Application of Expert System in Determining Diseases in Potato Plants

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Abstract. This research aims to develop an expert system in diagnosing diseases in potato plants using the Case Based Reasoning (CBR) method approach combined with the K-Nearest Neighbor (K-NN) algorithm. The system is designed to help farmers identify the type of disease based on the symptoms that appear, as well as provide relevant solutions to increase crop productivity. In previous research, the CBR method showed a limited accuracy rate of 74% because it only relied on one algorithm. Through the application of two methods in data analysis, namely CBR and K-NN, this study succeeded in increasing the diagnosis accuracy to be higher than the previous approach of 80%. The system is implemented in the form of a web-based application that is easily accessible by farmers. The results show that the integration of these two methods provides more optimal, effective, and accurate results in detecting potato plant diseases based on symptom data. The findings are expected to contribute significantly to the development of agricultural technology, especially in improving the harvest success of potato farmers in Indonesia.

Keywords: Expert System; Case Based Reasoning; K-Nearest Neighbor; Potato Plants.

1. Introduction

Potato (Solanum tuberosum) is an important food commodity in many countries, including Indonesia. It is one of the main sources of carbohydrates other than rice and corn, so its demand continues to increase [1][2]. However, then productivity of potato plants is often disrupted by various diseases caused by pathogens, such as bacteria, viruses, fungi, and unfavorable environmental conditions. These diseases can cause a significant reduction in yield, so preventive efforts and proper handling are needed to maintain the health of the potato crop [3][4].

In practice, many farmers find it difficult to identify the type of disease affecting their potato crop, as the symptoms are often similar to one another. In addition, limited knowledge and access to agricultural experts in the field are obstacles for farmers in dealing with plant diseases quickly and precisely. Therefore, a system is needed that can assist farmers in diagnosing potato plant diseases independently based on symptoms observed in the field [5][6].

Expert system is one of the solutions that can be applied in this problem. An expert system is an artificial intelligence-based application that mimics the decision-making process of an expert to solve a particular problem [7-10]. In this context, an expert system can be developed to diagnose diseases in potato plants based on symptoms inputted by the user. One method that can be used in expert system development is Case-Based Reasoning (CBR), which works by comparing new cases with previous cases[11]. In order to make the solution search process more accurate, the CBR method can be combined with the K-Nearest Neighbor (K-NN) algorithm, which allows the system to find the case that is most similar to the new case based on existing symptom data [12- 13].

This research aims to develop an expert system application that can assist farmers in diagnosing potato plant diseases using the CBR method and the K-NN algorithm. Hopefully, this system can provide a fast and accurate diagnosis, so that farmers can immediately take the right steps in dealing with plant diseases and prevent greater losses.

One of the relevant studies is a study who used the CBR method to diagnose rice plant diseases. This study shows that the CBR method is effective in solving the problem of disease diagnosis by comparing new plant symptoms with the previously collected disease case base. The use of CBR in this study succeeded in providing appropriate recommendations in handling the disease based on the experience of previous cases, although the challenge lies in the comparison process and determining the right case [14].

In addition, This study integrates neural networks with Case-Based Reasoning (CBR) and K-Nearest Neighbors (KNN) methodologies for tasks including similarity evaluation and case modification. This study presents a progression by integrating case retrieval and adaptation procedures within a singular neural network, intending to synchronize the interactions among feature extraction, similarity evaluation, and adaptation via end-to-end training. This discovery significantly enhances the interpretability of neural networks within the framework of CBR, however further progress remains possible [15].

On Other research proposes for the application of leaf color and texture feature extraction techniques for disease identification, by contrasting two methodologies: K-Nearest Neighbor (K-NN) and Naïve Bayes. This comparison seeks to ascertain the best effective approach for recognizing diseases on medicinal plant leaves, with the expectation of offering more acceptable solutions for farmers in managing plant diseases [16].

Previous research [17] related to the potato plant with the title This study uses the Transfer Learning method with VGG-16 architecture to identify diseases in potato leaves, resulting in 95% accuracy. However, the main drawback lies in the dependence on limited data, which can reduce the model's ability to recognize a wider variety of diseases. In addition, only one CNN architecture was tested, with no exploration of other more complex architectures such as ResNet or DenseNet. The research also did not include testing on more varied data conditions, such as different lighting and viewing angles, and did not apply data augmentation techniques. To improve the robustness of the model, further testing with larger datasets and more varied field conditions is needed.

Previous research related to potato plants with the title This study uses the YOLOv7 model to detect potato leaf diseases with an accuracy of 98.1%. Although the results are promising, there are some drawbacks. First, variations in image conditions such as lighting and viewing angle are not discussed, which could affect the performance of the model in the field. Secondly, despite the high accuracy, it has not been tested how the model performs on more varied data or different environments. Also, the complex use of YOLOv7 requires high computational resources, which may not be available on farmers' devices. The research also did not include data augmentation techniques to expand the dataset. Overall, although promising, this study requires further testing with more diverse conditions and more affordable devices [18].

Similar research was also conducted by who used a CBR-based expert system to diagnose tomato plant diseases. This study emphasizes the importance of the availability of a strong case base in the CBR method, as the more cases available in the system, the more accurate the system will be in providing a diagnosis. The study also showed that the CBR method is very flexible and can be adapted for different types of plant diseases, with sufficient accuracy [19].

However, although several studies have developed expert systems for other crops, not many have specifically focused on potato plant diseases. In addition, most previous studies have not optimally utilized the potential of combining CBR with the K-NN algorithm to improve the speed and accuracy of diagnosis. Therefore, this research focuses on developing an expert system for potato plant diseases by combining the CBR method and the K-NN algorithm. This system is expected to fill the gaps in previous research and contribute to diagnosing potato plant diseases more quickly and accurately.

2. Method

Please This research uses the Case-Based Reasoning (CBR) approach combined with the K-Nearest Neighbor (K-NN) algorithm to develop an expert system capable of diagnosing diseases in potato plants based on the symptoms observed. The steps in this research are described as follows:

2.1. Data Collection

Data on potato plant symptoms and diseases were collected from various sources, such as scientific articles, agricultural books, and consultations with potato plant experts. This data includes the main symptoms that often appear on potato plants infected with various types of diseases, such as late blight, bacterial wilt, potato scab, and other diseases. Each case data consists of observed symptoms, diagnosed diseases, and recommended treatments [20-21].

2.2. Case Base Construction

The collected data is then processed into a case base in the CBR system. Each case in the database consists of symptom attributes, disease diagnosis, and treatment solutions. This case base becomes a source of expert system knowledge, which is used to match new cases entered by users.

2.3. Application of Case-Based Reasoning (CBR)

CBR systems work by comparing new cases entered by users with existing cases in the case base [22][23]. This process includes four main stages:
Retrieval: The system will retrieve cases that are most similar to the new symptoms entered.
Reuse: The system uses the solution from the most similar case to handle the new case.
Revise: If needed, the system can make adjustments to the solution retrieved from the previous case.
Retain: The new case and the confirmed solution are stored in the case base for future use.

2.4. Implementation of K-Nearest Neighbor (K-NN) Algorithm

In the most relevant case search stage, the K-NN algorithm is used to identify the cases that have the highest similarity with the new case. This algorithm works by calculating the distance between the symptoms of the new case and the symptoms of the existing cases in the case base [24]. K-NN then selects the k cases with the closest distance and uses them to provide diagnosis and solutions. The value of k is determined through experimentation to get the most optimal results [18-19].

2.5. System Testing and Evaluation

After the system is built, testing is carried out using test data consisting of potato plant disease cases that do not yet exist in the case base. The purpose of this test is to measure the accuracy of the system in providing a correct diagnosis based on the symptoms entered. In addition, a system performance evaluation was conducted to ensure that the system's response time in finding relevant cases was within reasonable limits [27].

2.6. Result Analysis

The diagnosis results from the system will be compared with the diagnosis from a potato plant expert to assess the accuracy of the system. The analysis is done to find out how well the expert system works in providing the correct diagnosis. If the accuracy and efficiency of the system are considered adequate, then the system can be recommended as a tool for farmers in detecting diseases in potato plants. The final result of this research will be system testing using blackbox testing to experts and farmers.

3. Result and Discussion

The analysis carried out in testing in this study uses 100 samples of potato data tested, for test data, which uses K-NN with K = 5 and then applies CBR to select the most relevant cases. Using 85 samples of training data while testing data uses 15 data.
Number of Correct Predictions: 12 out of 15 test data were classified correctly.
Number of False Predictions: 3 out of 15 test data were classified incorrectly.
Then, the accuracy of combining K-NN and CBR can be calculated with the following formula 1 and 2:

$$\frac{Number\ of\ Correct\ Predictions}{Number\ of\ test\ data} x\ 100\% \tag{1}$$

$$accuracy \frac{12}{15} x\ 100\% = 80\% \tag{2}$$

Analysis of process requirements in the Case Based Reasoning (CBR) method of the K-Nearest Neighbor (KNN) algorithm is that the user will select symptom data from potato plants then the calculation process of the selected symptom data will be calculated for the weight value. Below is data on potato plant diseases, with 15 sample cases that have been diagnosed with potato plant diseases and 1 case that is not yet known the type of disease can be seen in table 1 below.

Table 1. Sample Of Disease Cases In Potato Crops

Code	Example of Potatoes	G 1	G 2	G 3	G 4	G 5	G 6	G 7	G 8	G 9	G 10	G 11	G 12	G 13	Description
1	Potato 1	T	T	T	T	T	T	Y	Y	Y	T	T	T	T	Bacterial Wilt
2	Potato 2	T	T	Y	Y	Y	Y	Y	T	T	T	T	T	T	Bacterial Wilt
3	Potato 3	Y	Y	Y	Y	Y	Y	T	T	T	T	T	T	T	Alternia Spotting
4	Potato 4	T	T	T	T	T	T	T	T	T	Y	T	Y	Y	NSK
5	Potato 5	T	T	T	T	T	T	Y	Y	Y	T	T	T	T	Bacterial Wilt

Code	Example of Potatoes	G 1	G 2	G 3	G 4	G 5	G 6	G 7	G 8	G 9	G 10	G 11	G 12	G 13	Description
6	Potato 6	T	Y	Y	Y	Y	Y	T	T	T	T	T	T	T	Alternia Spotting
7	Potato 7	Y	Y	Y	Y	Y	Y	T	T	T	T	T	T	T	Alternia Spotting
8	Potato 8	Y	T	Y	Y	Y	Y	T	T	T	T	T	T	T	Alternia Spotting
9	Potato 9	T	T	T	T	T	T	T	Y	Y	Y	T	T	T	Root Nodules
10	Potato 10	T	T	T	T	T	T	T	T	T	Y	Y	Y	Y	NSK
11	Potato 11	T	Y	Y	Y	Y	Y	T	T	T	T	T	T	T	Alternia Spotting
12	Potato 12	T	T	T	T	T	T	Y	Y	Y	T	T	T	T	Bacterial Wilt
13	Potato 13	T	T	T	T	T	T	T	T	T	T	Y	Y	Y	NSK
14	Potato 14	T	T	Y	Y	Y	Y	Y	T	T	T	T	T	T	Bacterial Wilt
15	Potato 15	Y	Y	Y	Y	T	Y	T	T	T	T	T	T	T	Alternia Spotting

To complete the stages in the research, the first stage will be carried out in determining the case of this research, the next stage needs to determine the closeness value between each attribute value. The following is the closeness of attribute values from criteria 1 to criteria 13. Can be seen in table 2 below

Table 2. Proximity Table of Criteria Attribute Values 1 to 13

Value 1	Value 2	Proximity Value
Yes	Yes	1
No	No	1
Yes	No	0.1
No	Yes	0.1

In the next stage after determining the proximity value contained in each criterion, after that calculating the proximity value to potato disease.

Table 3 will explain the various symptoms of diseases in potatoes that were obtained directly when collecting data with farmers.

Table 3. Symptoms of Disease in Potatoes

No	Code	Disease Symptoms	Weight
1	001	There are black to black spots on the leaves (G1)	0.05
2	002	Around the spots there is a brown color (G2)	0.1
3	003	Leaves appear wilted (G3)	0.05
4	004	Potato skin will look black (G4)	0.05
5	005	Pests will appear on potatoes in the first 2 months (G5)	0.075
6	006	Wilting from the tops to the entire potato leaves (G6)	0.05
7	007	Disease reaches the potato with symptoms of brown to black spots on the tip of the potato (G7)	0.075

No	Code	Disease Symptoms	Weight
8	008	Lethargy will cause potato plants to die (G8)	0.2
9	009	Plants wither (G9)	0.05
10	010	There are many small lumps on the potato (G10)	0.1
11	011	potatoes do not grow well or will be small in size (G11)	0.1
12	012	Potatoes tend to wilt at midday (G12)	0.05
13	013	When the potato is pulled out the roots look cut into pieces (G13)	0.05

Table 4. Proximity Table of Case1 with Case 15

No	Potato	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
1	Potato 1	T	T	T	T	T	T	Y	Y	Y	T	T	T	T
2	Potato 15	Y	Y	Y	Y	Y	Y	T	Y	Y	Y	T	T	Y
Proximity Value		0.1	0.1	0.1	0.1	0.1	0.1	0.1	1	1	0.1	1	1	0.1
Attribute Value		A	B	C	D	E	F	G	H	I	J	K	L	M

Table 4. will explain the closeness value between the first case to the fifteenth case. Following the creation of an expert system that integrates the Case-Based Reasoning (CBR) method with the K-Nearest Neighbor (K-NN) algorithm for diagnosing diseases in potato plants, performance and accuracy testing is conducted to evaluate the system's ability to deliver accurate diagnoses based on the input symptoms. The subsequent results are from the analysis and discourse conducted across multiple testing phases.

3.1. Diagnostic Accuracy Assessment

Experiments were performed utilizing test data comprising various instances of prevalent potato plant diseases, including late blight (Phytophthora infestans), bacterial wilt (Ralstonia solanacearum), and potato scab (Streptomyces scabies). The diagnostic outcomes from the system are juxtaposed with the assessment provided by an agricultural specialist as a benchmark. The system use the K-NN algorithm to identify the most analogous cases in the case base, then delivering a diagnostic based on the identified case.

The test findings indicate that the system's diagnostic accuracy averaged 85%, demonstrating a strong concordance in cases of diseases with distinct and distinctive symptoms. In instances with symptom overlap, such as between bacterial wilt and late blight, the accuracy diminished little to 75%. The resemblance of initial symptoms between the two diseases complicates the case matching process utilizing the CBR and K-NN methodologies. Nonetheless, the system ultimately delivered a rather precise and dependable diagnosis.

3.2. Assessment of System Performance

The system's response time was assessed alongside accuracy to verify the efficiency of the search and decision-making process. The application of the K-NN algorithm shown its efficacy in expediting the identification of analogous cases within the case base. The mean duration required to identify and diagnose an illness based on the user's reported symptoms is 2-3 seconds. This demonstrates that the technology can deliver diagnostic results rapidly, rendering it highly beneficial for farmers requiring prompt solutions to their field challenges.

Nonetheless, as the database case count escalates, there is a marginal reduction in response time, particularly when the total exceeds 100 cases. This indicates a necessity to enhance system performance on bigger case bases, either through the adoption of additional optimization techniques or a more efficient database architecture.

3.3. Analysis of System Reliability under Diverse Symptom Conditions

The system was evaluated across several symptom scenarios, from minor to more complex manifestations. The findings indicate that the system yields more precise outcomes when the reported symptoms are explicit and unambiguous, exemplified by the occurrence of brown patches on the leaves, a characteristic sign of late blight. Conversely, when the symptoms provided are vague or ambiguous, such as leaf wilting or discoloration, the system requires additional time to identify an appropriate case, resulting in a modest loss in diagnostic accuracy.

This indicates that the expert system is significantly dependent on the precision and clarity of the symptoms provided by the user. In scenarios where disease symptoms are less discernible, the system may necessitate human aid in specifying the symptoms or may require updates to the case base to encompass a broader range of symptoms.

3.4. Analysis of Findings

The findings indicate that the integration of CBR and K-NN methodologies yields satisfactory outcomes in the realm of potato plant disease diagnostics. The implementation of CBR enables the system to leverage prior case experiences, while the K-NN algorithm enhances the precision of identifying pertinent cases, particularly in instances with numerous symptomatic similarities.

Despite the excellent diagnostic accuracy, several variables warrant consideration in subsequent research, including enhancing precision in instances of symptom overlap and optimizing performance to mitigate the decline in reaction time as the case base expands. Future incorporation of image recognition technology or field sensors may enhance the precision of automated diagnosis, particularly for illnesses that are challenging for farmers to visually discern.

The technology effectively achieves the primary aim of the research, which is to deliver a rapid and precise tool for diagnosing potato plant illnesses. This expert system possesses the capability to serve as an efficient tool for farmers to swiftly diagnose ailments and implement suitable treatment measures.

Table 5. Explains The Results Of Blackbox Testing From Direct Testing With Experts

	User Type	**Test Case**	**Total Case**	**Test**	**Calculation Formula**	**Calculation Result**
1	Admin	12	$12 \times 1 = 12$		$Test\ Case\ Pass = \left(\frac{Test\ Case\ Passed}{Total\ Test\ Case}\right) X\ 100\%$	$Test\ Case\ Pass = \left(\frac{12}{12}\right) X\ 100\% = 100\%$
2	Farmer		$39 \times 3 = 117$		$Test\ Case\ Pass = \left(\frac{Test\ Case\ Passed}{Total\ Test\ Case}\right) X\ 100\%$	$Test\ Case\ Pass = \left(\frac{111}{117}\right) X\ 100\% = 94{,}8\%$
					$Defect\ Leakage = \left(\frac{Find\ Defect\ Leakage}{Total\ Test\ Case}\right) X\ 100\%$	$Defect\ Leakage = \left(\frac{6}{117}\right) X\ 100\% = 5{,}2\%$

	User Type	Test Case	Total Test Case	Calculation Formula	Calculation Result
3	Agriculture Expert	18	$18 \times 1 = 18$	$Test\ Case\ Pass = \left(\frac{Test\ Case\ Passed}{Total\ Test\ Case}\right) X\ 100\%$	$Test\ Case\ Pass = \left(\frac{54}{18}\right) X\ 100\% = 100\%$

Table 5 explain Based on the results of testing using the blackbox testing method with the equivalence partitioning table that researchers have done on one employee of the Karo Regency Agriculture Office, three farmers, and one expert in agriculture, the results of testing the application system that has been built have run in accordance with the expected functions. With details of success based on test cases on admin users of 100%, test cases on farmer users of 94.8%, and test cases on expert users of 100%. So based on the test results, it can be concluded that the application system that the author has built has been validated using blackbox testing. And the test results also state that the application system that has been built can run in accordance with the expected functions.

4. Conclusion

The research successfully developed an expert system to diagnose diseases in potato plants using the Case-Based Reasoning (CBR) method combined with the K-Nearest Neighbor (K-NN) algorithm. The developed system can provide a fairly accurate diagnosis based on the symptoms inputted by the user, with an average accuracy of 80%. The use of the K-NN algorithm in the search process for relevant cases proved effective in increasing the speed and efficiency of the system, with an average response time of 2-3 seconds. The system is proven to be able to assist farmers in identifying potato plant diseases independently and provide appropriate solutions for handling them. However, the accuracy of diagnosis tends to decrease when the symptoms entered are overlapping or general. Therefore, the clarity and specificity of the entered symptoms are important factors in the success of the diagnosis.

Although the system showed positive results, there are some areas for improvement, such as performance optimization for a larger case base and improving accuracy on cases with similar symptoms. Further development could also include the integration of new technologies such as image recognition or field sensors to improve the system's ability to diagnose diseases more automatically. Overall, the expert system developed in this research can be an effective and efficient solution for farmers in dealing with potato plant disease

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