes, which is predicted to rank among the top seven causes of death and disability by 2030. The age-adjusted prevalence of diabetes in this country was approximately 6% as of 2017. Though type 1 and type 2 diabetes are well-known, a more recent variety called type 3 diabetes (T3DM) has been discovered (Anggrawan & Mayadi, 2023) (Alam et al., 2021). T3DM is

characterized by insulin resistance in the brain, which can impact neurocognitive function and hasten the onset of Alzheimer's disease (AD) (Nguyen et al., 2020). AD is the sixth most common cause of death overall and the fifth greatest cause of death for people 65 years of age and older in a major Western nation. The optimization of prediabetes diagnosis by knowledge-based systems is the focus of this work. Using the collected data, this application can diagnose diabetes-related illnesses, provide diabetes management solutions, and let patients speak with clinicians face-to-face.

Currently, AI has become a technology which have various tools such Knowledge based system (KBS). is an advanced framework that integrates and utilizes specialized knowledge from various sources to facilitate complex decision-making and problem-solving, particularly valuable in optimizing and transforming organizational processes and operations (Khan et al., 2021). KBS, originally known as expert systems (ES) (Imamah & Siddiqi, 2019);(Indriani, 2017). Incorporated high-level, specialized knowledge from human experts. Over time, the terms KBS and ES (Nazarian-Jashnabadi et al., 2023) have become interchangeable, used depending on the context(Segreto, 2016).

These systems are applied across various sectors, including healthcare diagnostics, financial investment analysis, counseling, and production management (Segreto, 2016);(Marzukhi et al., 2018);(Khan et al., 2021). The framework for a KBS designed to aid in peacekeeping operations. This system integrates data mining techniques to analyze and extract valuable information from various sources. By utilizing this system, peacekeeping personnel can make more informed decisions, thanks to the insights and patterns revealed through data analysis. The system is particularly tailored for use with rugged tablets or similar equipment in field operations, emphasizing its practical application in challenging and dynamic environments (Marzukhi et al., 2018) (Fig. 1).



**Figure 1. KBS Discovery**

The optimization of prediabetes diagnosis by KBS is the focus of this work. Using the collected data, this application can diagnose prediabetes-related illnesses, provide diabetes management solutions, and let patients speak with clinicians face-to-face. The KBS can give the people feel secure and confident in how to make decision and solving problems especially in health, and also have been a lot applied in a variety of industries (Confalonieri et al., 2021), including self-driving technology, healthcare diagnostics (Wardana et al., 2020), and finance (Isizoh et al., 2021), has led to a resurgence of interest in the explainability element of AI. Explainability has received a lot of attention lately, but its origins may be found in the time when

AI systems were mostly knowledge-based expert systems (Confalonieri et al., 2021) (Khan et al., 2021). KBS can be more sophisticated to be used to analyze user behavior and identify patterns to create an enlightened decisions.

## RESEARCH METHODS

This study is an experimental nature. The current study aims to experiment with the design and development of a health web for diabetes diagnosis using the knowledge engineering Method (Fig. 2).

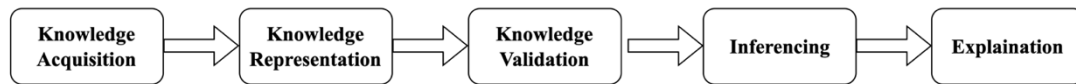


Figure 2. Knowledge Engineering Method

**Knowledge Acquisition.** In this phase, this study approach includes gathering insights pertinent to the research from multiple channels. This encompasses engaging in direct interactions with diabetes specialists, reviewing scholarly articles about diabetes, watching videos concerning diabetes, and exploring recent developments about diabetes online.

**Knowledge Representation.** Knowledge representation is a continuation of the knowledge acquisition process. Once expertise has been obtained from specialists, the next step is to translate these forms of knowledge into a format recognizable by the system.

**Knowledge Validation.** Following the completion of the representation phase, case testing is implemented to preserve the original quality. This process is essential for confirming the correct functioning of the system. The system's diagnostic output includes a probability percentage of having diabetes, which is then compared with traditional manual computation methods. This research employs Bayes' theorem to determine the percentage of uncertainty or to draw conclusions.

**Inferencing.** During the inference phase, the operational mechanism of inferential tracing is depicted through an inferential diagram, ultimately leading to a conclusion. The inference strategy begins with the identification of known facts, and new facts are derived using rules that are aligned with these identified facts. This process is repeated until either the intended goal is reached or there are no more applicable rules based on the existing facts. In rule-based expert systems, inference control is managed through two primary methods: backward chaining and forward chaining. There are three different search strategies for forward chaining: best-first search, breadth-first search, and depth-first search. The depth-first search strategy is used in this investigation.

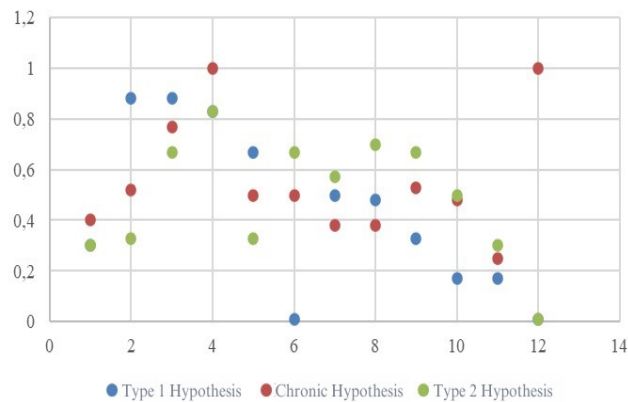
**Explanation.** This phase comprehensively covers how the application functions, from a user initiating it to a member carrying out a diagnosis and obtaining its outcomes. Fundamentally, this explanation stage acts both as an actual test of the system's effectiveness and as an instructive guide for the users.

## RESULTS AND DISCUSSION

Based on the literature study, the factors and symptoms are confirmed by an internist specialist (Dr. dr. Fatimah Eliana Taufik, Sp. PD-KEMD.) and also verified by interviews. This section presents the process of implementation as an application.

### Acquisition Output

The following are the assigned values for various symptoms and diseases used in estimating the probability of diabetes. Factors such as age and gender play a role in the risk of diabetes. Men are generally at higher risk compared to women, and individuals over 40 are more prone to type 2 diabetes, while younger people are more affected by type 1. These factors, however, are not the primary determinants of risk, as diabetes can affect anyone who does not manage their diet well. It's best to combine these demographic factors with each of the symptoms for a more accurate assessment (Fig. 3).



**Figure 3. Acquisition mapping**

For type 1, type 2, and chronic diabetes, the values are 0.3, 0.4, and 0.3, respectively: A symptom like feeling persistently hungry despite eating adequately scores 0.88 for type 1, 0.52 for chronic, and 0.33 for type 2 diabetes. A symptom of persistent thirst despite drinking plenty of fluids scores 0.88 for type 1, 0.67 for type 2, and 0.77 for chronic diabetes. Dizziness and nausea following other symptoms are valued at 0.83 for both type 1 and type 2 diabetes and are a definitive indicator of chronic diabetes with a value of 1. A feeling of weakness and fatigue scores 0.67 for type 1, 0.33 for type 2, and 0.5 for chronic diabetes. Rapid weight loss following frequent measurements has a value of 0.001 for type 1, 0.67 for type 2, and 0.5 for chronic diabetes.

Blurred vision as an aftereffect of other symptoms is a strong indicator of type 2 diabetes with a value of 0.57, compared to 0.5 for type 1 and 0.38 for chronic. Slow-healing external wounds are valued at 0.48 for type 1, 0.38 for chronic, and 0.70 for type 2 diabetes. skin infections after wound healing are valued at 0.67 for type 2, 0.33 for type 1, and 0.53 for chronic. Nightly tingling sensations score 0.17 for type 1, 0.5 for type 2, and 0.48 for chronic diabetes. The highest

value for frequent urination is 0.43 for type 2, while it is 0.17 for type 1 and 0.25 for chronic. Urine attracting ants is a sign of high glucose levels, with the values being 0.001 for both type 1 and type 2, and 1 for chronic diabetes, though research in this area is limited.

### Representation Output

The acquired knowledge will be filtered and then represented in a knowledge representation format, enabling the system to read and display appropriate diagnostic results. The literature review explains that there are four methods of representation, with the chosen method being the use of a database system table1.

**Table 1. Representation output**

Id_ symptom	question	Fact_yes	Fact_no	Syptom_on	Sympyom_chronic	Symptom_to	rute	Rute_bassic
g1	Do you eat a lot but are often hungry? R1	Yes, eat a lot but still feel hungry	No, eat regularly and rarely fell hungry	0,88	0,52	0,33	g2	IF E1, E2, E3 AND THEN H1
g10	Do you sometimes have difficulty urinating? (R10)	Yes, sometimes have difficulty	No, normal	0,17	0,25	0,3	g11	IF E1, E2, E9 AND THEN H1
g11	After urinating, do you notice ants being attracted to your urine	Yes, ants are attracted to the urine	never	0	1	0	Final	IF E1, E2, E3, E6, E7 AND THEN H2
g2	Do you drink a lot but are often thirsty	Tes, drink a lot but still feel thirsty	No, normal thirst	0,88	0,77	0,67	g3	IF E1, E2, E3, E6, E7 AND THEN H2
g3	Do you feel dizzy and nauseus?(E3)	Yes, often dizzy and neaseous	No, often tired, just normal	0,67	1	0,83	G4	IF E1, E2, E3, E4, E5, E6, E7, E8, E9, E10, E11, AND THEN H2
g4	Do you feel weak and easily tired? (E4)	Feeling tired at time	No often tured, just normal	0,67	0,5	0,33	g5	IF E1,E2, E3, E4, E5, E6, E7, E8, E9, AND THEN H2
g5	If your body weight droppung quickly? (E5)	Yes, rapid weight loss	No, normal body weight and no loss	0	0,5	0,33	g6	IF EI,E2,E3, E10, E11, AND THEN H3
g6	Has Your vision become blurry? (E6)	Vision becomes blurry	No, normal vision	0,5	0,38	0,57	g7	IF E6, E7, E8, E10 AND THEN H3
g7	Does it take a long time fot your wounds to heal? (E6)	External wounds take a long time to heal	No, heals as usually	0,48	0,38	0,7	g8	IF E5, E7, E8 E9 AND THEN H3
g8	Do you have frequest skin infections? (E8)	After recovering from illness, often getting infected again	Never had recurring infections	0,33	0,53	0,67	g9	IF E7, E8 E9, AND THEN H3

g9	Do you often get Frequent tingling at night?	No frequent tingling at night	0,17	0,48	05	g10	IF E1, E2, E3, E4 AND THENH1
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**Validation Output**

To maintain the quality of a system or application, case testing must be conducted to determine if the outcomes from knowledge acquisition are consistent with manual calculations, or if the conclusions drawn by the expert system align with manual trial results. Manual calculations are carried out using bayes' theorem. Two experiments are conducted to assess two possibilities of a patient suffering from diabetes. The first case is for calculating type one diabetes, and the second case for type two diabetes calculations. The formula used is multi-evidence, as equation:

$$p(H_1 | E_1 E_2 \dots E_n) = \frac{p(E_1 | H_1) \times p(E_2 | H_1) \times \dots \times p(E_n | H_1) \times p(H_1)}{\sum_{k=1}^m p(E_1 | H_k) \times p(E_2 | H_k) \times \dots \times p(E_n | H_k) \times p(H_k)}$$

- P(Hi | Ei) : The likelihood of Hi if evidence is provided Ei
- P((Ei | Hi) : The likelihood of finding evidence E if it is determined that hypotheses Hi are true
- $\sum_{k=1}^m p(E_i | H_k)$  : Probabilities of Hk, without any supporting evidence
- M : The number of hypotheses

In the initial step, the task is to establish the probability of hypotheses P(Hi), specifically P(H1, H2, H3), based on the data presented Fig. 4. Here, H1 corresponds to Type 1 Diabetes, H2 to chronic conditions, and H3 to Type 2 Diabetes. Subsequently, the focus shifts to determining the probability of the evidence given the hypothesis (P(Ei | Hi)), referencing the quantity of available evidence, for example, 3 out of 11 pieces of evidence. And the final is calculate of P(Ei | Hk) involves multiplying P(Hi) by P(Ei | Hi). Step Two involves performing detailed calculations. In case one, if the patient is found to exhibit symptoms E1, E2, E3, which are (frequent overeating and constant hunger, increased fluid intake and persistent thirst, regular dizziness and feelings of sickness), as shown in Table 2.

**Table 2. Probability Score Case 1**

Hyphotesis	Evidence H1	Evidence H2	Evidence H3
P(H1)=0.3	P(E1   H1)=0.88	P(E1   H2)=0.52	P(E1   H3)=0.33
P(H2)=0.4	P(E2   H1)=0.88	P(E2   H2)=0.77	P(E2   H3)=0.67
P(H3)=0.3	P(E3   H1)=0.83	P(E3   H2)=1	P(E3   H3)=0.83

Upon establishing the initial probabilities for each hypothesis H1, H2, and H3, as well as the conditional probabilities of E1, E2, and E3 contingent upon each hypothesis as shown in Table 1, this study apply Bayes' rule to calculate the posterior probabilities for each hypothesis given that evidence E1, E2, and E3 has occurred. The application of bayes' rule to compute these posterior probabilities, resulting in the updated probabilities for H1, H2, and H3 after taking into account all available evidence, as equation:

$$p(H_1|E_1, E_2, E_3, E_4) = \frac{(0.88 \times 0.88 \times 0.83) \times 0.3}{((0.88 \times 0.88 \times 0.83) \times 0.3) + ((0.52 \times 0.77 \times 1) \times 0.3) + ((0.33 \times 0.67 \times 0.83) \times 0.3)} = 0.47 \quad (3)$$

$$p(H_1|E_1, E_2, E_3, E_4) = \frac{((0.52 \times 0.77 \times 1) \times 0.3)}{((0.88 \times 0.88 \times 0.83) \times 0.3) + ((0.52 \times 0.77 \times 1) \times 0.3) + ((0.33 \times 0.67 \times 0.83) \times 0.3)} = 0.39 \quad (4)$$

$$p(H_1|E_1, E_2, E_3, E_4) = \frac{(0.33 \times 0.67 \times 0.83) \times 0.3}{((0.88 \times 0.88 \times 0.83) \times 0.3) + ((0.52 \times 0.77 \times 1) \times 0.3) + ((0.33 \times 0.67 \times 0.83) \times 0.3)} = 0.13 \quad (5)$$

The initial calculation is employed to ascertain the probability of H1, H2, H3 given certain symptoms or evidence. Finding the hypothesis with the highest probability value among them comes next, after calculations have been made for each hypothesis. The highest hypothesis value turns out to be the probability of H1, leading to the conclusion that the patient is likely suffering from H1 or Type 1 Diabetes, with a probability of 0.47 or 47% when expressed in percentage terms. The results from each hypothesis probability should approximate or equal one. Moving forward, a more comprehensive testing procedure will be conducted to ascertain the presence of type two diabetes. This process will be based on four documented evidences or symptoms, ensuring an accurate and effective diagnosis, as shown in Table 3.

**Table 3. Probability Score Case 2**

Hypohotesis	Evidence H1	Evidence H2	Evidence H3
P(H1)=0.3	P(E6 H1)=0.5	P(E6 H2)=0.38	P(E6 H3)=0.57
P(H2)=0.4	P(E7 H1)=0.48	P(E7 H2)=0.38	P(E7 H3)=0.70
P(H3)=0.3	P(E8 H1)=0.33	P(E8 H2)=0.53	P(E8 H3)=0.67
	P(E10 H1)=0.17	P(E10 H2)=0.25	P(E10 H3)=0.30

Upon examining the probabilities of each hypothesis (H1, H2, H3) and the likelihood of associated events (E6, E7, E8, E10) as presented in the Table 3, this study apply bayesian inference to calculate the conditional probabilities of each hypothesis. The calculations enable this study to assess the strength of each hypothesis based on the available evidence by considering all pertinent information, as equation:

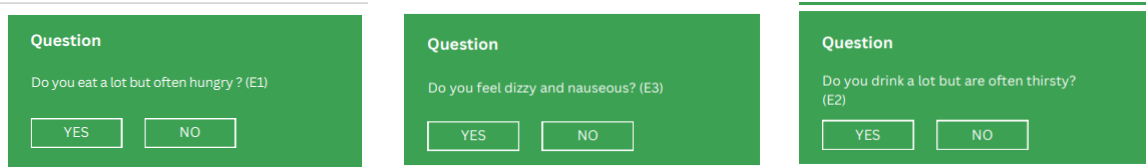
$$p(H_1|E_6, E_7, E_8, E_{10}) = \frac{(0.5 \times 0.48 \times 0.33 \times 0.17) \times 0.3}{(0.5 \times 0.48 \times 0.33 \times 0.17 \times 0.3) + (0.38 \times 0.38 \times 0.53 \times 0.25 \times 0.4) + (0.57 \times 0.7 \times 0.67 \times 0.3 \times 0.3)} = 0.11 \quad (6)$$

$$p(H_1|E_6, E_7, E_8, E_{10}) = \frac{0.38 \times 0.38 \times 0.53 \times 0.25 \times 0.4}{(0.5 \times 0.48 \times 0.33 \times 0.17 \times 0.3) + (0.38 \times 0.38 \times 0.53 \times 0.25 \times 0.4) + (0.57 \times 0.7 \times 0.67 \times 0.3 \times 0.3)} = 0.21 \quad (7)$$

$$p(H_1|E_6, E_7, E_8, E_{10}) = \frac{0.57 \times 0.7 \times 0.67 \times 0.3 \times 0.3}{(0.5 \times 0.48 \times 0.33 \times 0.17 \times 0.3) + (0.38 \times 0.38 \times 0.53 \times 0.25 \times 0.4) + (0.57 \times 0.7 \times 0.67 \times 0.3 \times 0.3)} = 0.67 \quad (8)$$

Based on the calculations, it is evident that the most significant hypothesis is H3, which holds a value of 0.67, equivalent to 67%. This substantial percentage strongly suggests that the patient's diagnosis is likely to be H3, commonly known as type two diabetes. Then, step three involves conducting a trial calculation with the system to determine if its calculations are consistent with manual ones, where a patient exhibiting symptoms E1, E2, E3 (frequent overeating and constant hunger, increased fluid intake and persistent thirst, regular dizziness and

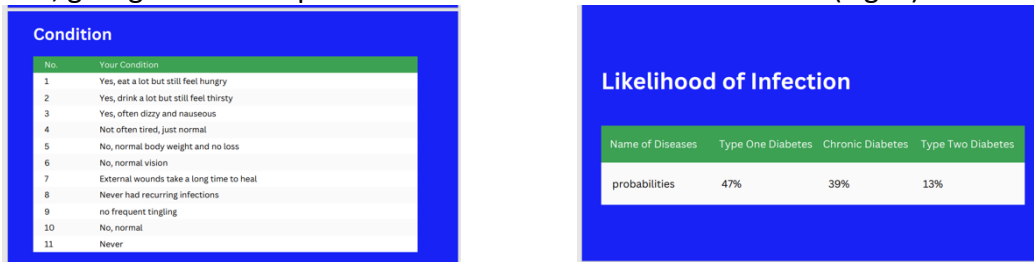
feelings of sickness) leads to calculation results indicating the most significant hypothesis is 47% or H1 for type one diabetes (Fig. 4).



(a) Evidence 1 (b) Evidence 2 (c) Evidence 3

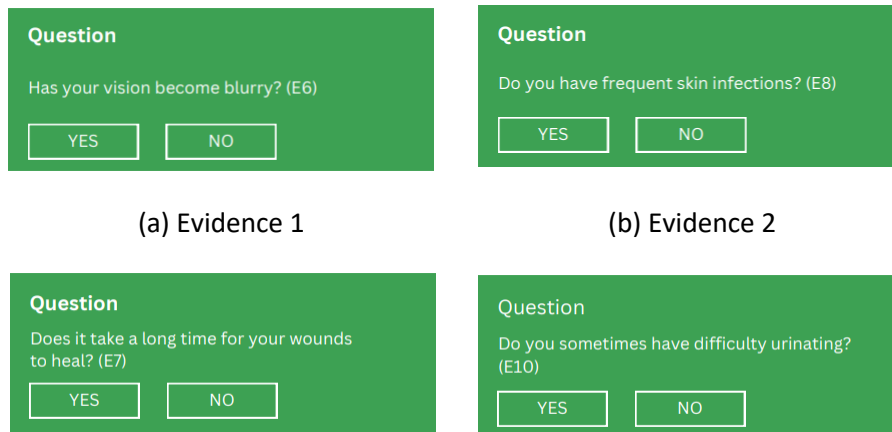
**Figure 4. Case 1 Evidence Questions: (a) Evidence 1, (b) Evidence 2, (c) Evidence 3**

After completes the evidence question, this study processes the provided information and generates a condition report. This report includes a calculated percentage, indicating the likelihood of a diabetes diagnosis based on the evidence gathered. The percentage result is derived from an algorithm that compares responses against known patterns and risk factors for diabetes, giving the user a quantifiable measure of the health status (Fig. 5).



**Figure 5. Case 1 Result**

After conducting a comprehensive trial calculation using the system, it was found that the outcomes are consistent, showing H1 at 47%, H2 at 39%, and H3 at 13%. Therefore, it can be concluded that the patient is diagnosed with type one diabetes (H1). The second case, the patient presents with symptoms E6, E7, E8, E10, which include blurred vision, delayed external wound healing, recurring skin infections, and frequent urination. Subsequent calculations reveal that the predominant hypothesis stands at 67%, towards H3, which indicates type 2 diabetes, according to the system's evaluation (Fig. 6).



(a) Evidence 1 (b) Evidence 2

(c) Evidence 3

(d) Evidence 4

**Figure 6. Case 2 Evidence Question**

After responding the evidence question, the outcome is recorded as symptom of diabetes. This process is the part of a screening or assessment for diabetes diagnosis. The resulting percentage from this assessment likely determines the probability or risk level of a diabetes diagnosis, with percentage in the context of the overall symptoms evaluated (Fig. 7).

**Figure 7. Case 2 Result**

The system calculation indicates results that are consistent with the manual calculation, with values of  $H_3=67\%$ ,  $H_2=21\%$ , and  $H_1=11\%$ , where the highest value concludes that the patient suffers from the condition. The incidence of Type 2 diabetes, or  $H_3$ , is 67%. The conclusion from the knowledge validation is deemed valid.

### Inference Result

The inferencing process incorporates two methodologies: forward chaining and backward chaining. The methodology applied in this research is forward chaining, which involves tracking available information and integrating rules to formulate a conclusion, executing the process in a sequential manner from the problem's inception to its resolution. Within the forward chaining approach, there are three strategies: depth-first search, breadth-first search, and best-first search. The strategy chosen for this research is the depth-first search. Additionally, the inference diagram is displayed using the depth-first search method. Depth-first search is a systematic blind search process that expands a path towards problem resolution before exploring other paths. The search process follows a single path until a conclusion is reached. If the search process arrives at a conclusion, depth-first search will backtrack to the last node to check if that node has any unexplored branch paths. If there are no more branches to explore, the process will return to the initial node and commence the search for unexplored branches from that starting point (Fig. 8).



Figure 8. Inference Diagram

**CONCLUSION**

This study is dedicated to the development of a web application aimed at diagnosing diabetes, offering effective solutions, and suggesting preventive measures. It involves a comprehensive process, starting with the acquisition of data through direct interviews with experts, followed by the meticulous storage of this data in a database to ensure the accuracy of the conclusions drawn. The application operates through three essential interface stages: member registration, self-diagnosis facilitated by answering relevant questions, and the presentation of conclusive results. Additionally, the application provides a user-friendly interface for direct consultations with experts, enhancing its practicality. To maintain its dynamic functionality, the application relies on the use of programming languages such as PHP and JavaScript, with Notepad++ serving as the editor and web browsers for execution. Looking ahead, the study offers recommendations for further enhancement, including expanding the range of member services, automating calorie calculations for diabetes patients upon displaying the diagnosis results, and exploring the development of a mobile application version to ensure broader accessibility.

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