Expert System for Diagnosing Dengue Fever Using Decision Tree Classification

Aris Rakhmadi*[1], Bangun Sri Langgeng Anggoro[2], Ihsan Cahyo Utomo[3], Muhammad Syahriandi Adhantoro[4], Yudi Wahyu Wibowo[5]

[1,2,3] Department of Informatics Engineering, Faculty of Communication and Informatics, Universitas Muhammadiyah Surakarta

e-mail: *[1]aris.rakhmadi@ums.ac.id

Abstract *- Dengue fever remains a significant public health concern, particularly in tropical regions, where early diagnosis is crucial to reducing the risk of severe complications. This study presents the development of a web-based expert system for preliminary dengue diagnosis using a decision tree classification approach. The system was built using medical record data collected from RSUD dr. Mangun Soemarso Wonogiri, comprising 150 patient cases with binary symptom attributes. A decision tree algorithm was applied to generate rule-based logic, which was then implemented in a web application that allows users to perform self-assessment through a series of yes/no symptom-related questions. Functional testing using the blackbox method confirmed that all system modules operated as intended. Rule validation ensured the correctness of the decision logic, while evaluation by a general practitioner affirmed the clinical relevance of the diagnostic rules. The expert system offers an accessible and interpretable tool for early detection of dengue fever, particularly in areas with limited access to healthcare. Further enhancements are recommended, including dataset expansion, probabilistic reasoning, and integration with telemedicine services.*

Keywords – components; Expert System, Dengue Fever, Decision Tree, Medical Diagnosis, Rule-Based Classification

I. INTRODUCTION

Dengue Hemorrhagic Fever (DHF), commonly known as dengue fever, is a vector-borne viral disease transmitted primarily by the Aedes aegypti and Aedes albopictus mosquitoes. This disease remains a persistent threat in tropical and subtropical regions, particularly in countries with warm climates and high rainfall. The widespread nature of the dengue virus poses a persistent public health challenge, particularly in densely populated areas [1].

Dengue fever is characterized by several clinical symptoms, including sudden high fever, severe headaches, muscle and joint pain, nausea, vomiting, skin rash, and fatigue [2], [3]. In more severe cases, it may lead to internal bleeding, low platelet counts, and circulatory failure, which can be fatal if not promptly treated. Early identification of these symptoms is essential in ensuring proper medical intervention and reducing the risk of complications .

One of the challenges in addressing dengue fever is the difficulty of early detection, especially in regions with limited healthcare infrastructure. Many patients only seek medical help when symptoms worsen, which delays treatment and increases the risk of severe outcomes. There is a critical need for accessible tools that support early diagnosis, especially for individuals in remote or underserved communities [4].

In recent years, advances in information technology have opened opportunities to develop intelligent systems that can support clinical decision-making [5]. Expert systems, which replicate the reasoning processes of human experts, have been increasingly applied in the medical field to assist in diagnosis and treatment planning [6]. These systems operate based on a set of rules derived from expert knowledge or empirical data.

Among the techniques employed in expert systems, the decision tree algorithm has gained popularity due to its simplicity, interpretability, and effectiveness in handling classification tasks. A decision tree mimics the human decision-making process by structuring decisions in a tree-like format, allowing users to follow a logical path from symptoms to diagnosis. This visual and rule-based nature makes it particularly suitable for healthcare applications.

The use of decision tree models in diagnosing diseases has been explored in various studies, demonstrating their ability to extract meaningful patterns from medical data [7]. These models are especially useful when dealing with binary or categorical variables, such as the presence or absence of specific symptoms. By generating understandable rules, decision trees can help bridge the gap between clinical data and user-friendly diagnostic tools.

This study proposes the development of a web-based expert system for diagnosing dengue fever using the decision tree method. The system is designed to facilitate early self-diagnosis by enabling users to input symptoms and receive a diagnostic prediction. This approach aims to empower users with preliminary insights while reducing the dependency on immediate clinical consultation.

The system was developed using actual patient data collected from RSUD dr. Mangun Soemarso Wonogiri. This dataset was derived from medical records and served as the foundation for generating decision rules through the decision tree classification process. The extracted rules were then implemented into a web-based platform that allows users to navigate through a series of questions and receive a diagnosis based on symptom input.

To ensure its reliability and usability, the system underwent a series of evaluations, including functional testing and expert validation [8]. These assessments were conducted to verify the accuracy of the diagnostic rules and to confirm that the system met the intended design and functionality requirements. The results of these evaluations indicate that the system is capable of supporting early detection efforts for dengue fever.

The development of this expert system represents a step forward in utilizing artificial intelligence for health diagnostics. By providing a simple, accessible, and informative platform, the system supports public health initiatives aimed at the early identification and prevention of dengue fever. Future improvements can include expanding the dataset, integrating real-time updates, and refining the user interface to facilitate broader adoption.

II. LITERATURE REVIEW

Dengue fever is a mosquito-borne viral infection that continues to pose significant health threats, especially in tropical and subtropical countries. The disease is transmitted by the Aedes mosquitoes, which breed in stagnant water and are most active during daylight hours. As urbanization, climate change, and population density increase, the risk of dengue outbreaks becomes more widespread. Early detection and prevention efforts remain crucial to mitigate the adverse health impacts associated with this disease [9].

Dengue fever presents a range of symptoms that often resemble other common illnesses, particularly in the early stages. Patients may experience high fever, nausea, headaches, skin rashes, and general weakness. In severe cases, the disease can cause internal bleeding and lead to a life-threatening condition known as dengue hemorrhagic fever. Because there is no specific antiviral treatment for dengue, supportive care and timely diagnosis are essential components of disease management.

The application of information technology in the medical field has paved the way for new approaches in disease diagnosis and healthcare delivery [10]. One such approach is the development of expert systems—computer programs that emulate the decision-making ability of human experts in specific domains. Expert systems typically consist of a knowledge base, an inference engine, and a user interface. They are beneficial in situations where specialist availability is limited or where initial assessments are required before professional consultation.

In the context of medical diagnosis, expert systems can analyze patient data and symptoms to provide a likely diagnosis or suggest further action. These systems are designed to reduce the cognitive load on healthcare workers, support consistency in decision-making, and enable broader access to health information. A well-designed expert system can serve as an effective decision-support tool, especially in areas with constrained medical resources [11].

One of the most commonly used classification methods in expert systems is the decision tree algorithm. A decision tree is a flowchart-like structure in which each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label or decision [12]. This structure enables users to trace the decision path from input features to the final output, thereby enhancing transparency and trust in the system.

Decision trees are widely appreciated for their simplicity, interpretability, and ability to handle both categorical and numerical data. They are especially effective when the dataset contains distinct and well-defined features, such as binary symptom indicators (e.g., presence or absence of fever, vomiting, or rash). Additionally, decision trees do not require extensive preprocessing or normalization, making them suitable for healthcare applications with limited computational resources.

Several studies have employed decision tree methods for disease classification tasks [13], [14], [15], [16]. These include diagnosing diabetes, predicting heart disease, identifying tuberculosis, and detecting malaria, among others. The success of these studies demonstrates that decision tree models can extract meaningful rules from medical datasets, enabling accurate and explainable classification outcomes. In many cases, decision trees have outperformed more complex algorithms due to their interpretability and ease of understanding [17], [18].

In the development of medical expert systems, the decision tree algorithm often functions as the core mechanism for rule generation. The process involves feeding a labeled dataset into the algorithm, which then analyzes the attribute-value combinations and produces a tree-based model that encapsulates the decision logic. This model can be translated into a set of if-then rules that form the diagnostic reasoning of the expert system [19].

To build a robust expert system, the quality and relevance of the input data are crucial. In the case of dengue diagnosis, features such as fever, nausea, weakness, decreased appetite, skin rash, and bleeding symptoms can serve as indicators [20]. The presence or absence of these symptoms can be used to create classification paths that lead to a positive or negative diagnosis. The effectiveness of the system depends heavily on how well these features are defined and represented.

Moreover, combining expert judgment with algorithmic rule generation can enhance the system's validity. While the decision tree provides data-driven rules, incorporating feedback from medical professionals ensures that these rules are clinically meaningful and reflect real-world practice. This hybrid approach strengthens the credibility and usability of the system in actual healthcare scenarios [21].

The integration of expert systems and decision tree algorithms presents a promising solution for enhancing the early detection of diseases, such as dengue fever. By leveraging clinical data and automated reasoning, these systems can facilitate faster and more consistent diagnoses. They also provide a foundation for developing accessible, low-cost diagnostic tools that can be implemented in various healthcare settings, especially in resource-constrained environments.

III. METHODOLOGY

This research employs a system development approach that integrates knowledge-based rule extraction and decision tree classification to construct an expert system for diagnosing dengue fever, as illustrated in Figure 1. The methodology consists of several key stages: data acquisition, data preprocessing, decision tree model construction, system implementation, and validation. Each stage is designed to ensure that the resulting system is both accurate in diagnosis and practical in usage.

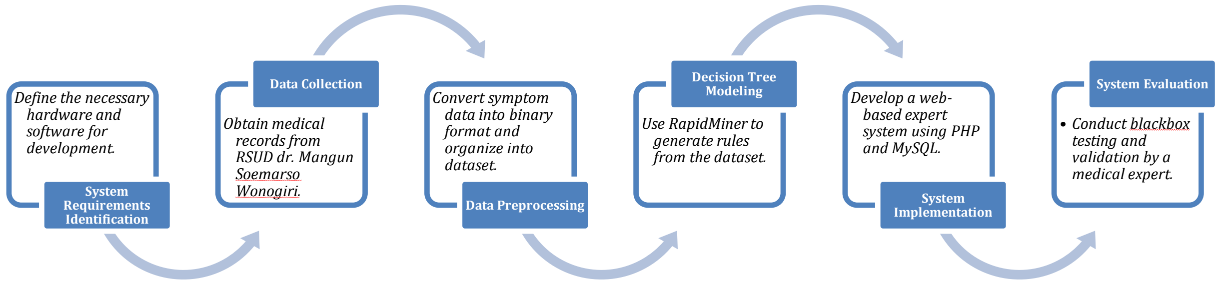

Figure 1. Integrated Knowledge-based Rule Methodology

The stage involved data collection from RSUD dr. Mangun Soemarso Wonogiri, a regional hospital in Indonesia. The data were obtained from medical records containing symptoms and diagnosis results for patients suspected of having dengue fever. A total of 150 anonymized patient records were collected, consisting of 138 confirmed positive cases and 12 negative cases. These records were used as the primary dataset for training and testing the decision tree model.

After collecting the data, the relevant symptoms were extracted and organized into a structured format using spreadsheet software. Each symptom was labeled as a binary attribute with values of "Yes" or "No". The selected features included fever, nausea or vomiting, body weakness, loss of appetite, sweating, red spots on the skin, constipation, dizziness, restlessness, bleeding, diarrhea, and pain. The target variable was the dengue fever diagnosis result, labeled as either positive or negative.

The features used in this study consist of a set of symptoms commonly associated with dengue fever, each represented as a binary (Yes/No) attribute. These features form the basis of the classification process conducted by the decision tree algorithm. A total of 12 symptom attributes were identified from patient records, including fever, nausea and vomiting, body weakness, loss of appetite, sweating, red spots, constipation, dizziness, restlessness, bleeding, diarrhea, and general pain. The target variable, labeled as "Dengue Diagnosis," indicates whether the patient was diagnosed as positive or negative for dengue fever.

Each symptom was recorded as a binomial input to simplify the classification model and reduce computational complexity. This binary representation allows the decision tree to form clear, interpretable branches and decision paths. Furthermore, the selected features were chosen based on their clinical relevance and frequency of occurrence in the collected patient data. Table 1 presents a summary of the input features, their data types, and brief descriptions to provide context on their diagnostic significance.

Table 1. Symptoms Recorded as Binomial Input

No	Symptom	Type	Values	Description
1	Fever	Binomial	Yes / No	Sudden high body temperature (≥38°C)
2	Nausea & Vomiting	Binomial	Yes / No	Feeling sick or throwing up
3	Body Weakness	Binomial	Yes / No	Lack of physical strength
4	Loss of Appetite	Binomial	Yes / No	Reduced food intake
5	Sweating	Binomial	Yes / No	Increased sweating
6	Red Spots	Binomial	Yes / No	Small reddish dots on the skin
7	Constipation	Binomial	Yes / No	Difficulty defecating
8	Dizziness	Binomial	Yes / No	Spinning sensation or lightheadedness
9	Restlessness	Binomial	Yes / No	Irritability or inability to relax
10	Bleeding	Binomial	Yes / No	Nosebleeds, gum bleeding, or bruising
11	Diarrhea	Binomial	Yes / No	Frequent loose bowel movement
12	Pain	Binomial	Yes / No	Pain in muscles or joints
13	Dengue Diagnosis	Binomial	Yes / No	Final classification result (Target)

The preprocessed dataset was then imported into RapidMiner Studio, a data science platform used for model training and evaluation. The Decision Tree algorithm was chosen due to its interpretability and ability to generate rule-based outputs. The algorithm was applied to the dataset to identify patterns and relationships between the symptoms and the diagnosis result. The output of this process was a decision tree model that formed the diagnostic logic of the expert system.

The resulting decision tree was translated into a set of if-then rules, where each path from the root to a leaf node represented a diagnostic scenario. These rules were used as the foundation of the expert system's inference engine. The clarity of the decision paths allows users to trace how a particular set of symptoms leads to a diagnostic outcome, enhancing the transparency of the system.

Following rule extraction, the system was implemented as a web-based application to enhance accessibility and usability [22]. The system was developed using a combination of technologies, including PHP for server-side programming, MySQL for database management, and HTML/CSS for the user interface. The system consists of several modules: home page, information on dengue fever, self-diagnosis feature, and result display. Each module was designed to be user-friendly and intuitive for non-expert users.

The expert system operates by presenting users with a series of questions related to symptoms. Users answer each question with "Yes" or "No" based on their current condition. Once all inputs are collected, the system processes them through the decision rules to generate a diagnostic prediction. The result is then displayed to the user, along with a brief explanation based on the rule path used.

```
Fever = No: Negative {Positive = 0, Negative = 6}
Fever = Yes
 ├── Nausea/Vomiting = No
 │    ├── Bleeding (Nose/Gums) = No: Negative {Positive = 0, Negative = 3}
 │    └── Bleeding (Nose/Gums) = Yes: Positive {Positive = 2, Negative = 0}
 └── Nausea/Vomiting = Yes
     ├── Body Weakness = No
     │    ├── Pain = No
     │    │    ├── Loss of Appetite = No
     │    │    │    ├── Red Spots & Itching = No: Negative {Positive = 0, Negative = 1}
     │    │    │    └── Red Spots & Itching = Yes
     │    │    │         ├── Dizziness = No: Negative {Positive = 0, Negative = 1}
     │    │    │         └── Dizziness = Yes: Positive {Positive = 2, Negative = 1}
     │    │    └── Loss of Appetite = Yes: Negative {Positive = 0, Negative = 1}
     │    └── Pain = Yes: Positive {Positive = 14, Negative = 1}
     └── Body Weakness = Yes: Positive {Positive = 119, Negative = 0}
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To support the diagnosis process, a database was designed and implemented using phpMyAdmin. The database consists of three main tables: attributes, questions, and responses. The attributes table contains information about each symptom, while the questions table maps each question to its respective attribute. The responses table stores user inputs and links them to the decision rules for processing.

System validation was conducted through three methods. First, blackbox testing was used to evaluate each system feature and ensure it functioned as expected. Test cases included navigation between questions, answer selection, and result generation. Second, algorithm validation was performed by comparing the decision tree output with manual rule-based classification on sample data. The results were consistent, indicating that the system correctly implemented the decision logic.

A domain expert (general practitioner) reviewed the generated rules and confirmed their clinical relevance. The medical professional validated the symptom logic and decision paths, affirming that the rules reflected reasonable diagnostic reasoning for dengue fever. This expert validation added credibility to the system's inference capability and confirmed its potential as a preliminary diagnostic tool.

The methodology employed in this study combines empirical data, algorithmic modelling, and expert feedback to develop a functional expert system. The use of a decision tree ensures interpretability and ease of rule extraction, while the web-based implementation broadens accessibility for the early detection of dengue fever.

IV. RESULTS AND DISCUSSION

The expert system developed in this study was implemented as a web-based application to provide users with accessible and user-friendly dengue fever diagnostics. The interface consists of four primary modules: *Home*, *Dengue Info*, *Check Dengue*, and *About*. These modules are designed to simplify user interaction and to facilitate the diagnostic process.

A. *Implementation Results*

The homepage (Figure 6) serves as the entry point, offering clear navigation options that lead users to either informational content or the diagnostic interface. The visual design features a minimalist and intuitive layout that accommodates users with varying levels of technical literacy. This ensures that individuals, including non-medical users, can interact with the system comfortably.

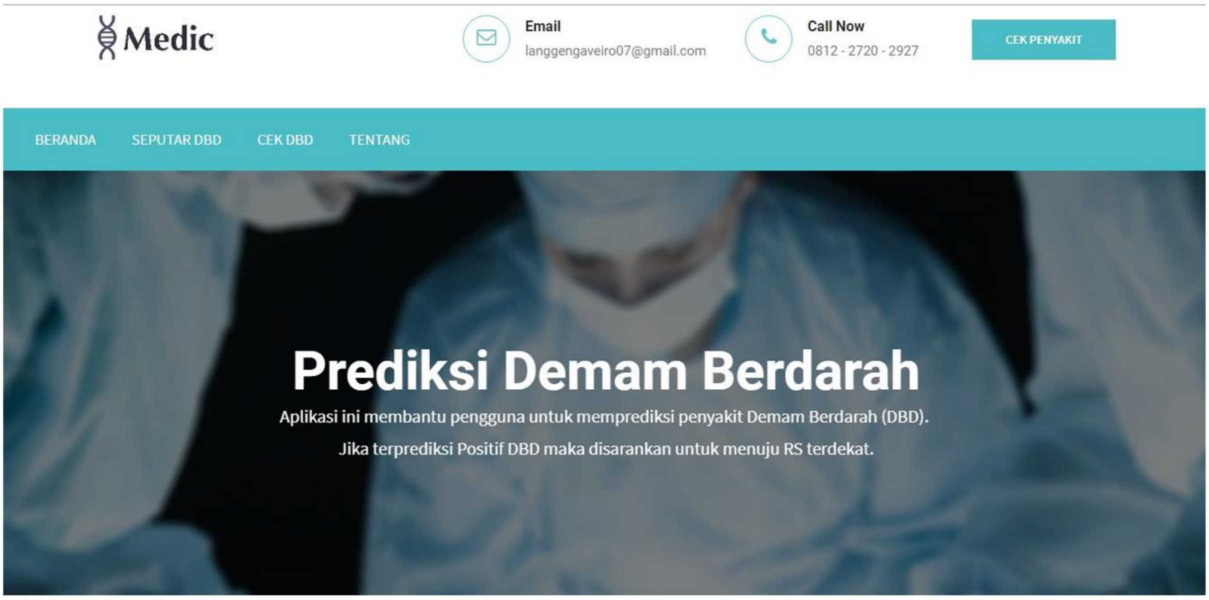

Figure 6. Homepage of the Dengue Diagnosis Expert System, providing users with access to general information and navigation toward the diagnostic module.

The primary feature of the system is the Check Dengue module, where users respond to a sequence of binary questions related to common dengue symptoms. This interface is shown in Figure 7. Each question corresponds to a specific symptom derived from clinical data, and users must answer "Yes" or "No" based on their current condition. The navigation buttons (Next, Back) allow the user to proceed step-by-step through the diagnostic form.

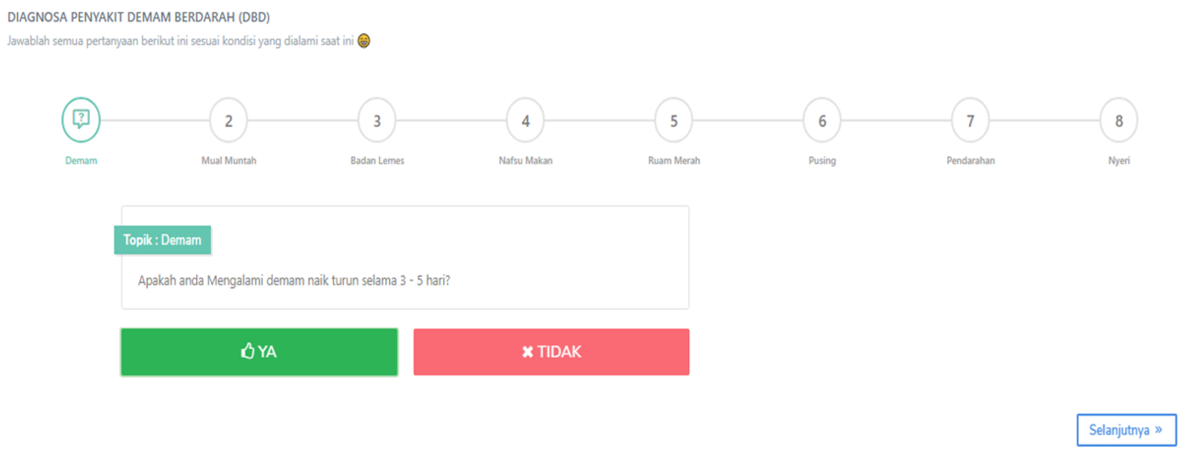

Figure 7. Diagnosis interface showing symptom-based questions. Users answer each question with "Yes" or "No" before proceeding to the next step.

Once all responses are submitted, the system processes the input using predefined rules generated from the decision tree model. The outcome is displayed to the user, indicating whether they are likely to have dengue fever. Figure 8 shows the final output, which also includes a concise explanation of the decision path used. This explanation is based on key symptoms that influenced the system's classification, increasing transparency and user confidence.

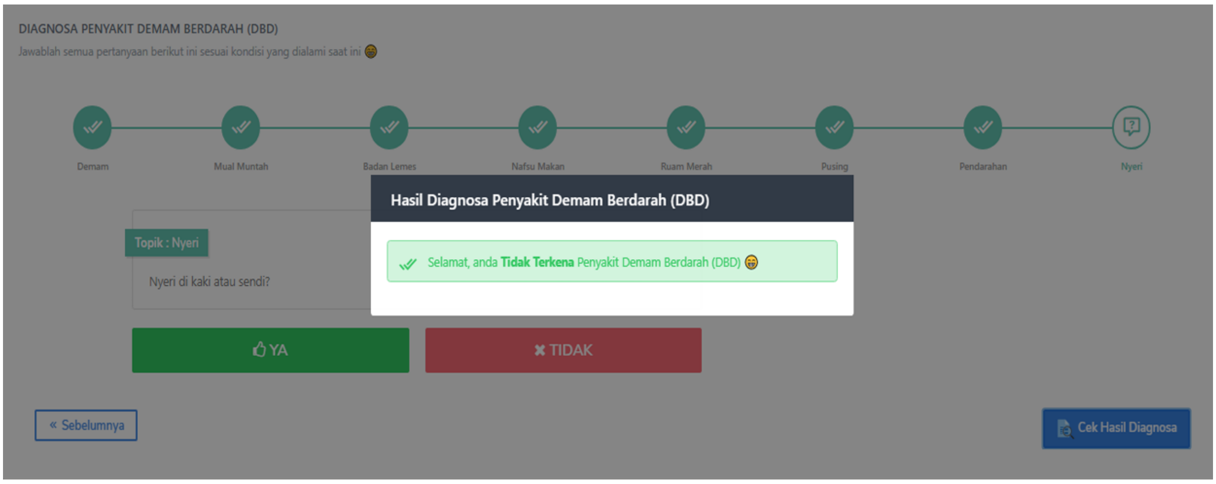

Figure 8. Diagnosis result screen showing the output of the expert system based on user input. The system provides a final classification and a brief explanation of the decision path.

B. *Functional Testing*

To ensure that the system performs according to its design, functional testing was conducted using the blackbox method. This type of testing focuses on input–output validation without examining the internal code structure. Each module and user interaction flow was tested to verify that the application responds correctly to various input scenarios.

A series of test cases was executed to assess menu functionality, response storage, navigation controls, and the generation of final diagnoses. Table 3 summarizes the blackbox test results, including the expected behavior and the observed outcomes for each tested feature.

Table 3. Blackbox Testing Results of the Dengue Diagnosis Expert System

Module / Feature	Test Case	Expected Result	Actual Result
Home	Click "Home"	Displays homepage	Valid
Dengue Info	Click "Dengue Info"	Displays information page about dengue	Valid
Dengue Check – Step Input	Select symptom answers	Saves the selected answers	Valid
Dengue Check – Navigation	Click “Next”	Proceeds to the next question	Valid
Dengue Check – Navigation	Click “Back”	Returns to the previous question	Valid
Dengue Check – Result	Click “Check Diagnosis”	Displays the diagnosis result based on decision rules	Valid

The blackbox testing showed that all system functions performed as intended. The navigation between menus, progression through the symptom questionnaire, and diagnosis result generation all yielded correct and consistent behavior. No errors or unexpected system responses were observed during the testing process.

C. *Rule Validation*

Rule validation was conducted to ensure that the decision tree-based logic implemented in the system accurately represented the rules derived from the training data. Several test cases with known outcomes were submitted to the system, and the results were compared with manual rule tracing.

In each scenario, the system output matched the expected diagnosis. This consistency confirmed that the rules extracted from the decision tree were correctly implemented and that the diagnostic logic operated following the intended classification paths. The use of a binary feature set (e.g., *Fever = Yes/No*) further simplified the decision-making process and minimized ambiguity.

D. *Expert Evaluation*

To assess the clinical validity of the expert system, an evaluation was conducted by a certified general practitioner. The expert reviewed the structure of the diagnostic questions, the logical flow of the decision tree, and the relevance of the symptoms included.

The expert concluded that the selected symptoms—such as *fever*, *nausea*, *bleeding*, *dizziness*, and *red spots*—were medically appropriate for early detection of dengue. The diagnostic rules were deemed consistent with basic clinical reasoning, making the system suitable as a preliminary diagnostic aid, particularly in areas where immediate access to healthcare professionals is limited.

The practitioner also emphasized that while the system could provide an early indication, it should be treated as a screening tool rather than a substitute for medical consultation. The system was considered especially useful for raising awareness and encouraging timely medical follow-up.

E. *Discussion and Interpretation*

The results of system implementation, functional testing, and expert validation collectively demonstrate that the expert system operates reliably and fulfills its intended purpose. The rule-based engine generated by the decision tree algorithm provides transparent and explainable diagnostic decisions, which is particularly valuable in medical applications.

One of the key strengths of this system is its accessibility. The web-based interface allows users to conduct self-diagnosis without technical barriers, while the simplicity of binary responses reduces user error. The visual presentation of results, accompanied by a clear rationale, enhances user understanding and confidence in the diagnosis.

However, some limitations were identified. The dataset used to train the system was limited in size and sourced from a single hospital. This may affect the generalizability of the rules to wider populations or different geographic regions. Additionally, the current version only supports binary input, which may not accurately capture the severity or nuance of specific symptoms.

For future development, the dataset can be expanded to include more diverse cases and institutions. The system can also be enhanced by incorporating probabilistic reasoning or fuzzy logic to handle uncertainty in symptom expression. Furthermore, usability testing with a broader audience could provide valuable insights into interface improvements and the need for multilingual support.

The system demonstrates the potential of expert systems and decision tree logic to support early diagnosis in public health contexts, especially in dengue-endemic regions. With continued refinement, it may be extended to support other infectious diseases or be integrated into telemedicine platforms.

V. CONCLUSION AND RECOMMENDATION

This study presented the development of a web-based expert system for the early diagnosis of dengue fever using a decision tree classification approach. Built upon clinical data from RSUD dr. Mangun Soemarso Wonogiri employed a system that used binary symptom attributes to generate diagnostic rules through a decision tree model. These rules were implemented into a user-friendly application that enables users to conduct self-assessments by responding to a series of symptom-based questions.

The system demonstrated functional reliability through blackbox testing, where all modules—including navigation, input handling, and rule execution—performed as expected. Rule validation against manual calculations confirmed the correctness of the decision logic, and expert evaluation by a medical practitioner supported the clinical relevance of the symptoms and diagnostic paths used. The integration of decision tree logic provided not only accuracy but also interpretability, allowing users to understand how their symptoms led to a specific diagnosis.

While the system performed effectively within its current scope, several areas for future enhancement were identified. Expanding the dataset with more diverse clinical records from multiple healthcare institutions would improve the generalizability and robustness of the model. Incorporating non-binary symptom inputs and probabilistic reasoning could also allow the system to handle symptom variability more effectively. Furthermore, adding multilingual support, mobile responsiveness, and integration with telemedicine platforms would extend the system's accessibility and impact.

Overall, this expert system contributes to the growing field of intelligent health diagnostics, providing a lightweight and accessible tool for the early detection of dengue fever. With continued development and wider validation, it holds significant potential as a decision-support application for both public health awareness and clinical triage in dengue-endemic regions.

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