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Rice Deep Knowledge Graph-Based Expert System: An Intelligent Solution for Identifying Rice Pests and Diseases

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Abstract. *Accurate diagnosis of rice pests and diseases is essential but often challenging using traditional methods, which are time-consuming and prone to human error. In this study, we propose the Rice Deep Knowledge Graph (RiceDKG) Expert System, which integrates deep learning techniques, particularly Long Short Term Memory (LSTM), with a Knowledge Graph to enhance symptom pattern-based diagnosis accuracy. This hybrid approach captures relationships among rice plant symptoms while leveraging systematically constructed domain knowledge. The system was evaluated on a dataset of 25 test cases, encompassing various symptoms such as brown spots, leaf curling, and fungal damage. Evaluation results demonstrate an overall accuracy of 84%, with 21 out of 25 cases correctly diagnosed, compared to expert evaluations. These findings indicate that integrating LSTM with knowledge graphs improves the system's ability to handle diverse diagnostic scenarios.*
Keywords: *Knowledge Graph; Long Short Term Memory; Expert System; Rice Pests and Diseases.*

Type of the Paper: Regular Article.

1. Introduction

The world population is projected to increase by over 35% by 2050. With a population of 275 million and an annual growth rate of 1.3%, Indonesia is expected to experience significant demographic changes. As the population grows, so does the demand for rice, the nation's primary staple food. Agriculture remains critical for developing and expanding Indonesia's Gross Domestic Product (GDP) [1]. Renowned for its agricultural country, Indonesia extensively cultivates various food crops, with rice as the predominant staple [2]. Despite the sector's importance, farmers face substantial losses, primarily due to crop failures caused by pests and diseases. These challenges stem from inadequate pest management and insufficient information on pest and disease control. Traditional knowledge on plant pests and diseases, which relies heavily on plant experts, often results in limited and static information [3].

The knowledge base on plant pests and diseases remains conventional and primarily dependent on plant experts, resulting in limited and static information [4]. However, agricultural production and related studies on pest insects and plant diseases generate vast volumes of data [5–

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8]. A major challenge in agricultural knowledge management is the effective integration of this extensive information [9]. Knowledge graphs offer a promising approach for integrating information [3,10–14]. Their semantic interoperability enables comprehensive and efficient exchange, supporting integration of information on pests and diseases [15]. Consequently, large-scale knowledge acquisition and pest and disease management methods can be modeled using knowledge graphs [12].

With the advancement of artificial intelligence (AI) technology, researchers are leveraging AI to build knowledge bases and expert systems in agriculture. AI has emerged as a transformative tool for pest and disease management, enabling precise, timely, and scalable solutions to longstanding challenges in crop protection. Over the past decade, AI applications in rice pest and disease management have advanced rapidly, with various deep learning approaches demonstrating high accuracy on controlled datasets. For instance, Xiong et al. [16] developed a convolutional neural network (CNN) model with data augmentation to detect 10 common rice pests, achieving 98.7% accuracy on field images. Similarly, Mardedi et al. [17] attained 96.45% accuracy in classifying rice leaf diseases with complex backgrounds. Additionally, the integration of knowledge graphs with AI, as proposed by Yan et al. [18], covers relevant information on crop diseases and pests in China, featuring 8 primary entities such as diseases, symptoms, and crops, linked through seven relationships, including primary occurrence locations, affected parts, and suitable temperature.

This research aims to develop knowledge graph-based expert systems to transform farmers' management of pests and diseases, ultimately improving Indonesia's agricultural productivity and food security. This research aims to develop a Rice Deep Knowledge Graph-Based (RiceDKG) Expert System, which leverages artificial intelligence techniques, particularly knowledge graphs and Deep Learning. This system aims to enhance pest and disease management in rice cultivation by integrating extensive agricultural data, facilitating more accurate decision-making for farmers.

2. Materials and Methods

A systematic and detailed methodology is essential to develop an effective expert system for diagnosing rice pests and diseases using a deep knowledge graph [3]. The methodology encompasses several stages, each contributing to the construction of a robust and reliable system, as presented in Fig.1.

Based on the RiceDKG expert system methodology, the first stage involves defining the knowledge domain, ensuring that all relevant concepts and entities are accurately identified and represented [19]. This foundational step involves extensive consultations with domain experts, thorough reviews of agricultural literature, and analysis of existing data sources to gather essential information [20,21]. The subsequent ontology design and construction phase create a structured and formal representation of the knowledge domain, establishing transparent relationships among classes and entities [22]. This structured approach is vital for ensuring consistency and clarity in the data [23]. Based on the ontology, the next phase involves the construction of the knowledge graph, which integrates diverse data sources to populate the ontology with real-world instances [24–26]. The next stage was deep knowledge graph modeling, leveraging advanced artificial intelligence techniques, which includes machine learning and deep learning [27]. These techniques enable the system to uncover hidden patterns and relationships within the data and thereby enhance its reasoning and decision-making capabilities [28–32].

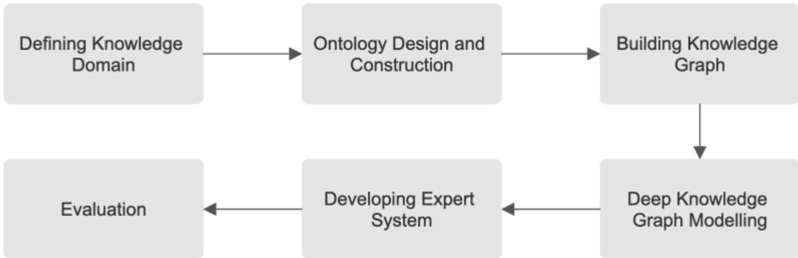

Fig. 1. RiceDKG-Based Expert System Development Methodology

Based on the rice pests and diseases knowledge graph, advanced deep learning methods, specifically Long Short-Term Memory (LSTM) networks, are employed to model and predict the pest and disease dynamic. LSTM is well-suited for handling sequential data and capturing long-term dependencies [33,34]. Integrating LSTM with the knowledge graph enables the system to utilize historical data on pest and disease occurrences, along with other relevant factors, to forecast future outbreaks and their potential impact [35,36]. To implement this, the LSTM network is trained on historical data from the knowledge graph, including time-stamped records of pest and disease incidents, environmental conditions, and agricultural practices [37]. It learns to recognize patterns and correlations within this data, accurate prediction of future pest and disease occurrences based on current and past conditions. Key components of the LSTM network include: the forget gate, input gate, candidate cell state, cell state update, output gate, and hidden state update [38]. The operations within an LSTM cell are described in Eq. (1) to (6), respectively.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$
$$\widetilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \tag{4}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$
$$h_t = o_t \odot \tanh(C_t) \tag{6}$$

The LSTM uses several gates to manage information flow. The forget gate f_t determines which information from the previous cell state to discard. The input gate i_t controls what new information to incorporate into the cell state. The candidate cell state $\widetilde{C_t}$ generates potential new values for the cell state. The cell state update C_t combines the previous and new candidate values, modulated by the forget and input gates. The output gate o_t determines which information to output. Finally, the hidden state update h_t computes the new hidden state by applying a hyperbolic tangent function to the updated cell state, filtered by the output gate [38]. By combining the structured knowledge from the graph with the predictive power of LSTM, the system provides more accurate and actionable insights for farmers and agricultural experts [39]. It also enhances their ability to anticipate and mitigate the effects of pest and disease outbreaks in rice cultivation.

The development of the expert system itself emphasizes a user-friendly interface, robust reasoning algorithms, and actionable recommendations for pest and disease management [40]. Finally, a comprehensive evaluation phase validates the system's accuracy and reliability through extensive testing and user feedback, enabling iterative refinements to enhance overall performance and usability [19]. The RiceDKG Expert System was evaluated for its effectiveness in diagnosing rice pests and diseases based on symptoms observed [3]. Testing employed real-world rice plant symptoms data and corresponding diagnoses, encompassing diverse symptoms to ensure comprehensive evaluation across various rice diseases and pests. The following metric was used to evaluate the performance of the expert system, as shown in Eq. (7).

$$Accuracy = \frac{Number\ of\ Correct\ Diagnoses}{Total\ Number\ of\ Cases} \times 100\% \tag{7}$$

3. Results and Discussion

In building a knowledge graph, the initial phase involves defining the knowledge domain, specifically focusing on rice plant pests and diseases, encompassing entities and relationships [12,41,42]. This domain involves identifying, preventing, and controlling pests and diseases that afflict rice plants [43], which is crucial for farmers and agricultural experts to mitigate threats to rice production. Defining this knowledge domain is achieved through comprehensive reviews of various literature on rice pests and diseases [19]. Within this domain, it is essential to understand the various types of pests and diseases that can affect rice plants, including pests such as planthoppers, stem borers, armyworms, and rats, as well as diseases such as blast, leaf blight, and sheath blight. Each pest and disease has unique characteristics and impacts on rice plants, necessitating deep knowledge for effective identification and management.

Additionally, understanding the life cycles of pests, their spread mechanisms, and the symptoms and signs of diseases forms a critical component of this domain [43]. With a thorough comprehension of the characteristics of rice pests and diseases, farmers and agricultural experts can swiftly identify infestations or infections, enabling timely preventive or control measures [44]. This foundational work is pivotal for the ontology design and construction phase, where knowledge is systematically structured. Constructing a knowledge graph involves a systematic process to build an organized knowledge structure [45]. The initial phase is gaining a deep understanding of the knowledge domain represented in the graph [19], including identifying relevant domain entities, concepts, and relationships. This includes defining classes and subclasses for various entities, such as types of pests, diseases, symptoms, and their interactions [3,13]. Tools like Protégé are used to formalize these entities and relationships into an ontology, creating a structured framework [46]. The ontology is then populated with real-world data, integrating information from diverse sources to ensure completeness and accuracy [47].

Tabel 1. Description of subclasses in the ontology of rice pests and diseases

Main Class	Subclass	Description
Plant	Rice	The main subclasses of plants are the main research objects.
Pests	Rice Pests	Organisms that cause damage or disturbance to rice plants directly or indirectly
Pathogen	Rice Pathogen	Microorganisms that cause disease in rice plants. Some common rice pathogens include fungi, bacteria, and viruses.
Pest control	Biology	Using other organisms is a way to control pests, such as insects, mites, weeds, and plant diseases.
	Chemical	The use of chemicals or pesticides to reduce the population of pests that damage plants.
	Integrated control	A broad-based approach that integrates chemical and non-chemical practices for economical pest control.
	Cultural	Cultural pest control manipulates crop production systems or cultural practices to reduce or eliminate pest populations.
...	....	...
Disease	Rice Diseases	Disorders or abnormalities that occur in rice plants due to attack by pathogens such as fungi, bacteria, or viruses.

In the context of rice pest and disease ontology, defining classes is essential to formulate highly accurate concepts related to pests and diseases affecting rice plants [13]. This process involves careful, methodical steps following formal principles to achieve a precise and consistent ontology. The class definitions are based on a conceptual model developed in the preliminary phase [3], which outlines seven main classes: (1) plants, (2) pests, (3) diseases, (4) symptoms, (5) pathogens, (6) pest control, and (7) disease treatment. Subclasses were defined from these seven main classes for each primary class, as described in Table 1 below. Defining classes and subclasses organizes concepts within the knowledge domain, ensuring that hierarchies and relationships are clearly and consistently represented. The ontology hierarchy for rice pests and diseases is illustrated in Fig. 2.

Once the ontology is established, it is populated with real-world data from various reliable sources, including research papers, agricultural databases, and expert knowledge [19]. Neo4j, a graph database management system, is employed to store and manage this data [48,49]. Advanced data integration techniques link related entities across different datasets, creating a cohesive graph structure [50]. The knowledge graph enables efficient data retrieval and reasoning by leveraging Neo4j's powerful querying capabilities and its ability to handle complex relationships [23]. The knowledge graph of rice pests and diseases visualized in Neo4j represents structured knowledge on pests, diseases and their associated attributes and interactions [13]. The knowledge graph organizes, stores, and analyzes information about various types of pests and diseases that attack rice plants and the relationships and attributes associated with these entities. By leveraging Neo4j, each entity, such as a specific pest or disease, is represented as a node, while the interactions and relationships between these entities are depicted as edges [13]. As a dynamic and interactive tool, the knowledge graph enhances understanding and supports decision-making by providing actionable insights based on comprehensive data integration and analysis, as presented in Fig. 3.

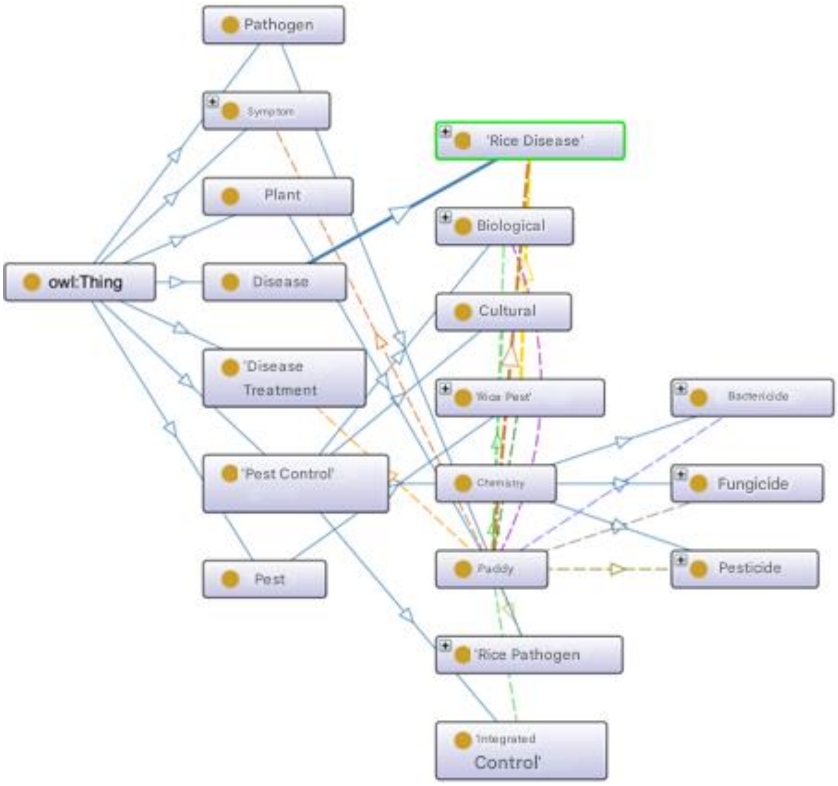

Fig. 2. Rice pests and diseases ontology hierarchy

Based on Fig. 3, the knowledge graph represents rice pests and diseases based on their symptoms, with nodes distinguishing pests, diseases, and symptoms [13]. The edges indicate relationships between these entities, such as which pests or diseases cause specific symptoms. Analysis of the graph enables the identification of symptom clusters that frequently occur together and their corresponding pests or diseases, supporting differential diagnosis. Highly connected nodes represent common symptoms linked to multiple issues, serving as key diagnostic indicators. This graph facilitates the identification of underlying problems in rice plants and informs targeted treatment and prevention strategies [51].

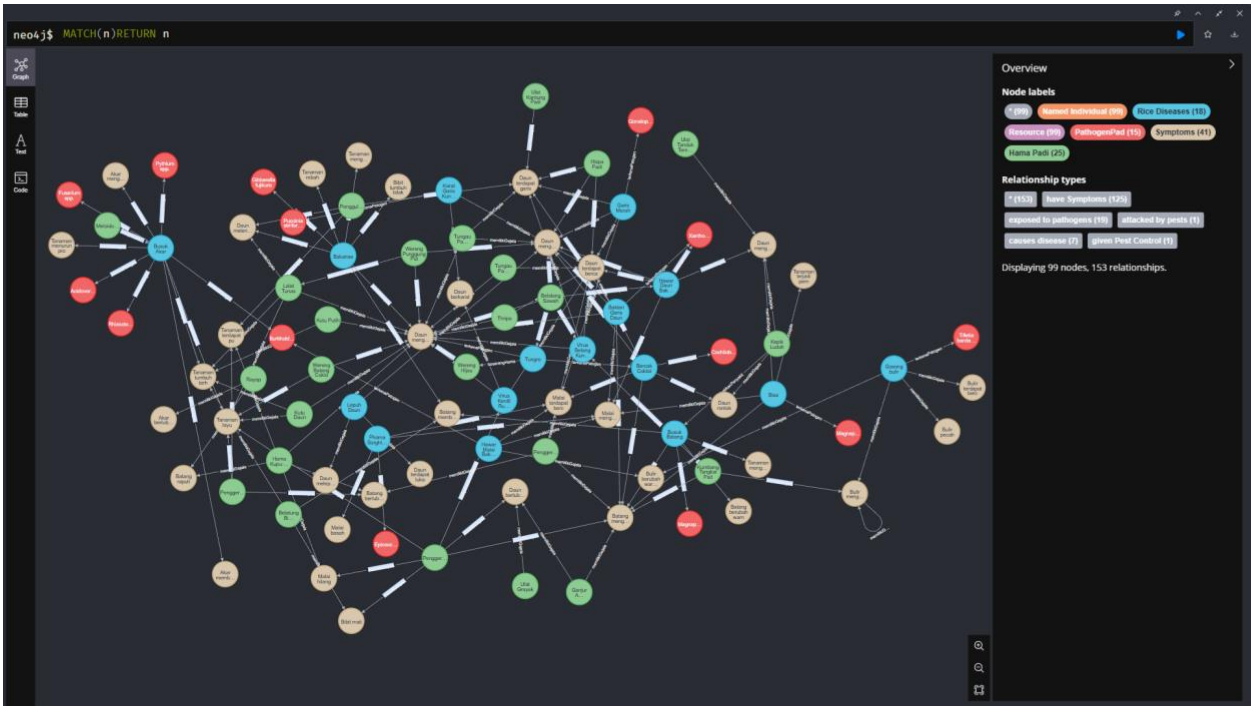

Fig. 3. Rice pests and diseases knowledge graph

After training the model, the next step is implementing the web-based expert system for rice pest and disease management. First, the system architecture design must include a frontend that enables user interaction through input forms and a backend that handles application logic and integrates with the trained model. The front end, built using HTML, CSS, and JavaScript, provides a user interface for data entry, while the back end, developed using a framework such as Flask, manages requests from the front end and manages the model to provide predictions. The trained model, such as the LSTM, is integrated into the backend to process data and generate relevant results. This implementation allows users to access the expert system via a web interface, input the necessary data, and receive accurate and timely predictions and recommendations for managing rice pests and diseases. The results of RiceDKG Expert System development are presented in Fig. 4 and Fig. 5 respectively.

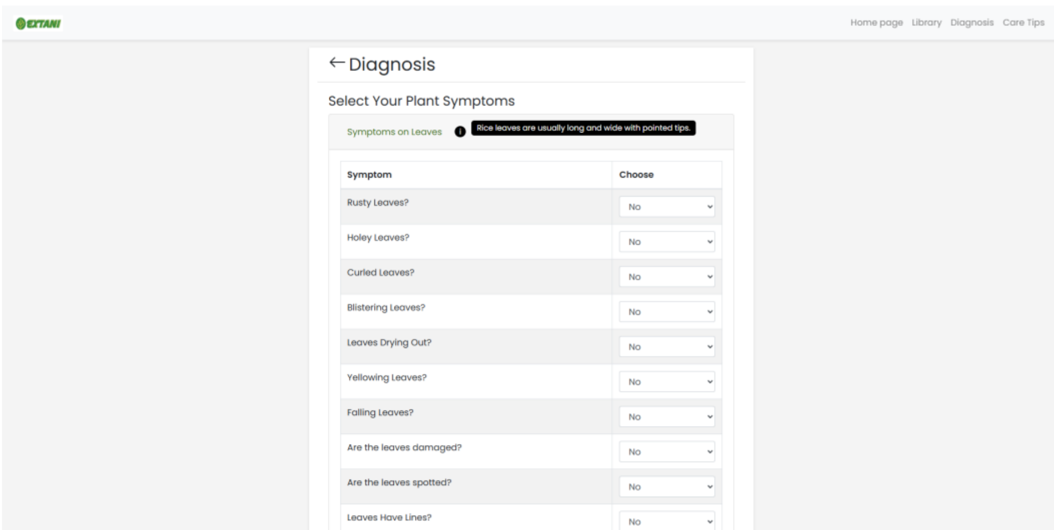

Fig. 4. Rice pests and diseases symptom-based diagnosis interface

Fig. 4 illustrates the diagnosis interface of the RiceDKG, which allows users to input observed symptoms on the leaves of rice plants. The interface is user-friendly, enabling selection or description of various symptoms to ensure accurate data entry. The underlying knowledge graph analyzes the symptoms and maps them to potential diseases or pests affecting the rice plants [13]. This step is crucial as it leverages the integrated natural language processing and machine learning models to identify the correct entities and relationships within the agricultural knowledge graph. Fig. 5 shows the diagnosis results interface. After symptom inputs, the expert system processes the data and provides a diagnosis, displaying the identified disease or pest along with detailed information such as its name, characteristics, and possible treatments. The results are derived from the interconnected entities within the knowledge graph, offering users precise and actionable insights. The interface may also provide recommendations for managing or mitigating the identified issues, helping farmers in making informed decisions to protect their crops.

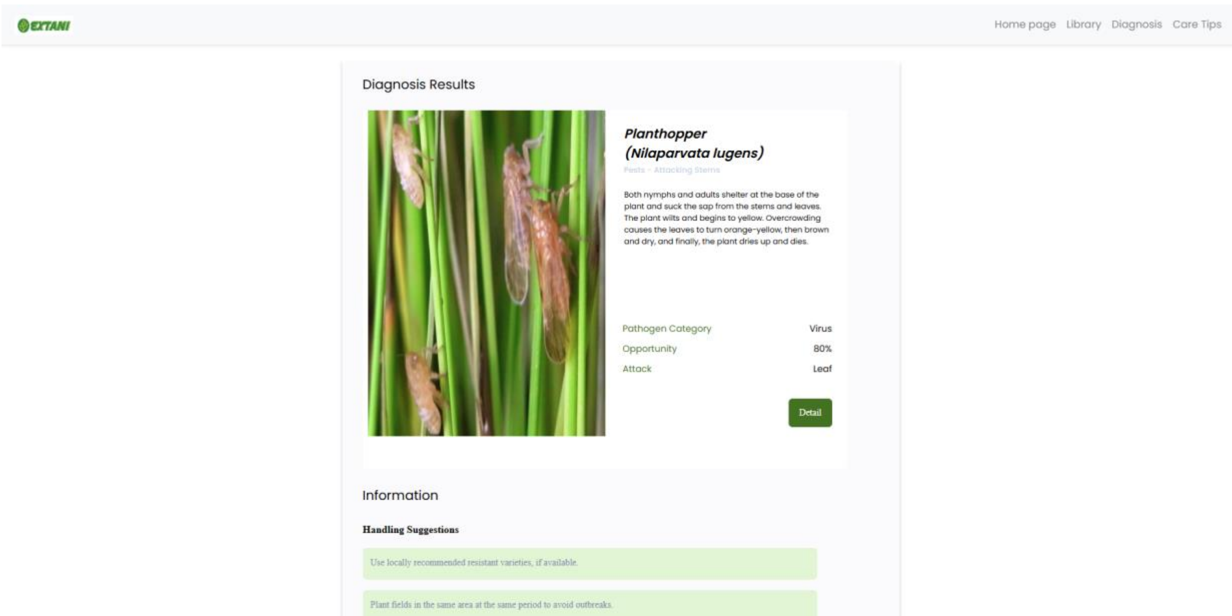

Fig. 5. Rice pests and diseases diagnosis Results Interface

The RiceDKG Expert System was rigorously evaluated using 25 rice plant symptoms cases to assess its diagnostic accuracy. Table 2 summarizes the test cases used in this evaluation.

Table 2. RiceDKG expert system test cases

Case No.	Symptoms Observed	Expert Diagnosis	System Diagnosis	Result
1	Brown, irregular spots on leaves	Rice Blast	Rice Blast	Correct Diagnosis
2	Curling and distortion of leaves	Insect Infestation	Fungal Infection	Incorrect Diagnosis
3	Excessive leaf shedding	Bacterial Blight	Bacterial Blight	Correct Diagnosis
4	Patchy yellow areas on leaves	Chlorosis	Chlorosis	Correct Diagnosis
...	...	...	...	...
25	Wet, mushy spots on leaves	Soft Rot	Soft Rot	Correct Diagnosis

The performance metrics summarized in Table 3 shows the total number of cases, number of correct diagnoses, and overall accuracy, highlighting the effectiveness of the RiceDKG based on these test cases.

Table 3. Evaluation metrics of RiceDKG expert system

No	Metric	Value
1	Total Number of Cases	25
2	Number of Correct Diagnoses	21
3	Accuracy	84%

The evaluation of the RiceDKG Expert System reveals a robust performance, achieving an accuracy of 84%, indicating its effectiveness in diagnosing rice pests and diseases. This high accuracy reflects the system's ability to identify issues based on various symptoms, including leaf discoloration, spots, and mold. Compared to previous studies, such as the ESforRPD2 Expert System, which reported 87.5% sensitivity in detecting 48 symptoms and 8 types of rice plant diseases from 16 data tests [52], the RiceDKG system shows competitive performance, though slightly lower, while integrating knowledge graphs for broader symptom inference. In contrast, a machine learning-based rice leaf disease detection systems using VGG16 reported a test accuracy of 60% [53], highlighting the RiceDKG's relative strength in rule-based expert systems. The system performed well across various cases, aligning closely with expert diagnoses and demonstrating its practical utility in agricultural settings.

However, the system faced challenges, as evidenced by a 16% rate of incorrect diagnoses. This error rate is attributed to limitations in distinguishing similar symptoms, such as leaf curling and distortion, which are often misclassified between fungal infections (e.g., rice blast) and insect infestations (e.g., stem borers) due to overlapping visual profiles and insufficient nuanced data in the knowledge base. For instance, powdery white growth was sometimes misdiagnosed as bacterial leaf blight, reflecting gaps in handling rare or ambiguous cases. These issues align with findings in prior research; an ontology-based expert system for rice diseases reported challenges in symptom differentiation leading to errors in complex scenarios [54]. Similarly, AI detection system typically exhibit error rates of 10-20% without multimodal integration such as image analysis [55]. While enhanced classification systems combining color and texture features improve accuracy, they still face issues with visually similar diseases [56], underscoring the need for refined feature extraction.

These limitations suggest that the RiceDKG Expert System could benefit from refinements in its symptom analysis capabilities and an expanded knowledge base. Future efforts should focus on enhancing the system's ability to handle complex symptom patterns by incorporating detailed descriptions, updating the knowledge graph with the latest research on pest-disease interactions, and integrating real-world feedback from field trials, as demonstrated in forward-chaining expert systems [57]. Additionally, the misdiagnosis of powdery white growth further highlights areas for improvement [58], indicating that the RiceDKG Expert System could benefit from refinements in its symptom analysis capabilities and an expanded knowledge base.

Future efforts should focus on enhancing the system's ability to handle complex symptom patterns, incorporating detailed descriptions, and updating the knowledge graph with the latest research [19]. The RiceDKG Expert System can be further improved by addressing these limitations and integrating real-world feedback to achieve even higher diagnostic accuracy and reliability. By addressing these areas and drawing from established methods in studies such as the website-based diagnostic tool [59], the system can achieve higher diagnostic accuracy and reliability.

4. Conclusions

The RiceDKG Expert System has demonstrated strong performance, with an accuracy of 84% in diagnosing rice pests and diseases. This result highlights the system's effectiveness in accurately identifying various symptoms, including leaf discoloration, mold, and spots, which are crucial for effective pest and disease management in rice cultivation. Its strong alignment with expert diagnoses underscores its practical utility and potential as a valuable tool for farmers and agricultural professionals. However, the system faced challenges, particularly in distinguishing similar symptoms and providing accurate diagnoses in complex cases.

Several key areas for future work are recommended to enhance the RiceDKG Expert System and address its limitations. First, refining symptom analysis capabilities is crucial, especially for distinguishing similar or overlapping symptoms. Second, expanding and updating the knowledge graph with recent research, field observations, and additional pest and disease data will improve the system's diagnostic accuracy and coverage. Additionally, exploring the integration of machine learning techniques to continuously improve diagnostic rules based on new data could further enhance the system's performance.

Abbreviations

AI	artificial intelligence
CNN	convolutional neural network
CSS	cascading style sheet
GDP	gross domestic product
HTML	hypertext markup language
LSTM	long short term memory
RiceDKG	rice deep knowledge graph

Data Availability Statement

Data will be shared upon request by the readers.

CRediT Authorship Contribution Statement

Muhammad Ariful Furqon: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Investigation, Writing – Original Draft, Visualization. **Muhammad Arief Hidayat:** Methodology, Software, Validation, Formal Analysis, Writing – Review & Editing. **Windi Eka Yulia Retnani:** Data Curation, Investigation, Resources, Writing – Review & Editing. **Gayatri Dwi Santika:** Project Administration, Funding Acquisition, Writing – Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Use of AI in the Writing Process

Nothing to disclose.

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