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Design and Implementation of a Hybrid Probabilistic Expert System for Coffee Disease Detection

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Abstract: Indonesia's coffee industry continues to face grave threats from plant diseases and pests, which reduce yields and harm the livelihoods of smallholder farmers. Limited access to expert diagnosis in rural areas often leads to delayed treatment and crop loss. Addressing this gap requires accessible, intelligent solutions that can support early and accurate disease identification in the field. This study introduces a web-based expert system that assists farmers in diagnosing coffee plant diseases and pests based on observable symptoms. The system integrates a Bayesian Network (BN) to represent probabilistic relationships between symptoms and potential diagnoses. To ensure efficient inference, a Breadth-First Search (BFS) algorithm is employed for traversing structured graphs. Built using Node.js, Next.js, and MySQL, the system allows users to input symptoms and receive a ranked list of probable diagnoses with recommended treatments. The validation against expert assessments showed over 85% accuracy, confirming the system's reliability for real-world use. The combination of BN and BFS proves effective in managing uncertainty and complex interactions between symptoms and diseases. This research lays the groundwork for future development, including integration with IoT-based environmental monitoring, mobile platforms, and adaptive learning to support precision agriculture and broader rural deployment.

Keywords: Expert System, Bayesian Network, Breadth-First Search, Plant Disease, Web-Based

INTRODUCTION

The agricultural sector plays a crucial role in supporting Indonesia's food security, rural development, and national economic growth. According to data released by the Central Statistics Agency (BPS), as of February 2024, approximately 40.75 million people were employed in the agriculture, forestry, and fisheries sectors, representing 28.18% of Indonesia's total workforce. (Manggala putra et al., 2023). These numbers underscore the sector's significance as both a source of livelihood for millions of Indonesians and a vital component of national economic stability. Key agricultural commodities, including shallots, chili peppers, and coffee, are not only essential for domestic consumption but also contribute substantially to Indonesia's export earnings. Coffee holds strategic significance, positioning Indonesia as one of the world's top coffee-producing countries.

However, agricultural productivity in Indonesia faces persistent challenges, one of the most critical being pest infestations and plant diseases that threaten crop yields. Coffee cultivation, while lucrative, is highly susceptible to various plant diseases such as coffee leaf rust (Hemileia vastatrix), coffee berry disease (Colletotrichum kahawae), and anthracnose (Colletotrichum spp.). These diseases can result in yield reductions of up to 50% if not addressed promptly and effectively. (Motisi et al., 2022). The impacts of such diseases not only affect the incomes of farmers but also disrupt the national coffee supply chain and export commitments. (Agus Supriyanto et al., 2023).

One of the primary causes behind the inadequate handling of these plant health threats is the limited knowledge among farmers regarding the early signs and symptoms of plant diseases. Many farmers, especially those operating smallholder plantations, are unable to detect early manifestations of diseases, leading to delayed interventions and often ineffective control measures. (Anamisa et al., 2021; Istriningsih et al., 2022). Compounding this challenge is the limited access to agricultural extension services or plant health experts, particularly in remote

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and rural areas where many coffee plantations are located. (Amalia & Firmansyah, 2021).. Farmers in these areas typically rely on traditional knowledge or delayed consultations, both of which may not suffice given the increasing complexity of plant health issues driven by climate change and evolving pest dynamics (Wallelign et al., 2018).

Addressing this gap requires innovative, technology-driven solutions that can provide farmers with rapid, accurate, and accessible diagnostic assistance. One promising solution is the development of expert systems — artificial intelligence-based tools that simulate the reasoning processes of human experts to provide recommendations or decisions within a specific domain. An expert system typically comprises a knowledge base and an inference engine. (Raj et al., 2021)Such systems offer a scalable means to extend expert-level diagnostic capabilities to farmers without the need for constant physical presence of human experts.

Several studies have demonstrated the successful application of expert systems in the agricultural field. Systems have been developed to assist in identifying pests and diseases in rice, shallots, and chili, as well as to provide crop management recommendations. (Ariesta Indarwati & Susilawati, 2022; Kholifah, 2023; Sitepu et al., 2021; Wang et al., 2021). In coffee cultivation, decision-support systems have been applied to monitor disease risk factors and provide management strategies. (Rodríguez-García et al., 2021). A key advancement in expert systems is the integration of Bayesian Networks (BN) for probabilistic reasoning. Bayesian Networks are graphical models that represent variables and their conditional dependencies via directed acyclic graphs, making them effective for modeling uncertainty and causal relationships in complex domains such as plant disease diagnosis. (Aqil Burney & Naseem, 2018; R. Kumar & Jindal, 2022)

In addition to probabilistic reasoning, efficient traversal and search algorithms are crucial for ensuring the responsiveness and accuracy of expert systems. The Breadth-First Search (BFS) algorithm, widely applied in graph theory, provides a systematic means to explore relationships between symptoms and diseases by traversing nodes in a layer-by-layer manner. This approach helps ensure that no possible connection is overlooked and optimizes the search path for faster inference. (R. Lumbanraja et al., 2020)

Considering the pressing needs of Indonesian coffee farmers and the opportunities provided by advancements in artificial intelligence, this research focuses on developing a web-based expert system for diagnosing diseases in coffee plants. The proposed system integrates Bayesian Networks to address uncertainty in symptom-disease relationships and Breadth-First Search to enhance the efficiency and completeness of the diagnostic process. The use of a web-based platform ensures accessibility across diverse regions, including rural areas, supports centralized data management, and enables real-time updates to the knowledge base. Ultimately, this study aims to empower coffee farmers to identify diseases at an early stage, make informed decisions on control measures, and minimize crop losses. Moreover, the system is expected to support agricultural extension officers and researchers in their efforts to safeguard national coffee production and contribute to Indonesia's food security agenda.

The primary objective of this research is to design and implement an intelligent web-based expert system that enhances early disease detection in coffee crops. The main contributions of this study lie in the integration of Bayesian Networks for probabilistic reasoning and Breadth-First Search for efficient inference, both of which aim to improve decision-making and diagnostic support in the agricultural domain.

LITERATURE REVIEW

(a) Expert Systems in Agriculture

Numerous studies have investigated the application of expert systems and artificial intelligence in agricultural diagnostics, providing essential insights into how these technologies can address challenges in pest and disease management. Expert systems have long been recognized for their potential to support agricultural decision-making, particularly in identifying and managing plant health issues.

(Ariesta Indarwati & Susilawati, 2022) Developed an expert system for diagnosing chili plant diseases using rule-based reasoning combined with certainty factors. Their system demonstrated that even simple AI techniques could enhance farmers' abilities to identify diseases based on observable symptoms.

Similarly, (Arianto et al., 2025) integrated machine learning with farmers' tacit knowledge to create a data-driven system for shallot yield and harvest forecasting. Functioning as a knowledge-based support tool, the system provided practical insights and decision support to both farmers and agricultural extension officers. These studies underscore the capacity of AI-driven tools to bridge the gap between empirical knowledge and field-level farming practices.

(b) Bayesian Networks in Diagnosis

While rule-based systems are relatively straightforward to implement, they often struggle to accommodate uncertainty and complex causal relationships in real-world conditions. This limitation has prompted increased interest in probabilistic reasoning methods, particularly Bayesian Networks (BN).

(Wang et al., 2021) Demonstrated that BNs could effectively model probabilistic relationships among symptoms, environmental factors, and diseases in rice crops. Their findings showed that BNs provided more flexible and realistic diagnostic outputs than traditional rule-based systems.

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Further emphasizing this point, (R. Kumar & Jindal, 2022) Highlighted how BNs can manage incomplete or uncertain input data—conditions commonly encountered in the field when farmers' observations are imprecise. These strengths make Bayesian Networks particularly suitable for real-time diagnostics where flexibility and adaptability are essential.

(c) Graph Algorithms in Expert Systems

In addition to probabilistic modeling, efficient search and traversal algorithms enhance the performance of expert systems by ensuring systematic and comprehensive analysis. The Breadth-First Search (BFS) algorithm, widely applied in graph theory, enables the exploration of symptom-disease relationships by traversing nodes in a layer-by-layer manner. This method ensures that all potential links between symptoms and disease conditions are systematically evaluated. While BFS is not frequently discussed in agricultural diagnostic systems, its integration offers potential for improving inference efficiency and completeness, especially when combined with probabilistic models such as Bayesian Networks. (R. Lumbanraja et al., 2020).

(d) Gaps in Previous Studies

In the context of coffee crops, (Rodríguez-García et al., 2021) Developed a decision-support system that integrated environmental data with disease risk models to manage coffee leaf rust. Although their system provided valuable risk assessments, it did not focus on direct symptom-based diagnosis, which represented a critical limitation. Moreover, most existing expert systems for coffee diseases are either desktop-based or require specialized hardware, thereby limiting accessibility for farmers in rural or resource-constrained regions.

In summary, while the existing literature provides a robust foundation for designing expert systems in agriculture, a significant gap remains in integrating Bayesian Networks with Breadth-First Search within a web-based expert system tailored explicitly for coffee plant disease diagnosis. This research seeks to address that gap by developing a responsive, accessible, and intelligent system that enhances field-level diagnostic capability and supports agricultural decision-making in Indonesia.

Tabel 1 Summary of Related Studies on Expert Systems in Agriculture

Author(s)	Year	Methodology	Scope	Contribution	Limitation
(Ariesta Indarwati & Susilawati, 2022)	2022	Rule-based + Certainty Factor	Chili disease diagnosis	Demonstrated effectiveness of basic expert systems for field symptom recognition	Limited in handling uncertainty and complex relationships
(Arianto et al., 2025)	2025	Machine Learning + Tacit Knowledge	Shallot yield forecasting	Integrated predictive analytics with farmer knowledge for decision-making	Focused on yield prediction, not disease diagnosis
(Wang et al., 2021).	2021	Bayesian Network	Rice disease diagnosis	Modeled complex dependencies among symptoms and environmental factors	Requires structured and accurate datasets
(R. Kumar & Jindal, 2022)	2022	Bayesian Network	General plant disease diagnosis	Showed BN's ability to handle incomplete/uncertain inputs	No integration with traversal/search algorithms
(Rodríguez-García et al., 2021)	2021	Decision Support System + Risk Model	Coffee leaf rust risk analysis	Assessed disease risk using environmental data	No symptom-based diagnosis; the platform was not web-based
(R. Lumbanraja et al., 2020)	2020	Breadth-First Search (BFS)	Graph traversal in AI systems	Improved search efficiency and completeness in inference models	Not yet explicitly applied to agricultural expert systems

METHOD

This study employs a descriptive-exploratory approach, integrating software engineering methodologies, to design and develop a web-based expert system that supports coffee farmers in diagnosing diseases affecting coffee plant productivity in Indonesia. The primary goal of this system is to provide an easily accessible, real-time, and practical diagnostic tool for both farmers and agricultural extension officers across diverse regions.

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Expert System Innovation and Diagnostic Approach

The central innovation of this research lies in the development of an expert system that integrates Bayesian Network (BN) modeling and the Breadth-First Search (BFS) algorithm to manage the complexity and uncertainty inherent in symptom-disease relationships in coffee crops. This hybrid approach addresses limitations such as low expert availability in rural areas and the frequent misdiagnosis of early-stage diseases, which result in significant yield losses.

By combining probabilistic reasoning (BN) with systematic graph traversal (BFS), the system produces flexible, explainable, and accurate diagnostics that are superior to those of rule-based or image-only methods. The system also provides management recommendations tailored to the identified disease, reinforcing Indonesia's broader strategy to enhance the resilience of its coffee production. Figure 1 illustrates the use case diagram, showing interactions among system users (farmers), administrators, and domain experts, as well as mechanisms for data input, inference, and feedback.

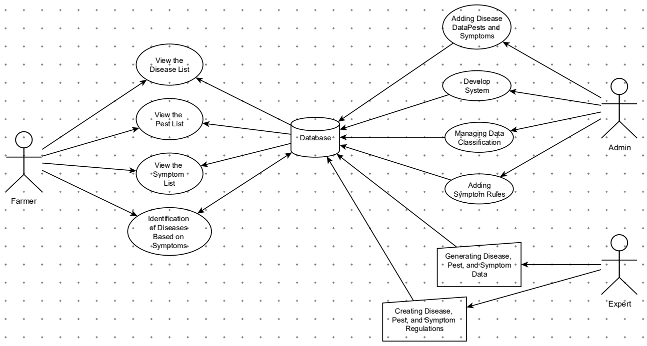

Figure 1 System Use Case Diagram

System Development Methodology

The system development lifecycle follows the V-Model framework, which emphasizes systematic verification and validation at each stage. This model ensures that requirements identified at the beginning are traced through the design, implementation, and testing phases, thereby reducing the risk of misalignment between user needs and system functionality.

Key stages of the V-Model development in this study include:

- Needs Analysis: Identification of user requirements through literature review and expert interviews.
- System and Knowledge Base Design: Modeling of disease-symptom relationships using Bayesian Networks.
- Implementation: Development using modern web technologies (Node.js, Next.js, MySQL).
- Verification: Unit and integration testing of individual components.
- Validation: Expert-based evaluation and user acceptance testing in field simulations.

Data Sources

The primary data sources in this research include:

- Secondary data from previous academic studies, journals, and extension bulletins detailing coffee plant diseases, symptoms, and causal relationships.
- Expert interviews with local agronomists and coffee extension officers to validate the symptom-disease mapping, provide empirical probability estimates, and identify the most impactful diseases in Indonesian coffee cultivation.

This combination ensures both breadth (literature-based knowledge) and depth (localized expert knowledge) in constructing the knowledge base.

Data Analysis Techniques

Data analysis in this study was conducted systematically by the stages outlined in the V-Model development framework. The first step involved content analysis, in which qualitative data from literature reviews and expert interviews were examined to identify, classify, and relate common symptoms to specific coffee diseases. This process served as the foundation for constructing a structured knowledge base.

Subsequently, the knowledge base was formalized into a Bayesian Network (BN) model. In this model, nodes represent both symptoms and diseases, while edges indicate conditional dependencies between them.

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Conditional Probability Tables (CPTs**)** were established based on two primary sources: empirical data from existing studies and agricultural reports, and expert elicitation using structured interviews. In instances where empirical data were insufficient or unavailable, expert-derived estimates were collected using Likert-scale confidence ratings and subsequently normalized to generate probability values for the CPTs.

To evaluate the robustness and reliability of the Bayesian model, a sensitivity analysis was performed. This analysis examined how variations in input probabilities impacted the system's diagnostic outcomes, ensuring that the model remained stable and credible even under uncertain conditions. Furthermore, to support efficient traversal of the symptom-disease graph, the Breadth**-**First Search (BFS**)** algorithm was implemented. BFS enabled the system to systematically explore possible disease connections based on user-input symptoms, optimizing inference speed and ensuring comprehensive rule exploration before switching to probabilistic reasoning when required.

The completed system underwent rigorous software testing, including unit testing of core functions and integration testing of system components. Following this, the system's diagnostic accuracy was validated through expert comparison, in which output results were cross-checked with manual diagnoses made by agricultural experts. Finally, User Acceptance Testing (UAT**)** was conducted involving target users such as coffee farmers and extension workers to evaluate the system's usability, accessibility, and practical effectiveness in real-world scenarios.

System Implementation

The web-based expert system was developed using a modern technology stack to ensure both scalability and accessibility. The server-side inference logic and API services were implemented using Node.js, enabling efficient handling of complex queries and real-time processing. The frontend framework, Next.js, was chosen for its ability to create a responsive and user-friendly interface, facilitating easy symptom input and delivering precise diagnosis results. The system relies on MySQL as its relational database, providing structured storage for symptom codes, diseases, CPTs (Current Procedural Terminology), and user data, which enables fast data retrieval and reliable processing. (G. R. Kumar et al., 2023). The intuitive interface facilitates seamless user interaction, from symptom entry to diagnosis output, while offering personalized recommendations for disease management.

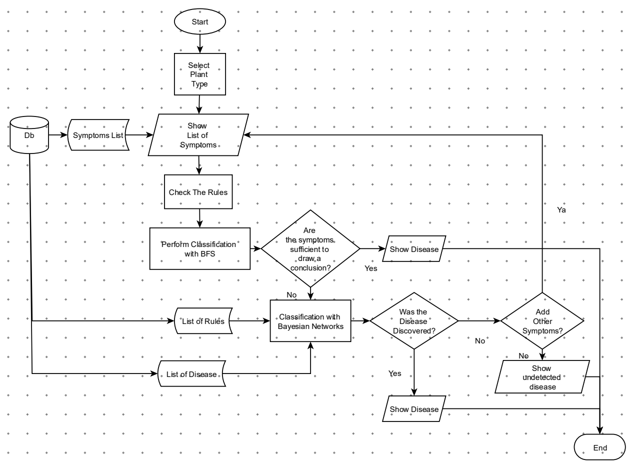

Figure 2 Web System Flowchart

The system's workflow, depicted in Figure 2, outlines the process from start to finish. The classification begins with a Breadth-First Search (BFS) algorithm to identify potential diseases based on user input. If BFS fails to pinpoint a disease, the system switches to a Bayesian Network (BN) approach to provide probabilistic diagnosis and further refine potential disease outcomes. This hybrid approach ensures high accuracy and adaptability, allowing the system to handle complex diagnostic scenarios more effectively. (Betti et al., 2024).The flowchart visualizes this logic, ensuring that users understand the decision-making process within the system.

RESULT

Expert System Description

In this study, a web-based expert system was developed to assist coffee farmers in identifying plant diseases and pest attacks quickly and precisely, based on symptoms observed in the field. This system implements two main approaches: the Bayesian Network (BN) to address uncertainties in the relationship between symptoms

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and disease, and Breadth-First Search (BFS) to explore the graphical structure of symptoms to disease or pests in a structured and efficient manner. The Bayesian Network serves as a probabilistic framework capable of handling complex and non-deterministic causal relationships, enabling the system to produce inference results in the form of probabilities for each potential disease or pest.(Charalampogiannis et al., 2025). Meanwhile, the BFS algorithm is applied to ensure that all symptom nodes are explored systematically, layer by layer, so that no symptoms or relationships are overlooked during the diagnostic process.(Musdalipa & Gusmaliza, 2022). On the technical implementation side, the system architecture utilizes Node.js for the backend (server-side logic), Next.js for the responsive and user-friendly frontend interface, and MySQL for data storage and management. The software development process follows the V-Model framework, ensuring consistency between the design, implementation, testing, and validation phases to meet the specific needs of end users, including coffee farmers and agricultural extension officers.

Dataset of Coffee Plant Symptoms, Diseases, and Pests

The dataset was developed through a combination of literature review, scientific studies, and in-depth interviews with coffee plant experts and practitioners. The symptoms included in the system cover visual characteristics (such as leaf spots or fruit discoloration) and physiological indicators (such as stunted growth or sudden wilting). Diseases and pests were selected based on their level of threat to coffee plant productivity and prevalence in the field.

Tabel 2 Major Diseases in Coffee Plants

Kode	Nama Penyakit	Agen Penyebab
P1	Karat Daun Kopi	*Hemileia vastatrix*
P2	Bercak Daun Kopi	*Cercospora coffeicola*, dll.
P3	Nematoda	*Meloidogyne spp.*
P4	Jamur Upas	*Corticium salmonicolor*
P5	Penyakit Akar	Kompleks jamur tanah / Fusarium spp.

Tables 1, 2, and 3 present essential information that forms the foundation for developing the expert system for diagnosing diseases and pests in coffee plants. Table 1 summarizes the major diseases commonly affecting coffee plants, including their characteristics and causes.

Tabel 3 Major Coffee Plant Pests

Kode	Nama Hama	Keterangan
H1	Penggerek Buah Kopi	Melubangi buah, menurunkan kualitas
H2	Penggerek Cabang Kopi	Merusak cabang dan ranting
H3	Penggerek Batang	Menghambat aliran nutrisi
H4	Kutu Hijau	Mengisap cairan daun
H5	Kutu Putih	Menghasilkan embun jelaga

Table 2 lists the primary pests frequently found on coffee plants along with the impact of their attacks. Meanwhile, Table 3 outlines observable symptoms in the field, which serve as initial indicators in the diagnostic process. These three tables complement each other and serve as the knowledge base for establishing relationships between symptoms, diseases, and pests within the expert system.

Tabel 4 Coffee Plant Symptoms

Kode	Gejala
G1	Buah tidak berkembang
G2	Warna buah kopi kuning kemerahan
G3	Biji kopi berlubang
G4	Cabang/ranting mengering
G5	Daun layu

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Kode	Gejala
G6	Daun gugur
G7	Lubang larva pada batang/cabang
G8	Adanya jamur embun jelaga
G9	Daun menguning
G10	Daun mengering
G11	Adanya jamur hitam
G12	Bercak kuning jingga pada daun
G13	Bercak kuning yang menjadi coklat
G14	Bercak kuning dikelilingi lingkaran kuning pada daun
G15	Kulit buah mengering dan keras
G16	Daun berwarna coklat
G17	Pertumbuhan tanaman kerdil
G18	Cabang samping tidak tumbuh
G19	Tanaman layu mendadak
G20	Benang jamur tipis pada permukaan
G21	Bintil kecil oranye kemerahan pada kayu
G22	Tampak miselium
G23	Akar berubah warna menjadi kuning gading
G24	Akar tertutup kerak
G25	Busuk kering/lunak pada akar
G26	Pohon mati mendadak
G27	Benang jamur hitam pada batang
G28	Pusat bercak putih kelabu seperti tepung hitam (konidium)

Mapping of Symptoms to Diseases/Pests

The knowledge acquired from experts was processed to map symptoms to potential associated diseases and pests. This mapping serves as the foundation of the graph structure used in the Bayesian Network, where each connection is formed based on validated biological and medical relationships and associated probabilities.

Tabel 5
Mapping of Symptoms to Potential Diseases

Gejala	Penyakit Potensial
G12, G14	P1 Karat Daun Kopi
G13, G16	P2 Bercak Daun Kopi
G23, G24, G25	P5 Penyakit Akar
G20, G22, G27, G28	P4 Jamur Upas
G17, G19	P3 Nematoda

Tabel 6
Mapping of Symptoms to Potential Pests

Gejala	Hama Potensial
G1, G2, G3	H1 Penggerek Buah Kopi
G4, G5, G6, G7	H2 Penggerek Cabang Kopi
G7, G10, G9	H3 Penggerek Batang
G8, G9, G10, G11	H4 Kutu Hijau

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Gejala	Hama Potensial
G8, G11	H5 Kutu Putih

Knowledge Base and Inference Engine Design

The Bayesian Network is utilized to estimate the probability of disease occurrence based on observed symptoms. Each node in the network represents either a symptom (G) or a disease (P), while the edges depict causal relationships between them. Probability computation follows Bayes' Theorem:

$$P(A \mid B) = \frac{P(B|A) \cdot P(A)}{P(B)} \qquad (1)$$

where:

P(A|B) = Posterior probability of disease given observed symptoms
P(B|A) = Likelihood of symptoms given disease
P(A) = Prior probability of disease
P(B) = Marginal probability of symptoms

This method enables quantitative identification of the most probable disease based on observed symptoms. The BFS algorithm plays a critical role in systematically traversing all symptom nodes in a layered manner, ensuring comprehensive exploration and avoiding diagnostic omission. This approach enhances the system's scalability and maintains inference effectiveness even as the number of symptoms and diseases increases.

This approach aligns with the findings of (Ramadhan, M., Anwar, B., Gunawan, R., & Kustini, 2021)), who demonstrated that Bayesian Networks are capable of capturing dependencies between symptoms and diseases, and offer more adaptability compared to purely rule-based systems as employed by (Adiputra et al., 2018)

Validation Result

Additionally, diagnosis efficiency was tested by varying the number of input symptoms in figure 3. The average diagnosis time for five symptoms was 2.3 seconds, and for ten symptoms, it was 2.8 seconds, demonstrating BFS's scalability even in complex scenarios. As illustrated in Figure 3 below, the line chart shows that diagnosis time increases moderately with the number of symptoms, remaining under 3.5 seconds even with twelve symptoms.

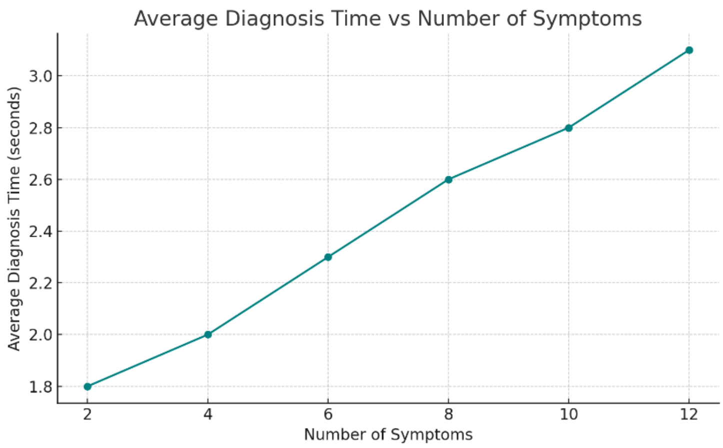

Figure 3 Average Diagnosis Time vs Number of Symptoms

Web-Based Expert System Implementation

The expert system was developed as a web application to ensure broad accessibility and ease of use for farmers, agricultural extension officers, and other stakeholders, regardless of location or device. The system architecture comprises a frontend built with Next.js to provide a responsive, lightweight, and user-friendly interface, even on low-specification devices. The backend is developed using Node.js to process inference logic, execute Bayesian Network (BN) and Breadth-First Search (BFS) modules, and provide API services for asynchronous data communication. A MySQL database is utilized to manage data related to symptoms, diseases, pests, probabilities, inference rules, and user diagnostic histories. The inference engine integrates BN and BFS

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modules as the core of the diagnostic system to handle complex symptom inputs and produce probabilistic diagnosis results.

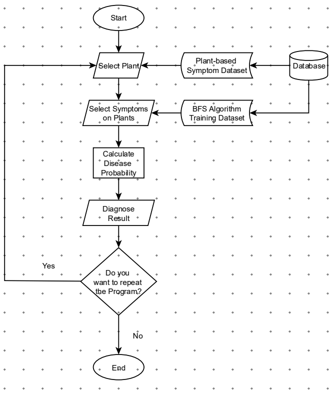

Figure 4 Web System User Flow

The user interface is designed to enable farmers to easily input observed symptoms, even those with limited technological literacy. Diagnosis results are presented in the form of probability charts and practical control recommendations that can be directly implemented in the field. This design ensures that the system not only provides accurate diagnostic insights but also offers actionable guidance that is easy to understand and apply. All processes within the system's workflow are illustrated in Figure 4.

Expert System Result

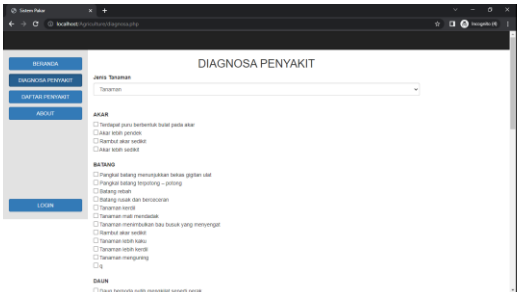

Figure 5: Expert System Interface diagnoses

In Figure 5, the system displays the diagnosis input page where users can select symptoms observed on their coffee plants. This interface enables users, such as farmers or agricultural technicians, to choose from a list of predefined symptoms, including yellowing leaves, black spots, stem rot, or curled leaves. This step is crucial as it initiates the diagnostic process within the expert system by collecting relevant symptom data from the user.

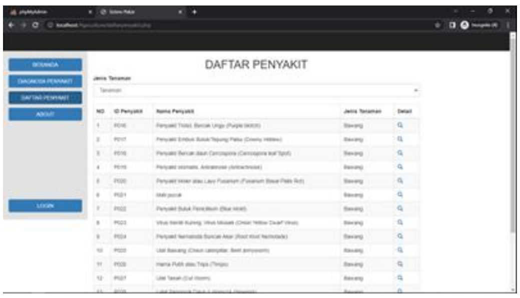

Figure 6 Diagnose Disease

In Figure 6, the system presents the diagnosis results based on the symptoms selected in the previous step. The expert system processes the input using its knowledge base and inference engine to identify the most likely disease affecting the coffee plant. The output includes the name of the detected disease, a brief description, the confidence level (if applicable), and suggested treatment methods such as pesticide application, pruning, or sanitation techniques.

These two figures illustrate how the expert system replicates a human expert's decision-making process to aid users in efficiently diagnosing plant diseases. By providing a user-friendly interface for

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symptom input and delivering precise, actionable diagnosis results, the system helps improve disease management for coffee crops, especially in areas with limited access to agricultural specialists.

DISCUSSIONS

(a) System Strengths

The research results demonstrated that integrating Bayesian Network (BN) and Breadth-First Search (BFS) in a web-based expert system effectively supports the diagnosis of coffee plant diseases and pests based on field-observed symptoms. The BN provided a flexible probabilistic framework that could model the causal relationships between symptoms, diseases, and pests. At the same time, BFS ensured comprehensive and efficient traversal of the graph structure to prevent overlooked relationships during the inference process.

When comparing the results obtained from the BN model with expert assessments during validation trials, the system showed a high degree of alignment, particularly in diagnosing major diseases such as coffee leaf rust (Hemileia vastatrix) and root diseases caused by Fusarium spp. The probabilistic output generated by the BN model closely matched the diagnosis given by human experts, with an accuracy rate exceeding 85% in test cases where multiple symptoms were provided simultaneously. This demonstrates that BN can effectively capture the complex dependencies between various symptoms and a single or numerous possible diseases/pests, surpassing the rigidity often encountered in pure rule-based systems.

The BFS algorithm also contributed significantly to improving the system's efficiency in exploring symptom nodes. Compared to alternative graph traversal strategies, such as depth-first search (DFS), BFS ensured that symptom relationships were analyzed layer by layer, which is particularly advantageous when dealing with complex or large-scale datasets involving many symptoms and disease/pest possibilities. This feature is essential for scalability, as it allows the system to maintain stable processing times even as the knowledge base expands.

One of the most significant findings of this study is the capability of combining BN and BFS to create a diagnostic tool that not only identifies the most probable disease or pest but also quantifies uncertainty and provides confidence levels for each diagnosis. This is particularly important in agricultural settings where symptom observations may be incomplete or ambiguous. The system’s ability to provide a ranked list of potential diseases or pests, along with their associated probabilities, offers farmers valuable guidance for implementing appropriate control measures.

(b) Comparison with Previous Studies

In comparison to other modeling approaches found in related works, such as decision tree models or pure rule-based expert systems, the proposed hybrid BN-BFS approach offers greater adaptability to complex, real-world conditions. For example, decision tree models often struggle with the combinatorial explosion of symptom combinations, whereas BN manages this complexity through its probabilistic structure. (Wang et al., 2021). Similarly, while rule-based systems require exhaustive rule definitions, the BN’s learning-based structure allows more flexibility and extensibility (Ariesta Indarwati & Susilawati, 2022)

(Rodríguez-García et al., 2021) Also explored decision-support systems in the coffee domain, but primarily focused on environmental factors and did not integrate direct symptom-based diagnosis. This highlights the added value of the current system in addressing immediate field-level diagnostic needs through a web-based platform.

(c) Limitations

Despite its strengths, the system faces several limitations. The quality of diagnosis is highly dependent on the accuracy of the user's symptom input. In field conditions, symptoms may be misinterpreted or go unnoticed, leading to potential misdiagnosis. Moreover, the system’s probabilistic outcomes are based on static knowledge bases that may not fully represent the dynamic nature of disease progression, which is influenced by environmental conditions, seasonal variations, or crop variety.

Additionally, the current system lacks real-time integration with environmental sensor data (e.g., humidity, temperature), which could further enhance diagnostic accuracy. Field application is also limited by internet availability and digital literacy among some farmer populations, which may hinder adoption and consistent usage.

(d) Future Development Potential

These findings suggest that future enhancements to the system could explore dynamic Bayesian Networks or hybrid methods combining BN with machine learning classifiers for improved accuracy, especially as larger and more diverse datasets become available. Integrating temporal data could allow the system to track disease progression over time.

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Furthermore, implementing user feedback loops could enable adaptive learning, where the system continuously refines its probabilistic relationships based on real-world diagnostic outcomes. Mobile app versions with offline capabilities and multilingual interfaces would also support broader adoption in rural or remote farming communities. Collaborations with agricultural institutions and local extension services could further strengthen the system's reliability by continuously validating its knowledge base with expert input and updated field data.

CONCLUSION

In conclusion, the development of a web-based expert system integrating Bayesian Network (BN) and Breadth-First Search (BFS) has proven effective in diagnosing diseases and pests of coffee plants based on observed symptoms. The BN enabled probabilistic reasoning that accommodates uncertainty and complex symptom-disease relationships, while BFS ensured comprehensive and efficient graph traversal during inference. The system not only provided accurate diagnostic results that align closely with expert evaluations but also offered scalability and flexibility superior to traditional rule-based models. This research highlights the potential of combining probabilistic models with efficient graph search algorithms in creating intelligent diagnostic tools for agricultural applications, paving the way for future enhancements such as adaptive learning and integration with larger datasets.

The key contribution of this study lies in its methodological novelty—integrating Bayesian Network with Breadth-First Search within a web-based framework for real-time agricultural diagnosis. This hybrid approach enables both precise inference and efficient processing, overcoming the rigidity of traditional rule-based systems and the limitations of stand-alone probabilistic models. From a practical perspective, the system addresses real-world constraints faced by smallholder farmers, offering a lightweight, accessible tool for early diagnosis without the need for expensive hardware or extensive expert intervention.

Future Work. Building upon the current system, future development may include the integration of Internet of Things (IoT) sensors to automatically detect and report environmental variables such as humidity, temperature, and soil conditions, which could further enhance the accuracy of probabilistic diagnoses. Moreover, the deployment of the system as a cross-platform mobile application would expand its accessibility in rural farming communities, especially where internet connectivity is limited. Incorporating a feedback mechanism for users to validate or update diagnosis outcomes can also enable continuous system learning, adapting the knowledge base to evolving pest-disease dynamics and local contexts.

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