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An In-Depth Comparative Analysis of Dempster-Shafer and Certainty Factor Approaches for Precision Cassava Disease Diagnosis

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Abstract

Cassava (Manihot esculenta Crantz) is a vital staple food and industrial raw material, particularly in Indonesia, where it holds significant economic importance. Despite its adaptability, cassava cultivation faces serious threats from plant diseases, leading to reduced productivity and quality. Traditional agricultural methods, often lacking modern technological interventions, exacerbate these challenges. To address this, a web-based expert system was developed to assist farmers in diagnosing and managing cassava diseases. The system integrates the Certainty Factor (CF) and Dempster-Shafer (DS) methods to handle uncertainty in disease diagnosis. Using the Adira 1 cassava variety, data was collected from a 2-hectare area in Bogor, focusing on five types of cassava diseases: Brown Leaf Spot, Blight Leaf Spot, Bacterial Blight, Anthracnose, and Root Rot. The CF method quantifies the certainty of specific facts, while the DS method combines evidence from various sources to determine the belief level of potential diagnoses. A comparative analysis of these models was conducted using 20 case studies. The results showed that the CF model achieved a 95% accuracy rate, slightly outperforming the DS model's 90% accuracy. Additionally, the system's usability was evaluated using the USE Questionnaire, which rated it as "Highly Suitable" with an overall score of 84.5%. This study demonstrates that while both CF and DS models are effective in diagnosing cassava diseases, the CF model offers slightly higher accuracy. The developed expert system is not only accurate but also user-friendly and accessible, making it a valuable tool for improving cassava disease management practices.

Keyword
Cassava, Disease Diagnosis, Certainty Factor, Dempster-Shafer, Expert System, Agriculture Technology.

1. Introduction
Cassava (Manihot esculenta Crantz) is a staple food for people in the world, one of which is Indonesia, in addition to being a staple food, cassava is also used as a raw material for industry and animal feed. Cassava is very easy to cultivate, even on marginal soils this plant can grow and give yield This plant first entered Indonesia in 1852. Damage to cassava plants is often caused by disease, which is a serious threat that can reduce cassava productivity. The countermeasures carried out are still limited and sometimes do not achieve the expected results. This can have a negative impact on the quality of crops and the level of productivity of the cassava commodity. Cassava plant

cultivation is carried out traditionally and simply, without utilizing modern planting technology. Therefore, a system is needed that can help the community, especially farmers, in detecting and diagnosing diseases and providing appropriate countermeasure solutions.

Traditional methods of diagnosing cassava diseases often involve visual observation of physical symptoms such as leaf discoloration, spots, and stem and root deformation. In addition, farmers or agronomists typically rely on local knowledge and field experience to identify diseases based on previously known attack patterns. Although this method is quite effective for common cases of disease, its limitations lie in its low accuracy and sensitivity, especially for diseases that have early symptoms that are difficult to detect or similar to other problems(Azeta et al. 2023). Reliance on individual experience can also lead to inconsistent diagnoses and potential mishandling errors. In addition, traditional methods are often incapable of detecting diseases caused by pathogens that are hidden or systemic spread within plants, such as viral or bacterial infections that do not cause obvious symptoms in the early stages. Visual observation is also limited in identifying the exact cause of the symptoms that appear, as many environmental factors such as nutritional deficiencies or pest infestations can mimic the symptoms of the disease. As a result, control decisions made based on these diagnoses may be inappropriate, leading to unnecessary use of pesticides or ineffective management measures(Pardo et al. 2023). Thus, there is an urgent need to develop more sophisticated and accurate diagnostic methods to improve disease management in cassava.

The Dempster-Shafer theory, also known as the proof theory or the combination of evidence theory, is a mathematical framework used to handle uncertainty in decision-making(Fei et al. 2024). Introduced by Arthur P. Dempster and further developed by Glenn Shafer, this theory allows the incorporation of various sources of information to reach stronger conclusions, especially when the available data is incomplete or ambiguous(Belmahdi et al. 2023). One of the main advantages of Dempster-Shafer theory is its ability to allocate degrees of confidence to multiple hypotheses simultaneously, without having to directly divide beliefs between two options as in traditional probability. This theory provides flexibility in managing uncertainty by allowing for more robust decision-making in situations where information is not fully known or definitive, so it is often used in a variety of applications, including disease diagnosis, decision support systems(Chang & Zhang 2024). In the context of disease diagnosis, Dempster-Shafer theory allows the incorporation of various data sources that may be conflicting or incomplete, thus helping to produce more accurate diagnoses even when the information available is limited(Xue et al. 2024). By giving each piece of evidence a weight of confidence and then combining the evidence, the theory can handle uncertainty better than traditional probabilistic approaches. In addition, the Dempster-Shafer theory allows for room for ignorance, which is when the information is not enough to support one of the hypotheses convincingly. This makes it a useful tool in situations where data is difficult to obtain or has high ambiguity(Hamda et al. 2023). Its use in decision support systems is becoming more widespread, especially in agriculture, medical, and technology, where the accuracy of decisions is often heavily influenced by data uncertainty(Tang et al. 2023).

Certainty Factor (CF) is a method in expert systems used to handle uncertainty in decision-making(Dong et al. 2024), specifically in rule-based diagnosis and reasoning. First introduced in the MYCIN medical expert system, CF serves as a measure of the level of confidence in a hypothesis or diagnosis based on available evidence(Fais et al. 2023). CF allows for the handling of uncertainty by combining beliefs from various relevant evidence or rules, thus allowing the system to provide more measurable and transparent conclusions(Eckerle et al. 2024). With its ability to account for confidence levels in each piece of evidence, CFs are often used in a variety of applications, including medical diagnosis, risk analysis, and other decision support systems, where accuracy and confidence in outcomes are critical. In addition, the Certainty Factor also allows the incorporation of beliefs from various sources of information that may have varying degrees of uncertainty. By using the CF combination rule, the final result can be obtained by considering how strong or weak the evidence supporting a hypothesis is. This approach provides flexibility for systems to adapt to incomplete or ambiguous data, which is often a challenge in real-world situations(Fitri et al. 2023). CF's main advantages are its simplicity and ability to be implemented in rule-based expert systems, making it a popular choice in many practical applications. Although this method is not as complex as some other probabilistic approaches, CF is still highly effective in providing a trustworthy diagnosis and is widely used in various fields such as agriculture, medicine, and other industries(Huang et al. 2024).

Dempster-Shafer and the Certainty Factor are two approaches used in knowledge-based systems for disease diagnosis in cassava, especially when faced with uncertainty in symptom information. The Dempster-Shafer method combines evidence from multiple sources to generate a degree of belief about the likelihood of a particular disease, allowing for the integration of incomplete or conflicting information. On the other hand, the Certainty Factor (CF) gives a certainty value to a particular rule or symptom based on the trust of the expert, which is then used to assess the likelihood of a disease in a more intuitive way. Both methods help in overcoming the weaknesses of traditional methods by offering a more flexible and quantitative approach, thus providing a more accurate and reliable diagnosis despite the uncertainty of the data. In the application of disease diagnosis in cassava, the use of Dempster-Shafer and Certainty Factor allows for the integration between the various symptoms and signs that appear on the plant, which may not always be consistent or obvious. With Dempster-Shafer, the system can combine a variety of evidence obtained from different symptoms to strengthen confidence in a diagnosis, even when there is a discrepancy in information. The Certainty Factor, with its simpler approach, allows for expert experience-based assessments to provide more specific treatment or preventive action recommendations. The combination of these two methods in a knowledge-based diagnosis system helps farmers and agronomists in making better and more timely decisions, which are crucial for effectively managing diseases and minimizing crop losses.

It is important to compare the Dempster-Shafer and Certainty Factor approaches in the context of cassava disease diagnosis because they offer different advantages in dealing with uncertainty and complexity of symptoms. Dempster-Shafer excels at combining a wide range of evidence from different sources, making it suitable for situations where the symptoms that appear are varied or uncertain. Meanwhile, Certainty Factor is simpler and more intuitive, making it easier to implement and understand for users who may not have a deep technical background. By comparing these two approaches, we can determine which method is more effective and efficient in providing an accurate diagnosis, as well as how they can be used complementarily to strengthen the cassava disease diagnosis system, thereby improving agricultural yields and reducing the risk of loss. This comparison is also important to understand the specific context in which each approach is most effective. For example, in cases where cassava symptom data are partial or conflicting, the Dempster-Shafer method may be more suitable due to its ability to combine various sources of information and produce more holistic conclusions. On the other hand, the Certainty Factor may be more useful in situations where there is more certainty data and reliable expert experience, due to its more direct approach to measuring the certainty of diagnosis. In addition, an evaluation of computing needs, ease of use, and flexibility in decision-making also needs to be considered when choosing between these two approaches. By conducting a thorough comparison, we can maximize the benefits of each approach and optimize the diagnosis process for specific conditions in cassava disease management.

1.1 Objectives

The purpose of this study is to comprehensively evaluate and compare the effectiveness of the two methods in accurate and precise diagnosis of cassava disease. This study aims to understand how each approach addresses uncertainty, integration of symptom data, and reliability in various disease scenarios that farmers may face. In addition, this study seeks to identify the advantages and disadvantages of each method in the operational context in the field, focusing on the speed, accuracy, and ease of implementation. The results of this study are expected to provide guidance for the development of a more sophisticated cassava disease diagnosis system, as well as provide insights for practitioners on the most appropriate methods to improve disease management and agricultural productivity.

2. Literature Review

Ramcharan et al. (2019) In this study, we evaluated the performance of a CNN model applied offline in real time on mobile devices to detect symptoms of cassava pests and diseases on leaves. Using a one-shot detector model, a CNN architecture optimized for mobile devices, we assessed the model's performance to detect clear and mild symptoms of 3 classes of disease. The results of this study also recommend the mobile CNN model to be used on the specific type of data it trains until there are enough training examples from various data sources to better capture the diversity of data happening in the real world(Ramcharan et al. 2019). Gao et al. (2021) The EfficientNet model trains pre-processed leaf images and extracts multidimensional depth, width, and resolution features in cassava disease monitoring based on HSV and EfficientNet color spaces, which can improve the monitoring and early warning of cassava virus disease, avoid the transportation and selection of diseased stems, and provide the necessary detection technology to ensure healthy cassava production(Gao et al. 2021). Mrisho et al. (2020) Nuru can be an effective tool for the diagnosis of cassava disease in the field and has the potential to be a quick and cost-effective means of disseminating knowledge from researchers to agricultural extension agents and farmers, especially about the identification of disease symptoms and its management practices(Mrisho et al. 2020).Ahishakiyeet al. (2023) The proposed deep gaussian convolutional neural network model with a set of pre-trained models, a move that could help improve the model's performance, shows that our proposed hybrid kernel function performs better in terms of accuracy of 90.1% when compared to an exponential quadratic kernel with an accuracy of 88.0% and a rational quadratic kernel with an accuracy of 88.5%(Ahishakiye et al. 2024).

3. Methods

Research methods are systematic and structured approaches used to collect, analyze, and interpret data in order to answer research questions or test hypotheses(Sulistiani et al., 2023). Research methods include a variety of techniques and procedures designed to ensure that research is conducted validly and reliably(Setiawansyah et al., 2023). Research methods are the steps taken in conducting research. The following is the flow of the stages carried out in the research presented in Figure 1.

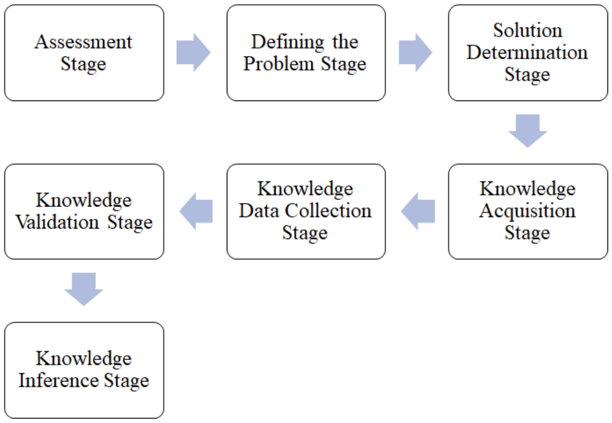

Figure 1. Research Stage

Assessment Stage: At this assessment stage, an initial analysis of the system to be built is carried out by defining the problems to the system to be created and built. The next step is to verify between the system to be created and the problem and the goal that has been defined. Defining the Problem Stage: detecting the disease in the cassava plant and measuring the level of uncertainty into a value that can be used to diagnose the disease.Solution Determination Stage: the creation of an application is expected to make it easier for humans to obtain information without having to wait for the presence of cassava plant disease experts, and is expected to reduce or even solve existing problems.
Knowledge Acquisition Stage: this stage starts from the acquisition or collection of knowledge, the representation of knowledge, the creation of a knowledge base, the validation of knowledge, inference, to the provision of explanations for the results of the inference. In this system, data and information about cassava plant diseases are collected. This data collection goes through the assessment stage that has been described, with the aim of obtaining accurate data, completing research and investigation, and processing the results obtained from the collection of disease data and symptom data.

Knowledge Data Collection Stage: establish the specification of the needs and identify existing problems. This planning stage is carried out by referring to literature studies and interviews with experts and farmers who have knowledge about cassava plant diseases, as well as conducting validity tests on these plants.
Knowledge Validation Stage: knowledge must be valid and tested based on data through library studies and provide validation papers to experts so that the quality can be accepted. The results of case tests are usually presented by experts to test the accuracy of the system. Knowledge Inference Stage: The inference machine functions as the brain of the expert system, executing the thinking mechanisms and reasoning patterns used by an expert. This mechanism guides the process of reasoning about a condition. In inference engines, there is a process of manipulating and directing rules, models, and facts stored in the knowledge base to reach solutions or conclusions in analyzing certain problems and finding the best answers. In designing this system, the authors use tracking inference techniques, because the problem solving is done by collecting data and then drawing conclusions.

4. Data Collection

Data collection is the process of gathering information or data necessary for research, analysis, or decision-making. The data collected can come from a variety of sources (Sulistiani et al., 2024). This process is one of the crucial stages in the research methodology, because the quality and accuracy of the data greatly affect the results and conclusions of the research. Primary data on the health condition of cassava plants was collected through field surveys, interviews with farmers, and direct observation of disease symptoms that appear on plants. Information on environmental factors that affect plant health, such as humidity, temperature, and soil conditions were also documented. Meanwhile, at Pakuan University Bogor, supporting data was obtained through laboratory analysis of infected plant samples, as well as the use of computer-based diagnostic technology that utilizes the Dempster-Shafer and Certainty Factor approaches. The combination of field and laboratory data aims to ensure the validity and reliability of the diagnosis results, as well as to compare the effectiveness of the two methods in providing an accurate diagnosis of cassava disease.

Furthermore, the data that has been collected from Batu Ngampar Village and Pakuan University Bogor is analyzed using special software that supports the application of Dempster-Shafer and Certainty Factor theories. In this process, the field data was converted into numerical input that could be used to test and compare the two approaches. In addition, data from Pakuan University was also used to perform cross-validation, to ensure that the diagnostic results from the Dempster-Shafer and Certainty Factor methods match the observations. Trials were conducted on various scenarios, including common cassava diseases such as mosaic and root rot, to assess the accuracy and precision of the diagnosis provided by each method. This research focuses not only on theoretical analysis, but also on practical application in the field, which is expected to provide stronger recommendations for farmers and agricultural practitioners in dealing with cassava diseases effectively.

5. Results and Discussion

5.1 Knowledge Acquisition Stage

This stage serves to gain knowledge about the problems to be discussed or to analyse what needs are needed in building a system which includes studies by conducting research into cassava fields directly with farmer groups in Sukaraja village, to get a second opinion about symptoms and diseases of cassava plants, and to gain knowledge related to the application of the Dempster shafer method and Certainty Factor in determining these symptoms based on the knowledge that has been obtained after conducting a literature study. The following are diseases and symptoms of cassava plants in Table 1.

Table 1. Diseases and Symptoms of Cassava Plants

DISEASE	SYMPTOM	CONFIDENCE VALUES
Brown leaf spot	Small white to light brown spots (G1)	1.0
	At the edges of the spots are bounded by a circle of slightly purple color (G2)	0.4
	Brown spots (G3)	0.8
	Wrinkling and easy fall on leaves (G4)	0.8
	Yellowing, drying, and premature fall of leaves (G5)	0.6
	On the side of the lower leaf you can see the structure of the fruit body of the fungus (G6)	0.4
Blending Leaf Spots	Small white to light brown spots (G1)	1.0
	Large-sized spots of brown with no clear borders (G7)	0.8
	Disease attacks on old leaves (G8)	0.6
	The spot is at the tip of the leaf shaped like an inverted V (G9)	0.4
	The undersurface of the center of the spot is brown with a grayish tint (G10)	0.8
Leaf Blight Bacteria	Attacks on leaves and stems (G11)	1.0
	Bacterial mass mucus that occurs on stalks, leaf blades, and stems (G12)	0.8
	Erectile dysfunction (G13)	0.8
Antraknose	Found on the surface of stems, petioles and leaves (G14)	0.8
	On the surface of the stem there are small protrusions (G15)	0.8

	The base of the stalk breaks easily so that the leaves become wilted (G16)	0.6
	On the cork there is a wrinkle (G17)	0.6
Rot at the base of the roots/tubers	Tuber rot (G18)	0.8
	Darker Bulb (G19)	0.8

5.2 Application of the Certainty Factor and Dempster-Shafer Method

In this study, the certainty factor method is used to calculate the weight of each pest or disease which will later be compared with the dempster Shafer method. The value of the certainty factor is based on the value of expert trust and the value of user trust. The value of expert trust is obtained from literature studies that have been carried out and then given different weights for each disease. The value of user trust is obtained from the user's answers that are weighted according to their level of confidence. As an illustration, users make a diagnosis about pests with the following symptoms.

1. Small white to light brown spots (G1)
2. At the edges of the spots are bounded by a slightly purple circle (G2)
3. Brown spots (G3)
4. Wrinkling and easy fall on leaves (G4)
5. Yellowing, drying, and premature fall of leaves (G5)
6. On the side of the lower leaf, the structure of the fruit body of the fungus (G6) can be seen

The calculation results are based on the Certainty Factor formula, CF symptoms = CF[user] × CF[expert] with the calculation as in Appendix 7.

Furthermore, to get the percentage of confidence from the calculation results in Appendix 7, the equation is used.

CF percentage = CF combine × 100%
= 0.966191464 × 100%
= 96.62%

Based on the example of the calculation above, it is concluded that the diagnosis based on the symptoms that have been selected by the user of the cassava plant is affected by Brown Leaf Spot disease with a confidence level of 96.62%

The results of the calculation of the Dempster-Shafer method and the symptoms selected by the user, we get the following results:

1. Process: New density = 0.92 for P001 disease (Brown Leaf Spot).
2. Process: New density = 0.064 for P001 (Brown Leaf Spot) and P002 (Mixed Leaf Spot) diseases.

This suggests that the most likely disease based on the symptoms given is "Brown Leaf Spot" with a 92% confidence level.

5.4 Validation

Validation tests are carried out to determine the accuracy of the data contained in the model with the aim of ensuring the suitability between the data input and the output generated by the method. This validation test uses a confusion matrix algorithm. The confusion matrix allows for direct and quantitative comparisons between two methods (Dempster-Shafer and Certainty Factor) based on the results of the predictions produced. This validation trial was carried out by comparing the output results of the two methods with the results of consultation based on 20 case studies and comparing the percentage results of the dempster-shafer method and certainty factor.The results of a total of 20 consultation case studies using certainty factors, there were 6 results indicated for brown leaf spot, 4 results indicated for mixed leaf spot disease, 4 results indicated for anthracnose disease, 1 result indicated for root rot / sweet potato and 1 result detected for 2 diseases which means that the results are included in the FP (False Positive) category. Based on the results of the consultation using the certainty factor, there is a calculation using a confusion matrix to determine the accuracy of the certainty factor method in diagnosing cassava plant diseases. The validation trial of the certainty factor method using the confusion matrix can be seen in Table 2.

Table 2. Certainty Factor Method Validation Trial

	Brown leaf spot	Blending Leaf Spots	Leaf Blight Bacteria	Antraknose	Rot at the base of the roots/tubers	2 Diseases Detected
Brown leaf spot	6	0	0	0	0	0
Blending Leaf Spots	0	4	0	0	0	0
Leaf Blight Bacteria	0	0	4	0	0	0
Antraknose	0	0	0	4	0	0
Rot at the base of the roots/tubers	0	0	0	0	1	0
2 Diseases Detected	0	0	0	0	0	1

Calculating the accuracy of the certainty factor method using a confusion matrix.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} = \frac{19 + 0}{19 + 0 + 0 + 1} = \frac{19}{20} = 0.95 \; x \; 100 = 95\%$$

Ha 3sil out of a total of 20 case studies of consultation using dempster-shafer, there were 6 results indicated brown leaf spot, 3 results indicated mixed leaf spot disease, 4 results indicated anthracnose disease, 1 result indicated root rot / sweet potato and 2 results detected 2 diseases which means that the results are included in the FP (False Positive) category. Based on the results of the consultation using the dempster-shafer, there is a calculation using the confusion matrix to determine the accuracy of the dempster-shafer method in diagnosing cassava plant diseases. The validation test of the dempster-shafer method using the confusion matrix can be seen in Table 3.

Table 3. Dempster-Shafer Method Validation Trial

	Brown leaf spot	Blending Leaf Spots	Leaf Blight Bacteria	Antraknose	Rot at the base of the roots/tubers	2 Diseases Detected
Brown leaf spot	6	0	0	0	0	0
Blending Leaf Spots	0	3	0	0	0	0
Leaf Blight Bacteria	0	0	4	0	0	0
Antraknose	0	0	0	4	0	0
Rot at the base of the roots/tubers	0	0	0	0	1	0
2 Diseases Detected	0	0	0	0	0	2

Calculate the accuracy of the dempster shafer method using a confusion matrix.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} = \frac{18 + 0}{18 + 0 + 0 + 2} = \frac{18}{20} = 0.90\ x\ 100 = 90\%$$

Based on the results of the accuracy calculation using the confusion matrix, it can be seen that the results of the comparison of the certainty factor method and the dempster-shafer method that have been validated by experts show that the Certainty Factor method has a larger percentage, namely 95%.

6. Conclusion

The results showed that the cassava plant disease suspicion assessment model using the Certainty Factor and Dempster-Shafer methods provided satisfactory results in disease diagnosis. Of the 20 case studies analyzed, the Certainty Factor method managed to achieve an accuracy level of 95%, while the Dempster-Shafer method achieved an accuracy level of 90%. Although both methods show strong ability in diagnosing cassava diseases, these results indicate that the Certainty Factor method is slightly superior in terms of accuracy compared to the Dempster-Shafer method. These findings provide valuable insights for practitioners in choosing the most effective method for precise diagnosis of cassava disease. In addition, the difference in accuracy between these two methods can also provide guidance for further research to optimize the use of each method in different contexts. Although the Certainty Factor shows superiority in accuracy, the Dempster-Shafer method still has strong potential, especially in situations involving high uncertainty and incomplete data. Both approaches can be used complementarily, depending on the specific condition and the need for diagnosis. Thus, this study not only highlights the advantages and limitations of each method, but also opens up opportunities for further development in the integration of the two methods, in order to improve the accuracy and effectiveness of cassava plant disease diagnosis in the future.

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