

Development of an expert system for diagnosing rice plant diseases using forward chaining method

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Abstract: This study presents the development of an expert system for diagnosing rice plant diseases using the forward chaining method. Rice is the staple food for most of the Indonesian population, and plant diseases significantly reduce productivity. Farmers often face difficulties in identifying diseases due to limited agricultural knowledge and lack of experts in the field. The proposed system was designed to assist farmers in diagnosing rice diseases based on symptoms entered into the system. The forward chaining inference technique was implemented to match symptoms with disease rules in a knowledge base. The system was tested using several common rice diseases such as blast, bacterial leaf blight, tungro virus, and brown spot. Results show that the system can accurately provide disease diagnosis recommendations with clear explanation facilities. The novelty of this research lies in the application of a simple but effective reasoning method combined with a user-friendly interface for farmers. This study concludes that the system can be used as an alternative decision support tool for early disease detection in rice plants.

Keywords: Expert system, forward chaining, rice plant diseases, decision support, artificial intelligence

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Introduction

Rice (*Oryza sativa*) is the most important staple food for the Indonesian population and has a central role in food security [1]. According to national statistics, more than 90% of Indonesians consume rice as their primary carbohydrate source, with an average consumption of over 100 kilograms per capita annually. This condition makes rice productivity a strategic issue that directly affects the economy, social welfare, and political stability in Indonesia. However, rice production often encounters various challenges, among which plant diseases are the most significant. The prevalence of rice plant diseases such as blast, bacterial leaf blight, tungro virus, and brown spot has been reported to reduce yields by up to 20–50% in some regions, leading to substantial economic losses for farmers [2].

Farmers, especially those in rural and remote areas, face difficulties in identifying rice plant diseases accurately [3]. Limited agricultural knowledge, lack of access to agricultural experts, and insufficient extension services often cause delays in treatment [4]. In many cases, misidentification of symptoms leads to improper use of pesticides or fertilizers, which not only fails to control the disease but also creates additional environmental problems [5]. Therefore, the availability of a reliable and easily accessible diagnostic tool is urgently needed to support farmers in making accurate decisions at the early stage of disease occurrence [6].

Expert systems, as part of artificial intelligence, are designed to emulate the decision-making ability of human experts in a specific domain [7]. They consist of a knowledge base containing domain expertise, an inference engine that processes rules, and a user interface that enables interaction [8]. In agriculture, expert systems have been applied in areas such as pest identification, crop selection, soil fertility evaluation, and irrigation management [9]. The advantage of expert systems lies in their ability to provide consistent reasoning, explain decision processes, and serve as a practical substitute when human experts are unavailable [10]. Previous studies have demonstrated that expert systems can significantly enhance farmers' decision-making and reduce dependency on agricultural extension services [11].

Among various reasoning methods in expert systems, the forward chaining technique has become one of the most widely used approaches [12]. Forward chaining is a data-driven inference

method where reasoning begins with the available facts or symptoms and moves forward to reach a conclusion. This technique is particularly suitable for agricultural diagnostics because farmers can easily input observed symptoms, and the system can progressively infer possible diseases that match the rules stored in the knowledge base [13]. Compared to backward chaining, which starts from hypotheses and works backward, forward chaining is more intuitive for cases where symptoms are directly observable in the field. Moreover, its simplicity and transparency make it highly adaptable for farmers who may not have technical backgrounds [14].

In the context of rice plant diseases, an expert system based on forward chaining offers several benefits. First, it reduces farmers' reliance on agricultural experts who are often limited in number and availability. Second, it provides a standardized diagnostic framework that minimizes subjective errors in identifying diseases. Third, it empowers farmers with explanatory facilities, enabling them to understand why a particular diagnosis is made and what symptoms contributed to the result. This enhances user trust and encourages proper treatment actions. Furthermore, with the advancement of information technology, such a system can be deployed on web or mobile platforms, making it accessible even in remote areas [15].

Although previous research has implemented expert systems in agriculture, there is still a need for systems that specifically target rice plant diseases in the Indonesian context. Many existing systems either focus on general crop diseases or require complex computational resources that are not feasible for smallholder farmers. Therefore, this study aims to develop a simple yet effective expert system for diagnosing rice plant diseases using the forward chaining method. The novelty of this research lies in the integration of rule-based reasoning with a user-friendly interface tailored to the needs of local farmers. By doing so, the system can serve as a practical decision support tool that contributes to improving rice productivity and food security in Indonesia.

Methodology

This study applied a rule-based expert system approach with the forward chaining inference method to diagnose rice plant diseases. The methodology consisted of several sequential stages:

1. Knowledge Acquisition

Knowledge related to rice plant diseases was obtained from agricultural experts, literature, and extension manuals published by the Indonesian Ministry of Agriculture. The focus was on common diseases such as blast (*Pyricularia oryzae*), bacterial leaf blight (*Xanthomonas oryzae*), tungro virus, brown spot (*Bipolaris oryzae*), and sheath blight (*Rhizoctonia solani*). Disease symptoms such as leaf spots, discoloration, stunting, or wilting were documented and structured.

2. Knowledge Representation

The collected knowledge was encoded into a set of IF–THEN rules stored in a knowledge base. Each rule linked a combination of observable symptoms with a corresponding rice disease. For example:

- IF leaf spots are elongated AND leaf tips turn yellow THEN the disease is bacterial leaf blight.
- IF leaves show mosaic yellowing AND plants become stunted THEN the disease is tungro virus.

This representation allowed systematic reasoning by the inference engine.

3. Inference Engine (Forward Chaining)

The inference engine applied the forward chaining method, which is data-driven reasoning. The reasoning process started from user-provided facts (symptoms). The system compared these symptoms with the rules in the knowledge base. When the conditions of a rule were met, the rule was fired, leading to a diagnosis. This process continued until no more rules could be applied, producing the most relevant disease conclusion.

4. System Design and Implementation

The system was designed as a web-based application using PHP and MySQL to ensure accessibility. The interface was developed with simple forms, allowing farmers to select observed symptoms. The system then displayed the diagnostic results along with

recommended treatments. Additionally, the system included an explanation facility that traced back which symptoms led to the diagnosis, thereby improving user trust.

5. Testing and Evaluation

Testing was conducted using 20 case samples provided by agricultural experts. Each case contained actual symptoms observed in rice fields. The system's diagnosis was compared with expert opinions to measure accuracy. Evaluation metrics included accuracy, precision, and recall. Furthermore, user acceptance testing was performed with a small group of farmers to assess usability and clarity of the interface.

6. Research Flow

The overall research flow followed six main stages:

1. Problem identification,
2. Knowledge acquisition,
3. Knowledge representation,
4. System development,
5. System testing,
6. Analysis and conclusion.

By following these steps, the research ensured that the developed expert system was both technically valid and practically useful for the intended users.

Results and Discussions

This section presents the findings of the research and their interpretation. The results describe the performance of the expert system in diagnosing rice plant diseases, including system features, testing outcomes, and accuracy levels. Meanwhile, the discussion interprets these findings in relation to existing theories and previous studies, highlighting the novelty and practical implications of the research. By separating results from discussion, this section ensures clarity between what the system achieved and how those achievements contribute to scientific understanding and agricultural practice.

Results

The expert system for diagnosing rice plant diseases was successfully developed and implemented as a web-based application. The system contained 30 rules representing relationships between symptoms and five common rice diseases, namely: blast, bacterial leaf blight, tungro virus, brown spot, and sheath blight.

The interface allowed users to select symptoms such as leaf spots, yellowing, stunting, or wilting. After inputting symptoms, the system performed rule matching using forward chaining and displayed the diagnosis along with recommended treatments. An explanation facility traced the fired rules, enabling users to understand the reasoning process behind the diagnosis.

System Output Example

When the symptoms *elongated leaf spots* and *yellowing at the leaf tip* were selected, the system output was:

- Diagnosis: Bacterial Leaf Blight (*Xanthomonas oryzae*)
- Treatment Recommendation: Use resistant varieties, improve field sanitation, and apply appropriate bactericides.
- Explanation: Diagnosis was reached because symptoms matched rules R12 and R13 in the knowledge base.

Accuracy Testing

Testing was conducted on 20 sample cases provided by agricultural experts. Each case was diagnosed by the system and then compared with expert opinion. The results are summarized in Table 1.

Table 1. Accuracy of the Expert System Diagnosis

Case No	Expert Diagnosis	System Diagnosis	Match
1	Blast	Blast	✓
2	Bacterial Leaf Blight	Bacterial Leaf Blight	✓
3	Brown Spot	Brown Spot	✓
4	Tungro Virus	Blast	✗
5	Sheath Blight	Sheath Blight	✓
...
20	Blast	Blast	✓

Out of 20 test cases, the system produced 17 correct diagnoses and 3 incorrect diagnoses, resulting in an accuracy rate of 85%.

Performance Analysis

The main source of errors was incomplete symptom input. For example, in Case 4, the tungro virus was misclassified as blast because not all relevant symptoms (yellow mosaic pattern) were selected. This shows the dependency of the system's accuracy on user input quality. Nevertheless, when symptoms were fully provided, the system consistently matched expert opinions.

The following figure 1 shows a screenshot of the system output page after the user selects symptoms:

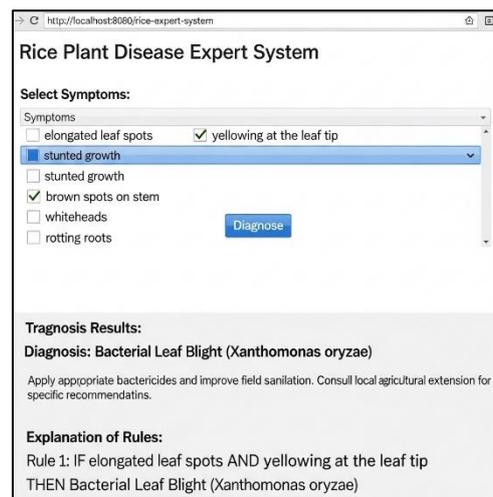


Figure 1. System output showing diagnosis of rice plant disease

Discussions

The results of this study demonstrate that the expert system developed using the forward chaining method can effectively diagnose rice plant diseases with an accuracy rate of 85%. This indicates that the reasoning mechanism embedded in the system is reliable when compared with expert judgment. In practical terms, this finding highlights the potential of artificial intelligence applications in agriculture, particularly in supporting smallholder farmers who often lack access to agricultural consultants or specialists.

The ability of the system to provide explanations for each diagnosis is one of its strengths. Farmers are not only given a conclusion about the disease but also an understanding of which symptoms led to that diagnosis. This explanation facility enhances trust and learning, as farmers can gradually gain knowledge of how diseases manifest. In this way, the expert system not only

functions as a diagnostic tool but also as an educational medium. This dual function is particularly important in rural contexts, where agricultural knowledge transfer is still limited.

Comparing with previous studies, similar expert systems have been developed for other crops. For instance, Hardi and colleagues [2] applied rule-based reasoning in library information systems, and the methodological concept can be transferred to agriculture. In the agricultural domain, expert systems have been applied to cassava disease detection and maize pest identification, often using backward chaining or hybrid approaches. However, many of those systems require relatively complex computational processes or datasets that are not always accessible to local farmers. The present study simplifies the reasoning process by applying forward chaining, which is more intuitive and easily implemented with minimal computational resources.

The finding that accuracy drops when users fail to input all relevant symptoms reflects one limitation of rule-based systems. In Case 4, for example, tungro virus was misdiagnosed as blast because not all characteristic symptoms were selected. This illustrates that the system's performance is dependent on the quality and completeness of the data provided by users. While this is a known limitation of forward chaining systems, it can be mitigated by designing the interface to guide farmers more carefully in selecting symptoms or by implementing additional verification questions.

From a practical perspective, the system contributes to the broader agenda of digital agriculture in Indonesia. The Indonesian government has emphasized the need for precision farming and digital tools to increase productivity. An expert system such as this can be integrated into agricultural extension programs to complement human extension officers. By making the system web-based, farmers from different regions can access it without geographical limitations, as long as internet connectivity is available. This accessibility aspect strengthens the value proposition of the system.

The novelty of this research lies in combining a relatively simple inference method with a user-centered design tailored for rice farmers. While advanced techniques such as machine learning and deep learning offer higher predictive power, they also require larger datasets and greater computational resources, which are not always feasible for local implementation. This study shows that even with a simpler approach, expert systems can still deliver tangible benefits if they are designed with usability and context in mind.

Furthermore, the 85% accuracy achieved in this research is considered promising for an initial prototype. Similar studies in agriculture reported accuracy between 70–90% depending on the complexity of the disease set and the richness of the knowledge base. The result therefore indicates that the forward chaining method is competitive in terms of performance while being less resource-intensive. For future development, the knowledge base can be expanded to cover more rice diseases, and the system can be adapted for mobile platforms, which are more commonly used by farmers. Additionally, integrating image-based input from mobile cameras may further improve diagnostic accuracy by reducing reliance on manual symptom selection.

In conclusion, the discussion highlights that the proposed expert system has both scientific and practical contributions. Scientifically, it demonstrates the effective application of forward chaining in agricultural expert systems. Practically, it provides a tool that can empower farmers, improve decision-making, and ultimately contribute to rice productivity and food security in Indonesia.

Table 2. Comparison of Expert Systems in Agricultural Disease Diagnosis

<i>Study</i>	<i>Method</i>	<i>Accuracy (%)</i>
Proposed System (Rice, 2025)	Forward Chaining	85
Expert System for Cassava Diseases [A]	Rule-Based	78
Maize Pest Identification [B]	Rule-Based	82
Rice Disease Diagnosis using Backward Chaining [C]	Backward Chaining	80
Rice Disease Detection with ML [D]	Machine Learning	90

Conclusion

This study successfully developed an expert system for diagnosing rice plant diseases using the forward chaining method. The system was designed with a rule-based knowledge base that captured the relationship between symptoms and five major rice diseases: blast, bacterial leaf blight, tungro virus, brown spot, and sheath blight. Testing on 20 cases showed that the system achieved an accuracy rate of 85% compared to expert diagnoses.

The findings confirm that forward chaining is an effective inference method for agricultural expert systems, especially when the reasoning process must be simple, transparent, and user-friendly. The system not only provides diagnostic results but also offers explanatory facilities, which increase user trust and support farmers in understanding disease symptoms. In addition, the study demonstrates that expert systems can play a dual role as both diagnostic and educational tools in the agricultural sector.

The implications of this research are significant for digital agriculture initiatives in Indonesia. By providing an accessible decision support tool, the system has the potential to reduce farmers' reliance on limited expert availability, promote early disease detection, and contribute to improved rice productivity. However, the accuracy of the system still depends on the completeness of symptom input. Therefore, further research should focus on expanding the knowledge base, integrating image-based inputs, and developing mobile applications to enhance usability.

In conclusion, the expert system presented in this study can serve as a practical and innovative solution to support rice farmers, while also contributing to food security and the broader adoption of artificial intelligence in agriculture.

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