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Chatbot-Based Expert System for Food Crop Disease Diagnosis

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ABSTRACT The agricultural sector plays an important role in supporting food security in Indonesia. However, plant diseases in rice, corn, and cassava often reduce crop productivity and cause significant losses for farmers. Limited access to agricultural experts also makes disease identification difficult, especially in rural areas. This study proposes a chatbot-based expert system for diagnosing food crop diseases using the Forward Chaining method. The system allows users to perform self-diagnosis by selecting symptoms experienced by the plants through an interactive chatbot interface. The inference process applies production rules to determine possible diseases based on the selected symptoms. The developed system was evaluated through functional testing, diagnostic accuracy testing, and usability testing. The accuracy test showed that 42 out of 48 diagnostic cases matched expert assessments, resulting in an accuracy level of 87.5%. In addition, usability evaluation using the System Usability Scale (SUS) obtained a score of 79.18, indicating that the system is easy to use and acceptable for users. The results indicate that the proposed system can support farmers in identifying food crop diseases more efficiently and provide practical assistance for early disease handling.

KEYWORDS: Expert System, Chatbot, Forward Chaining

I.INTRODUCTION

Food crops are agricultural commodities cultivated primarily to produce food for human consumption. In Indonesia, strategic food crop commodities include rice, corn, soybean, cassava, and sweet potato, which play an important role in supporting national food security[1]. In Indonesia, the agricultural sector plays a vital role in meeting national food needs. Rice, corn, and cassava are three of the many food crops that form the backbone of food security in Indonesia. Rice production has consistently ranked first in terms of food crop production levels from 2000 to 2015[2]. Corn, as an alternative source of carbohydrates, and cassava, as a higher energy source compared to corn, sweet potatoes, rice, and sorghum, also play equally important roles in fulfilling the food needs of the community[3].

However, significant challenges are faced by farmers in producing these three types of crops. Plant diseases are one of the main factors hindering the production of rice, corn, and cassava. If not properly managed, plant diseases can cause substantial losses, including crop failures. For instance, approximately 20 hectares of rice crops in one village experienced failure due to disease outbreaks. Similarly, diseases affecting corn and cassava can lead to significant reductions in production, directly impacting food security and farmers' welfare.

The increasing population, particularly within the middle class, accompanied by rising purchasing power, has caused the demand for food commodities to continue soaring. Without a corresponding increase in domestic production capacity, Indonesia will remain reliant on food imports to meet its domestic needs. To date, several food commodities, such as corn and soybeans, still need to be imported due to insufficient domestic production[4].

Early identification of plant diseases is important because delayed treatment may reduce crop quality and productivity. However, the limited number of experts with the knowledge, skills, and experience to diagnose plant diseases often presents a challenge. In practice, farmers often face difficulties in obtaining quick consultation services from agricultural experts. This condition encourages the development of a technology-based diagnostic system that can be accessed more easily.

Expert systems represent one solution that can address this need. An expert system is a computer-based system developed to imitate the reasoning process of human experts in solving specific problems[5]. This system utilizes the knowledge possessed by experts and stores it in a format accessible to the general public to solve problems that typically require expert intervention[6].

Several previous studies have applied expert systems for plant disease diagnosis using different inference methods. Yunita et al. [3] developed a web-based expert system for cassava disease detection, while Nur [6] implemented a Forward Chaining-based system for rice pests on a desktop platform. Other studies applied Certainty Factor and Bayes Theorem to improve diagnostic accuracy [7][8][9].

More recent research has further explored this domain. Apriyanto et al. [10] developed a mobile-based expert system for corn diseases using Forward Chaining and Certainty Factor, achieving 84% accuracy, but their system was limited to a single crop and lacked interactive features. Similarly, Agus et al. [11] developed ESforRPD2, a web-based system for rice diseases that achieved 87.5% sensitivity, yet it also focused on only one crop without chatbot integration.

Despite these contributions, several research gaps remain. First, most previous studies focus on a single crop, requiring farmers to use different systems when diagnosing diseases across multiple food crops. Second, many existing expert systems employ conventional web or desktop interfaces that may be less accessible for users with limited digital literacy. Third, only limited studies have integrated conversational chatbot interfaces into plant disease diagnosis systems. Fourth, studies combining Forward Chaining reasoning with chatbot interaction for multi-crop disease diagnosis are still relatively scarce. Therefore, this research proposes a chatbot-based expert system capable of diagnosing diseases in rice, corn, and cassava through a single interactive platform. The forward chaining method is one of the methods frequently used in expert systems. This method operates by performing forward searches based on known facts and predetermined rules to conclude or derive new facts. Forward chaining is particularly effective when the number of provided facts exceeds the conclusions to be drawn[7].

A chatbot is a computer program designed to simulate human conversation[12]. By leveraging chatbot technology, farmers can access information about plant diseases through dialogues that are easy to understand and can be executed on internet-connected devices. The chatbot can provide real-time diagnoses of plant diseases using the forward chaining method, which conducts searches based on known facts and established rules to conclude a diagnosis.

This research aims to develop a chatbot-based expert system capable of diagnosing diseases in rice, corn, and cassava using the forward chaining method. It is hoped that this chatbot will enable farmers to enhance their food crop production by preventing and effectively managing disease outbreaks in a timely manner. The following is a comparison table of previous research.

Table 1. Previous Research Comparison

Research	Method	Platform	Crop Type	Limitation
Yunita et al.	Expert System	Web	Cassava	Single crop
Nur	Forward Chaining	Desktop	Rice	No chatbot
Apriyanto et al.	Forward Chaining + Certainty Factor	Mobile	Corn	Single crop, no chatbot
Agus et al.	Expert System (Waterfall)	Web	Rice	Single crop, no chatbot
Proposed Study	Forward Chaining + Chatbot	Telegram	Rice, Corn, Cassava	Multi-crop interactive system

II.METHOD

A. Expert System

An expert system is a computer-based system developed to imitate the reasoning process of experts in solving specific problems[8]. In this study, the expert system was designed to assist farmers in identifying diseases in food crops such as rice, corn, and cassava.

The knowledge used in the system was obtained from literature studies and consultations with agricultural experts[12][9]. This knowledge was then represented in the form of production rules using the IF–THEN structure. The system processes symptoms selected by users and produces diagnostic results based on the rules stored in the knowledge base.

To make the system easier to access, the expert system was integrated with a chatbot interface. Through the chatbot, users can perform consultations interactively and obtain diagnostic information in real time[13].

B. Forward Chaining Method

The Forward Chaining method was used as the inference mechanism in this expert system[14]. The reasoning process starts from symptoms entered by users as initial facts. These facts are then matched with the rules available in the knowledge base to determine the most appropriate diagnosis.

The rules applied in the system follow the IF–THEN format. If the symptoms selected by the user satisfy the conditions of a rule, the system generates a conclusion in the form of a plant disease diagnosis. The inference process continues until no additional rules can be applied or a diagnosis has been obtained[15].

In this research, Forward Chaining was chosen because it is suitable for diagnostic systems that begin with observable symptoms before reaching a conclusion. The method also allows the system to provide diagnoses systematically based on predefined expert knowledge.

The forward chaining method was selected because the diagnostic process in agriculture starts from observable symptoms (facts) and proceeds toward a disease conclusion. This matches the forward-chaining working principle, unlike backward chaining which requires a hypothesis first. In addition, forward chaining is easier to implement for rule-based systems with a limited set of symptom–disease relationships.

A chatbot interface was chosen over conventional web forms to lower the technical barrier for farmers. Chatbots simulate natural conversation, allowing users to input symptoms through simple text interactions without navigating complex menus. This is particularly important for users in rural areas with limited digital literacy.

The Forward Chaining algorithm operates through an iterative, rule-based process to arrive at an optimal diagnostic conclusion. The formal stages of the Forward Chaining algorithm are as follows:

1. Initialization of Working Memory: The system allocates a working memory to store the initial set of facts (F_0), which are obtained from user input in the form of observed symptoms in food crops.
2. Construction of the Knowledge Base: The system maintains a Knowledge Base (KB) consisting of a set of production rules in the form:
   $R = \{r_1, r_2, ..., r_n\}$ where r_i: IF (antecedent) THEN (consequent)
3. Inference Mechanism : The system performs the match-select-execute cycle:
   - Match:
     Identify all rules $r_i \in R$ such that antecedent(r_i) $\subseteq F$
   - Select:
     Choose a rule r* from the Conflict Set based on a conflict resolution strategy
   - Execute:
     Execute the selected rule and add consequent(r*) to the working memory F

Mathematical Representation:

$\text{Conflict\_Set}(F) = \{r \in R \mid \text{antecedent}(r) \subseteq F \land \text{consequent}(r) \notin F\}$

$F' = F \cup \{\text{consequent}(r^*)\}$, where $r^* \in \text{Conflict\_Set}(F)$

4. Conflict Resolution Strategy : When multiple rules are applicable, the system applies the following conflict resolution strategies :
   - Specificity:
     Priority is given to rules with more specific (i.e., longer) antecedents.
   - Recency:
     Priority is given to rules involving the most recently added facts.
   - Means-End Analysis (MEA):
     Used to optimize the inference path toward the desired goal.
5. Termination Criteria: The inference process terminates when one of the following conditions is met:
   - $\text{Conflict\_Set}(F) = \emptyset$ (no more applicable rules remain)

The **goal state** is reached (a diagnosis for the food crop disease has been determined)

C. Chatbot

The chatbot functions as the main interface between users and the expert system. Through the chatbot, farmers can select plant types and input symptoms experienced by crops using an interactive conversation format[12].

After the symptoms are submitted, the system processes the data using the Forward Chaining method and returns the diagnostic results to users. The chatbot also provides additional information related to the identified disease, including descriptions and treatment recommendations.

The use of a chatbot interface is intended to improve accessibility and simplify the consultation process for users who may not have technical knowledge about expert systems.

D. Research Stages

The research process consisted of four main stages:

1. Data Collection

Data related to food crop diseases, symptoms, and treatment information were collected through literature studies and discussions with agricultural experts. The collected data focused on diseases affecting rice, corn, and cassava plants.

2. Knowledge Representation

The acquired knowledge was represented in the form of IF–THEN production rules. These rules were used by the inference engine to determine disease diagnoses based on user-selected symptoms.

The knowledge base developed in this study consists of 15 food crop diseases and 58 symptoms. The diseases are categorized into three crop groups, namely rice, corn, and cassava. Each disease is represented by one production rule, resulting in a total of 15 IF–THEN rules used by the Forward

Chaining inference engine. These rules were formulated based on expert knowledge and literature references related to food crop diseases.

3. System Development

The expert system was developed using the System Development Life Cycle (SDLC) approach. System modelling was carried out using several Unified Modelling Language (UML) diagrams, including use case diagrams, activity diagrams, and class diagrams.

4. System Testing

System testing was conducted to evaluate both functionality and diagnostic accuracy. Functional testing was performed using the black box testing approach, while accuracy testing compared the diagnostic results generated by the system with expert assessments.

III.RESULT AND DISCUSSION

A. System Design

The architecture of the chatbot is divided into three stages: Input, Process, and Output. This design combines expert knowledge, logical reasoning, and real-time chatbot interaction to deliver accurate and accessible plant disease diagnostics.

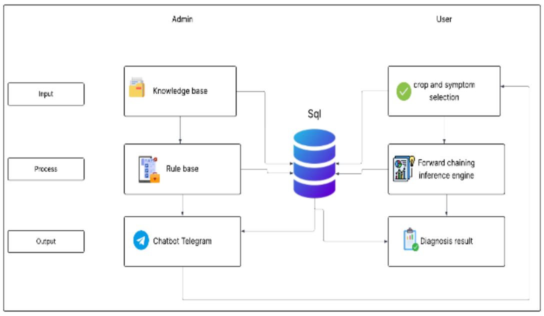

Figure 1. System Architecture Design

Data Input

- *Administrator*: Builds the knowledge base containing information on diseases of rice, corn, and cassava, including symptoms, causes, and treatments. This data is used to create inference rules.
- *User*: Interacts via Telegram chatbot by selecting crop type and symptoms. These inputs are used as initial facts for the reasoning process.

Data Process

- *Administrator*: Creates IF–THEN rules linking symptom combinations with diseases. These rules are stored in a relational database for efficient querying.
- *User*: The reasoning engine applies forward chaining, starting from user symptoms and matching them with rules. When conditions are met, a diagnosis is generated. If multiple rules apply, the system selects the most relevant based on the highest symptom match.

Data Output (Administrator): The expert system is integrated with a Telegram chatbot to provide easy access. Users can input symptoms and receive diagnoses directly, without needing technical knowledge of the system.

B. Data Acquisition

The data in this study focused only on the types of food crop diseases that are most commonly found in agricultural settings. The types of diseases identified and used in this expert system are described in Tables 2, 4, and 6. The detailed symptoms for each disease are presented in Tables 3, 5, and 7 for rice, corn, and cassava respectively. In addition, the disease data has been validated by an expert.

Table 2 Rice Plant Diseases

Disease Code	Disease Name
P1	Kresek Disease (Bacterial Leaf Blight)
P2	Rice Grassy Stunt Virus
P3	Blast Disease (*Pyricularia oryzae*)
P4	Tungro Virus
P5	Sheath Rot (*Rhizoctonia solani*)

Table 3 Symptoms of Rice Plant Diseases

Symptom Code	Symptom Description
G1	Leaf edges dry out and begin to turn yellow
G2	Curved green streaks appear near the leaf tips
G3	Infected leaves make a "kresek" sound when rubbed
G4	Stems may dry out
G5	Plant becomes stunted (grassy) due to inhibited rice growth
G6	Leaves become shorter, narrower, and stiffer
G7	Leaves turn light green to pale yellow
G8	Panicle formation is inhibited or does not occur
G9	Diamond or oval-shaped spots on leaves, gray or dark green in color
G10	Diamond or fish-eye shaped lesions on stems

G11	Brown spots appear on the panicle neck, where the stalk meets the stem
G12	Neck rot causes panicles to dry out
G13	Panicles are not fully filled
G14	Significantly stunted growth, plant appears dwarf-like
G15	Leaf color changes to yellow starting from the tip and spreading toward the base
G16	Leaves change shape and size, becoming shorter and stiffer
G17	Grayish green spots on the leaf sheath that eventually turn brown
G18	Lesions spread from the sheath to the leaf, causing wilting and drying
G19	Wet and soft rot on the sheath

Table 4 Corn Plant Diseases

Disease Code	Disease Name
P6	Downy Mildew
P7	Leaf Blight
P8	Leaf Rust
P9	Sheath Rot
P10	Smut Disease

Table 5 Symptoms of Corn Plant Diseases

Symptom Code	Symptom Description
G20	Chlorotic leaves
G21	Growth retardation
G22	White powder-like substance on upper and lower leaf surfaces
G23	Leaves curl and twist
G24	Disruption in cob development
G25	Infected leaves appear wilted
G26	Small spots merge to form larger lesions
G27	Light brown elongated spots shaped like a spindle or boat
G28	Brown elliptical spots
G29	Leaves appear dry
G30	Small brown or yellow spots on the leaf surface
G31	Yellowish-brown powdery spores appear
G32	Reddish spots on the sheath
G33	Irregular white then brown threads present
G34	Cob swelling
G35	White to blackish fungal growth on the kernels
G36	Swollen kernels
G37	Gland formation on the kernels
G38	Husk opens and abundant white to blackish fungus appears

Table 6 Cassava Plant Diseases

Disease Code	Disease Name
P11	Brown Spot
P12	Diffuse Leaf Spot
P13	Bacterial Wilt
P14	White Root Fungus
P15	Bacterial Leaf Blight

Table 7 Symptoms of Cassava Plant Diseases

Symptom Code	Symptom Description
G39	Irregularly shaped spots
G40	Discoloration in underground parts
G41	Brownish-gray leaf spots
G42	Vegetative growth ceases
G43	Cassava leaves become wrinkled
G44	White threads around the base of the stem
G45	Yellow leaves fall off
G46	Spots clearly visible on both leaf surfaces
G47	Spots turn light brown
G48	Leaves wilt
G49	Angular spots
G50	Poor plant growth
G51	Surrounded by dark green areas
G52	Leaves wilt simultaneously

G53	Round spots with a diameter of 3–12 mm
G54	Moisture presence
G55	Rotten tubers observed when uprooted
G56	Symptoms spread rapidly, spots turn light brown
G57	Uniform brown coloring on the surface of the spots
G58	Large leaf spots

C. Decision Tree

The decision tree was developed based on the previously constructed decision table and serves as the foundation for generating production rules within the expert system. Each decision tree outlines a logical pathway from the observed symptoms (represented by symptom codes "G") to the identification of specific diseases (denoted by disease codes "P"). These decision trees are then translated into a set of production rules that form the core of the inference engine, allowing the expert system to deliver automated and accurate diagnoses based on user-inputted symptoms.

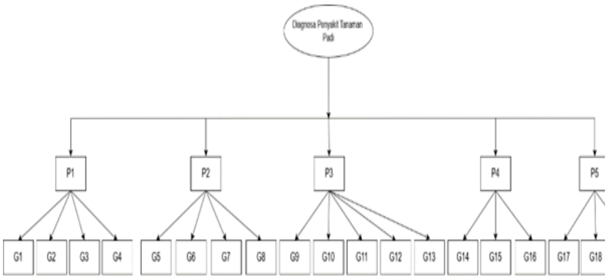

Figure 2. Rice Plant Decision Tree

- Rule 1: IF G1 AND G2 AND G3 AND G4 THEN P1
- Rule 2: IF G5 AND G6 AND G7 AND G8 THEN P2
- Rule 3: IF G9 AND G10 AND G11 AND G12 AND G13 THEN P3
- Rule 4: IF G14 AND G15 AND G16 THEN P4
- Rule 5**:** IF G17 AND G18 AND G19 THEN P5

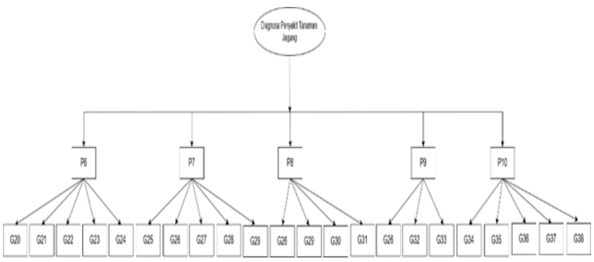
Figure 3. Corn Plant Decision Tree

- Rule 1: IF G20 AND G21 AND G22 AND G23 AND G24 THEN P6
- Rule 2: IF G25 AND G26 AND G27 AND G28 AND G29 THEN P7
- Rule 3: IF G26 AND G29 AND G30 AND G31 THEN P8
- Rule 4: IF G26 AND G32 AND G33 THEN P9
- Rule 5: IF G34 AND G35 AND G36 AND G37 AND G38 THEN P10

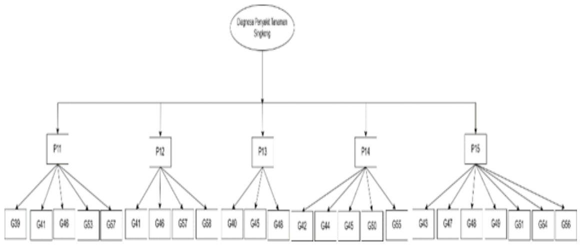
Figure 4. Cassava Plant Decision Tree

Rules:

- Rule 1: IF G39 AND G41 AND G46 AND G53 AND G57 THEN P11
- Rule 2: IF G41 AND G46 AND G57 AND G58 THEN P12
- Rule 3: IF G40 AND G45 AND G48 THEN P13
- Rule 4: IF G42 AND G44 AND G45 AND G50 AND G55 THEN P14
- Rule 5: IF G43 AND G47 AND G48 AND G49 AND G51 AND G52 AND G54 AND G56 THEN P15

After the production rules are established, the next step is to conduct a diagnostic experiment to ensure that the inference engine used functions correctly. The inference engine employed is Forward Chaining. To better understand the system's calculation process, here is a case example of performing manual calculations using the Forward Chaining method.

The farmer reports that their rice plants exhibit the following symptoms:

- G1: Leaf edges dry out and begin to turn yellow (symptom of P1)
- G3: Infected leaves make a "kresek" sound when rubbed (symptom of P1)
- G5: The plant becomes stunted due to inhibited rice growth (symptom of P2)
- G7: Leaves turn light green to pale yellow (symptom of P2)
- G8: Panicle formation is inhibited or does not occur (symptom of P2)

Forward Chaining Calculation:

Initial Facts: $F_0 = \{G1, G3, G5, G7, G8\}$

Rule Evaluation:

- R1 (P1): Requires G1, G2, G3, G4
  Met: G1, G3
  Not Met: G2, G4
  Result: Not triggered (2/4 = 50%)
- R2 (P2): Requires G5, G6, G7, G8
  Met: G5, G7, G8
  Not Met: G6

Result: Not triggered (3/4 = 75%)

- R3, R4, R5: No symptoms match (0%)

Conclusion:

No definitive diagnosis can be made as none of the rules are fully triggered.

Although no production rule was completely satisfied, the system evaluates the degree of rule matching to identify the closest possible diagnosis.

Rule R1 (P1) matched 2 out of 4 required symptoms (50%), while Rule R2 (P2) matched 3 out of 4 required symptoms (75%). Since Rule R2 achieved the highest rule-matching percentage, the system identified Rice Grassy Stunt Virus (P2) as the most probable disease.

This mechanism assists users in obtaining preliminary diagnostic information even when the observed symptoms are incomplete.

D. System Development

In the development of the Chatbot for Food Crop Disease Diagnosis Using the Forward Chaining Method, the interface implementation stage is a critical phase to ensure that user needs are effectively met when interacting with the chatbot. A well-designed interface greatly assists users in understanding the diagnostic processes performed by the system and enhances both the user experience and the overall system efficiency. This section presents two key chatbot interfaces developed in the system: the diagnosis page interface and the diagnostic results page interface. On the diagnosis interface page, users are presented with a selection of symptoms and conditions related to food crop diseases. Users must select the symptoms that match the observed condition of the plant in order to initiate the diagnostic process using the forward chaining method. The detailed layout of the diagnosis page interface is shown in Figure 5.

Figure 5.Chatbot Diagnostic Page Interface

Figure 6.Chatbot Diagnostic Page Interface Symptoms Selection.

Figure 7. Chatbot Diagnostic Results Page Interface

Figure 8. Chatbot Diagnostic Results Page Interface Including Sample Images of Infected Plants.

The expert system developed in this study applies the Forward Chaining inference method. The inference process begins with the user selecting the type of plant, followed by the selection of observed symptoms. These symptom data are then processed step by step based on a set of rules stored in the knowledge base. Each rule is structured in the form of IF (symptom) THEN (disease). The system evaluates the selected symptoms to determine whether a rule is satisfied. If all the required symptoms of a particular rule are identified, the system concludes a diagnosis of the corresponding disease. The diagnostic results are presented to the user in a comprehensive format, including the disease name, description, causes, sample images of infected plants, and recommended treatments. The system interface is illustrated in Figures 5, 6, 7, and 8.

E. Accuracy Testing

The final stage in the development of the Chatbot for Food Crop Disease Diagnosis Using the Forward Chaining Method is system testing. The testing phase involved evaluating the diagnostic accuracy of the developed expert system. Accuracy testing was conducted using 48 test cases validated by agricultural experts. The test cases were designed to represent various symptom combinations associated with the 15 diseases stored in the knowledge base. Each test case consisted of a set of symptoms entered into the system, and the resulting diagnosis was compared with the diagnosis provided by the expert. The evaluation aimed to measure the consistency of the expert system in replicating expert reasoning during disease identification.

Table 8 presents several sample scenarios used to assess the accuracy of the developed expert system.

Table 8 Accuracy Testing Scenario

Symptoms	**System**	**Expert**	**Result**
G1 Leaf edges dry out and begin to turn yellow G2 Curved green streaks appear near the leaf tips G3 Infected leaves make a "kresek" sound when rubbed G12 Neck rot causes panicles to dry out G17 Grayish green spots on the leaf sheath that eventually turn brown	P1 Kresek Disease (Bacterial Leaf Blight) (Rule Matching: 75%)	P1 Kresek Disease (Bacterial Leaf Blight)	Valid

G21Growth retardation G25 Infected leaves appear wilted G26 Small spots merge to form larger lesions G34 Cob swelling G35 White to blackish fungal growth on the kernels G37 Gland formation on the kernels G38 Husk opens and abundant white to blackish fungus appears	P10 Smut Disease (Rule Matching: 80%)	P10 Smut Disease	Valid
G39 Irregularly shaped spots G40 Discoloration in underground parts G45 Yellow leaves fall off G48 Leaves wilt	P14 White Root Fungus (Rule Matching: 100%)	P14 White Root Fungus	Valid

Based on the testing conducted, 42 out of 48 test cases produced diagnostic results that were consistent with expert assessments. Meanwhile, 6 cases showed discrepancies between the diagnosis generated by the system and the diagnosis provided by the expert. The accuracy of the expert system was calculated using the following equation:

Accuracy = Correct Diagnosis Data / (Total Diagnosis Data) × 100%
Accuracy = 42 / 48 × 100%
Accuracy = 87.5%

The obtained accuracy of 87.5% indicates that the proposed expert system is capable of producing diagnostic results that are largely consistent with expert assessments. The six mismatched cases were primarily caused by overlapping symptoms shared by multiple diseases, which created ambiguity during the rule-matching process. Since the system relies entirely on rule-based reasoning, incomplete symptom selection may also affect the final diagnosis. Nevertheless, the achieved accuracy demonstrates that the system is sufficiently reliable for preliminary food crop disease diagnosis and can assist farmers in obtaining early recommendations before consulting agricultural experts.

F. Usability Testing

Usability testing was conducted using the System Usability Scale (SUS) involving 52 respondents. The questionnaire consisted of ten standard SUS statements rated on a five-point Likert scale. Based on the evaluation results, the proposed system achieved a SUS score of 79.18, which falls into the Good category and indicates that the system is acceptable for practical use.

Table 9 Usability Testing Scenario

Evaluation Aspect	Value
Respondents	52
SUS Score	79.18
Grade	B
Acceptability	Acceptable
Interpretation	Good

G. Comparison with Previous Studies

The diagnostic accuracy of the proposed chatbot-based expert system (87.5%) is comparable to or higher than previous expert systems for plant disease diagnosis. As shown in Table 1, Agus et al. [11] achieved 87.5% sensitivity for rice diseases using a web-based expert system, while Apriyanto et al. [10] reported 84% accuracy for corn diseases using a mobile-based system with Forward Chaining and Certainty Factor. Nur [6] achieved 85% accuracy for rice pests using Forward Chaining on a desktop platform.

Although direct comparison is difficult due to different datasets, crops, and testing methodologies, the proposed system offers three key advantages over previous studies. First, it integrates multiple crops (rice, corn, and cassava) into a single platform, whereas previous studies focused on only one crop. Second, it incorporates a chatbot interface that simulates natural conversation, making the system more accessible to farmers with limited digital literacy. Third, the usability evaluation using the System Usability Scale (SUS) resulted in a score of 79.18, indicating that the proposed system is easy to use and acceptable for practical deployment. This usability aspect was not extensively discussed in most of the reviewed studies. These results demonstrate that combining Forward Chaining with a chatbot interface does not compromise diagnostic accuracy while significantly improving usability and accessibility for farmers in rural areas.

IV. CONCLUSION

The developed chatbot-based expert system was able to assist users in identifying diseases in rice, corn, and cassava through symptom-based diagnosis. The expert system in the form of a chatbot has been proven to help farmers diagnose diseases more quickly and efficiently without relying on direct assistance from agricultural experts. The application of the Forward Chaining method achieved an accuracy of 87.5% based on 48 test cases, with a SUS score of 79.18 indicating good usability. The evaluation results demonstrate that the system provides diagnostic results that are consistent with expert assessments and can contribute to improving food crop productivity in Indonesia.

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