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# Expert system for diagnosing diseases in corn plants using the navies bayes method

Gunawan Gunawan[1], Adhita Zulfa Sya'bani[2], Sawaviyya Anandianshka[3]
[1,2]Informatics Engineering, STMIK YMI Tegal, Indonesia
[3]Information System, STMIK YMI Tegal, Indonesia

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ABSTRACT

This research introduces an expert system using the Naive Bayes method to diagnose corn plant diseases, aiming to provide an automated, accurate, and scalable diagnostic tool. Traditional methods are often inefficient and error-prone, relying on expert knowledge and manual inspection. This study employs a quantitative approach, incorporating experimental design, data analysis, and model validation. Data on humidity, temperature, and soil conditions were collected from agricultural research centers and online databases. After preprocessing, key variables influencing disease occurrence were selected. The Naive Bayes model was optimized using cross-validation and implemented in Python, achieving an average accuracy of 92%. The model's performance, evaluated through accuracy, precision, recall, and F1-score, demonstrated the effective distinction between similar symptoms—the system's simplicity and computational efficiency suit resource-constrained environments like rural farms. By combining visual symptoms and environmental factors, the system minimizes dependency on expert knowledge, offering a comprehensive and scalable solution for disease management in agriculture.



*Corresponding Author:*

Adhita Zulfa Sya'bani,
Informatics Engineering,
STMIK YMI Tegal,
Jl. Pendidikan No. 1, Pesurungan Lor, Kec. Margadana, Kota Tegal, Jawa Tengah 52142, Indonesia.
Email: aditsya25@gmail.com

## 1. INTRODUCTION

Corn (maize) is a staple crop with global economic and food security significance. Its high yield potential and widespread cultivation make it a critical source of food, feed, and industrial raw materials. Early detection and accurate diagnosis of diseases in corn are crucial due to the rapid spread and severe impact of infections on large-scale plantations, which can lead to substantial economic losses and food shortages. Unlike some other crops, corn diseases can spread quickly due to the dense planting and the plant's growth characteristics, making timely intervention vital to prevent widespread crop failure (Savary & Willocquet, 2020).

The inverted pyramid approach to introducing this research article begins with a background on the significance of disease diagnosis in corn plants (Bhat & Huang, 2021).

Corn diseases can be caused by bacteria, fungi, viruses, or environmental factors, leading to symptoms such as discolored patches, wilting, stunted growth, and reduced yield (Fitriyani et al., 2020).

The traditional methods for diagnosing diseases in corn plants primarily involve manual inspection and expert interpretation, which are time-consuming and subject to human error. Visual inspections can miss early symptoms or misinterpret disease indicators, leading to inaccurate diagnoses and delayed treatment. Additionally, the reliance on expert knowledge limits the scalability of these methods, as not all farmers have access to agricultural experts. This gap in accessibility and the lack of rapid, reliable diagnostic tools underline the need for more efficient technological solutions (Yu et al., 2021).

This inquire about addresses the issue over by creating an master framework for diagnosing maladies in corn plants utilizing the Gullible Bayes strategy (Haider et al., 2021). Developing an automated diagnostic system will enable quick and accurate identification of diseases in corn plants, facilitating timely intervention and management strategies to mitigate the negative impact on crop yield.

It is imperative to discuss this research as it not only contributes to advancing the field of agricultural technology but also holds practical implications for farmers and agricultural stakeholders (Nelson, 2020). By improving the speed and accuracy of disease diagnosis in corn plants, this research can help farmers make informed decisions on disease management practices, leading to enhanced crop yield and sustainable agricultural practices.

The Naive Bayes method offers several advantages for disease diagnosis in agriculture, particularly in its simplicity and efficiency. Unlike more complex machine learning techniques that require extensive computational resources and large datasets, Naive Bayes is relatively easy to implement and can perform well even with limited data. This method assumes independence between features, which, while a simplification, allows for rapid training and prediction. It is particularly suited for agricultural applications where quick and accurate decision-making is essential to manage crop health effectively (Sharma et al., 2021). By training the expert system with a dataset of disease symptoms and diagnostic outcomes, the system can learn to predict the likelihood of a specific disease based on observed symptoms in corn plants. This automated approach streamlines the diagnostic process, enabling rapid and reliable identification of diseases (Blanquero et al., 2021).

This research is conducted to bridge the existing gaps in disease diagnosis in corn plants by leveraging advanced technological tools and techniques (Lv et al., 2020). By integrating the Naive Bayes method into an expert system for disease diagnosis, this study aims to improve the accuracy, speed, and accessibility of diagnostic services for corn plant diseases, ultimately benefitting farmers and the agricultural industry.

The methods used in this research will involve collecting a dataset of corn plant disease symptoms and corresponding diagnostic outcomes to train the Naive Bayes algorithm (Bhargava et al., 2024). The dataset will encompass a diverse range of diseases commonly affecting corn plants, ensuring the robustness and accuracy of the diagnostic model. Subsequently, the developed expert system will be tested and validated using real-world data to evaluate its performance and reliability in disease diagnosis (Tholl et al., 2021).

Within the current state of the craftsmanship, conventional strategies of infection conclusion in corn plants depend intensely on visual review and manual translation of indications by specialists. While these methods have been instrumental in disease management, there is a growing need for more efficient and data-driven approaches to enhance the accuracy and timeliness of disease diagnosis (Balafas et al., 2023).

The development proposed in this inquire about lies in creating an computerized master framework that leverages the Credulous Bayes strategy to analyze illnesses in corn plants (Shrivastava & Patidar, 2022). By integrating machine learning algorithms with agricultural diagnostics, this research introduces a novel approach to disease identification that can revolutionize how diseases are detected and managed in crops.

The research will focus on three main components: dataset collection and preparation, developing the expert system using the Naive Bayes method, and testing/validating the system with real-world data.

This research is expected to contribute significantly to agricultural technology by introducing an innovative expert system for disease diagnosis in corn plants. Through adopting the Naive Bayes method and advanced machine learning techniques, this study aims to empower farmers with a reliable and efficient tool for combating diseases and ensuring the health and productivity of corn crops.

Previous research in agricultural technology has made significant strides in disease diagnosis and management in various crop plants (Zhang et al., 2020). Several studies have focused on leveraging advanced technologies, such as machine learning and image analysis, to enhance the accuracy and efficiency of disease detection in crops.

Automated Detection and Classification of Plant Diseases: In a study, the researchers developed a computerized system for detecting and classifying diseases in tomato plants using deep learning algorithms. The research showcased the feasibility of utilizing advanced technologies for disease diagnosis in plants, underscoring the importance of automated systems in agricultural applications (Bazargani & Deemyad, 2024).

Advances in Agricultural Diagnosis Using Machine Learning: A comprehensive review surveyed the latest developments in agricultural diagnosis techniques, specifically emphasizing machine learning applications. The review highlighted the potential of machine learning algorithms in revolutionizing disease diagnosis and management strategies in agriculture, stressing the need for data-driven approaches in crop protection (Mesías-Ruiz et al., 2023).

Expert Systems for Plant Disease Diagnosis: An earlier study delved into developing expert systems for diagnosing diseases in various crop plants. The researchers explored integrating expert knowledge with computational techniques to improve disease diagnosis accuracy and efficiency. This work is a foundational reference for our research on developing an expert system for corn plant diseases.

## 2. RESEARCH METHODS

### 2.1. Research Objectives:

The primary objective of this study is to develop an expert system for accurately diagnosing diseases in corn plants using a quantitative approach with a combination design of experimental methods, quantitative analysis, and model validation (Whirl-Carrillo et al., 2021). The research aims to enhance disease detection accuracy and efficiency in corn plants by implementing the Naive Bayes algorithm. Previous studies have shown success in using machine learning for plant disease diagnosis, but often with more complex methods like deep learning, which require larger datasets and more computational power. For instance, Bazargani & Deemyad (2024) utilized deep learning for tomato plant disease detection, emphasizing the feasibility but also the resource intensity of such approaches. The current study aligns with the review by Mesías-Ruiz et al. (2023), highlighting the effectiveness of machine learning in agricultural diagnostics, but stands out by demonstrating that even simpler models like Naive Bayes can achieve significant results. Earlier efforts in developing expert systems for plant disease diagnosis (e.g., Zhang et al., 2020) provided foundational insights. Still, they often needed more integration of probabilistic methods like Naive Bayes, which can enhance the robustness and adaptability of diagnostic tools

2.2. Research Design:

This study adopts a quantitative research design that integrates experimental methods with quantitative analysis to develop and validate an expert system for corn plant disease diagnosis (Deepa et al., 2020). The research design involves collecting image data of diseased and healthy corn plants, preprocessing the data, selecting relevant variables for model optimization, implementing the Naive Bayes algorithm, configuring the algorithm parameters, and evaluating the model's performance.

This inquiry about strategy portrays almost all the steps connected to this investigation. The investigation system utilized can be seen in Figure 1, based on the existing system.

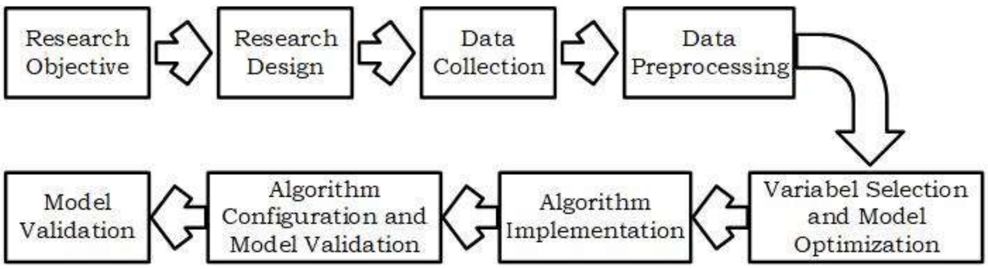


Figure 1. Research Method

In Figure 1, the research methodology starts with formulating specific Research Objectives to guide the study. The research design stage follows, where the methodological approach and analysis plan are selected. Data is collected from various sources (Chen et al., 2020) and processed in the Data Preprocessing stage, which includes cleaning and normalization. Variable Selection and Model Optimization are then performed using techniques like cross-validation to select relevant variables and optimize the model. Within the Calculation Usage organize, the machine learning calculation is connected to the prepared information. The demonstrate is configured and approved within the Calculation Setup and Demonstrate Approval arrange to guarantee ideal execution (Ali et al., 2019). Finally, the model is validated with new data to ensure its generalizability and avoid overfitting.

2.3. Data Collection:

Image data of corn plants exhibiting various disease symptoms will be collected from agricultural fields. The data collection will involve capturing high-resolution images of corn plants using digital cameras or drones. Each image will be labeled with the corresponding disease category (e.g., fungal infection, bacterial disease, viral infection) for training and testing the diagnostic model (Unal, 2020).

2.4. Data Preprocessing:

Before feeding the image data into the diagnostic model, preprocessing steps will be implemented to enhance the quality and suitability of the input data reader. Data preprocessing will involve resizing the images to a standard resolution, removing noise and artifacts, and normalization to ensure uniformity in the dataset.

2.5. Variable Selection and Model Optimization:

Feature extraction techniques will be applied to select relevant variables from the preprocessed image data that are most informative for disease diagnosis. These selected variables will be used to optimize the Naive Bayes algorithm for improved accuracy and efficiency in classifying diseased and healthy corn plants (Maurya et al., 2024).

2.6. Algorithm Configuration and Model Evaluation:

The Naive Bayes algorithm will be configured by tuning hyperparameters such as smoothing factors and feature distributions to optimize the model's performance (Valle-Torres et al., 2020). Cross-validation techniques will evaluate the model's accuracy, precision, recall, and F1 score. The model will be tested on a separate set of unseen data to assess its generalization capabilities and robustness in real-world scenarios. Accuracy: The proportion of actual results (both true positives and true negatives) among the total number of cases examined. Precision: The proportion of actual positive results among the total positive results predicted by the model. Recall (Sensitivity): The proportion of accurate positive results among the total actual positive cases. F1 Score: The harmonic mean of precision and recall, providing a balance between the two. Confusion Matrix: A table used to describe the performance of the classification model, outlining true positives, false positives, true negatives, and false negatives. ROC Curve (Receiver Operating Characteristic Curve): A graphical plot illustrating the diagnostic ability of the binary classifier system as its discrimination threshold is varied.

The equation for calculating accuracy, precision, recall, and F1 score in the evaluation model can be written as follows:

1. Accuracy:
$$Accuracy = \frac{TP + TN}{TP + FP}$$

2. Precision:
$$Precision = \frac{TP}{TP + FP}$$

3. Recall (Sensitivity):
$$Recall = \frac{TP}{TP + FN}$$

4. F1 Score:
$$F1\ Score = 2 \times\frac{Precision \times Recall}{Precision + Recall}$$

Where**,** TP (Genuine Positive): The number of exact hopeful forecasts, TN (Genuine Negative): The number of precise critical expectations, FP (Wrong Positive): The number of wrong hopeful expectations, FN (Wrong Negative): The number of dishonestly negative forecasts. Explanation**:** Accuracy measures how precise the model is in predicting correctly divided by the total predictions**;** Precision measures the proportion of optimistic predictions that are correct (true positive) from the total optimistic predictions**;** **r**ecall measures the proportion of positive cases correctly predicted by the model out of the total positive cases that actually exist**,** F1 Score is the harmonic mean of precision and recall, balancing the two.

2.7. Model Validation:

The expert system for diagnosing corn plant diseases will be rigorously validated by comparing model predictions to ground truth labels, measuring sensitivity and specificity. Validation metrics, including confusion matrices and ROC curves, will assess diagnostic performance. The Naïve Bayes Classifier, based on Bayes' theorem, will be used for classification, efficiently trained with minimal data (Blanquero et al., 2021). This classifier assumes independent variables, simplifying the determination of variable variations for each class (Bilal et al., 2022). The model's effectiveness will be validated using Bayesian probability calculations on modern and historical cases.

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)} \quad (1)$$

Where p(H|E) = likelihood of theory H happening in case prove E happens, p(E|H) = likelihood of rise of prove E on the off chance that theory H happens, p(H) = likelihood of speculation H notwithstanding of any prove, p(E) = likelihood of prove E independent of anything.

## 3. RESULTS AND DISCUSSIONS

Information procurement involves gathering data to create a master framework for diagnosing corn crop diseases and pests. This system needs information from reference books on crop diseases and farmer-provided data (Antwi-Agyei et al., 2021). Interviews with corn farmers yielded prior values, representing the percentage of each disease and pest, and probability values, indicating the likelihood of disease symptoms. A summary of corn crop diseases is provided in Table 1.

Table 1. Types of Diseases in Corn Crops

| Types of Diseases | *Prior* |
|---|---|
| Peronosclerospora maydis | 0,030 |
| Bipolaris maydis Syn | 0,030 |
| Puccinia polysora | 0,040 |
| Swollen Burnt | 0,010 |
| Leaf Blight | 0,030 |
| Stem and Cob Rot | 0,036 |
| Dwarf Mosaic Virus Disease | 0,050 |

Table 1 lists common plant diseases and their initial probabilities (prior probabilities), which indicate the relative prevalence of each disease before considering any additional observations or data. The columns in Table 1 include Types of Diseases (diseases that may attack plants) and Prior (the initial probability of each disease, showing its frequency in the plant population). Data on pests can be found in Table 2.

Table 2. Data Pets

| Types of Diseases | Prior |
|---|---|
| Earthworm | 0,03 |
| Grayak caterpillar | 0,07 |
| Seed Flies | 0,01 |
| Stem Borer | 0,04 |
| Cob Borer | 0,02 |
| Aphids | 0,06 |
| Horn Beetle | 0,01 |

Table 3 lists common plant pests and their initial probabilities (prior probabilities), indicating how frequently each pest occurs in the observed plant population before additional observations. The columns include the type of Pests (pests that may attack plants) and Prior (the initial probability of each pest type). Data on the likelihood values of corn crop symptoms can be found in Table 4.

Table 3. Data on the likelihood value of corn crop

| Code | Symptom | Probability |
|---|---|---|
| G001 | The presence of bite marks on the leaves | 0,5 |
| G002 | Withered leaves | 0,8 |
| G003 | The stem is broken near the ground | 0,5 |
| G004 | The presence of bite marks on the trunk | 0,7 |
| G005 | Damaged roots due to grub bite | 0,8 |

| | | |
|---|---|---|
| G006 | Plants wither | 0,5 |
| G007 | Partial or whole leaf chlorosis | 0,5 |
| G008 | Plants become dwarfs | 0,9 |
| G009 | Fruitless | 0,8 |
| G010 | The cob is not normal | 0,9 |
| G011 | Leaves are green and interspersed with yellow lines | 0,6 |
| G012 | Leaves look yellow-striped | 0,3 |
| G013 | The presence of short, dotted lines on the leaf bones | 0,3 |
| G014 | Leaves look long yellow, striped | 0,3 |
| G015 | Gray, brown spots on the leaf surface | 0,4 |
| G016 | Brown leaf surface | 0,5 |
| G017 | Widening spots on leaves | 0,5 |
| G018 | Grayish-red midrib | 0,1 |
| G019 | The presence of white granules | 0,5 |
| G020 | Broken leaf bone | 0,5 |
| G021 | Rotten stem | 0,6 |
| G022 | The top wither and dry | 0,7 |
| G023 | Broken cob | 0,5 |
| G024 | There are red-brown dots like rust | 0,9 |
| G025 | Cob wrapping broken | 0,8 |
| G026 | There is a caterpillar on the cob of corn | 0,5 |
| G027 | Leaf color from normal green to yellowish | 0,5 |
| G028 | Damaged young plant leaves | 0,9 |
| G029 | In the morning, on the underside of the corn leaves, there is a layer of white velvet | 0,5 |
| G030 | The lower and upper leaves are held without feeling the presence of spore powder | 0,5 |
| G031 | There is a small hole in the leaf | 0,7 |
| G032 | Slitting hole in the trunk | 0,8 |
| G033 | Fragile rod and tasse | 0,2 |
| G034 | Broken tassel pile | 0,5 |
| G035 | Seeds will be damaged and rotten, and even cobs can fall | 0,5 |
| G036 | The surface of the seeds is covered with mycelium, gray to black | 0,5 |
| G037 | Plants die fast or dry | 0,8 |
| G038 | Leaves become transparent | 0,2 |
| G039 | Hollowed even only bones | 0,5 |
| G040 | The base of the stem or cob is pink, red-brown, or brow | 0,5 |
| G041 | Are plants easily collapsed | 0,1 |
| G042 | Is the outer bark thin? | 0,1 |
| G043 | There is a yellow-brown powder | 0,5 |
| G044 | Black swollen corn | 0,5 |
| G045 | Some swollen corn seeds poking out | 0,5 |
| G046 | There is dirt in corn cobs | 0,5 |

Table 3 lists the various symptoms plants can observe and the probability of each symptom occurring. This probability shows how often or commonly the symptom is found in the observed plant population. The following explains the columns in Table 3: Code: Unique code for each symptom; symptom: A description of the symptoms observed on the plant; probability: The probability or likelihood of the symptom occurring.

The rule base of diseases and pests on corn crops can be seen in Table 4.

Table 4. Rule Base of Diseases On Corn Crops

| No | Diseases | Symptom |
|---|---|---|
| 1 | Bulai | g7, g8, g9, g10, g29 |
| 2 | Leaf Spots | g15, g16, g35, g36, g6 |
| 3 | Rust Disease | g24, g16, g43 |
| 4 | Burn Swelling | g24, g25, g44, g4 |

| | | |
|---|---|---|
| 5 | Blight Upih Leaves | g17, g16, g19 |
| 6 | Stem and Cob Rot | g21, g22, g23, g40, g41, g42 |
| 7 | Dwarf Mosaic Virus Disease | g11, g8, g30 |
| 8 | Earthworm | g3, g1, g28 |
| 9 | Grayak caterpillar | g8, g20, g38, g39 |
| 10 | Seed Flies | g1, g2, g27, g21 |
| 11 | Stem Borer | g12, g13, g14, g8, g6, g31, g32, g33, g34 |
| 12 | Cob Borer | g26, g23, g46 |
| 13 | Aphids | g14, g22, g27, g28 |
| 14 | Horn Beetle | g12, g2, g14, g8, g6 |
| 15 | Grasshopper | g1, g4, g20 |

Table 4 lists various diseases and pests that attack plants and their associated symptoms. Each row presents a specific disease or pest and the symptoms typically resulting from their attack. Columns include No (sequential number), Diseases (name of the disease or pest), and Symptom (codes for associated symptoms).

### 3.1 Corn Disease Prediction Using Naive Bayes

This dialog will give an illustration of calculating the gullible Bayes strategy to decide the conclusion of corn infection; within the early stages, we must have information on the side effects experienced by corn, specifically The Nearness of Chomp Marks on the Stem (G001), Plants Gotten to be Shriveled (G002), In part Or Whole LeafRying Clears out (G003). Based on the side effect information, at that point, decide the likelihood esteem of each side effect; G001 features a value of 0.5, G002 contains an esteem of 0.8, and G003 contains an esteem of 0.5. After getting the likelihood esteem, at that point, explore for the evidence coming about from the number of side effects shown. Evidence = G001 + G002 + G003 = 0.5 + 0.8 + 0.5 = 1.8

### 3.2 Approval of Achievability of Expert System for Diagnosing Illnesses and Bugs in Corn Plants.

Framework approval involves testing the system's performance or success level after its design and implementation. The validation process includes inputting test data to determine the system's accuracy. In this study, the system's success rate is measured based on diagnostic accuracy, calculated by comparing the system's conclusions with expert conclusions, then dividing by the total number of tests and multiplying by 100%.

Table 5. Identify Plant Diseases and Pests

| No | Symptom | Expert Identification | System Identification |
|---|---|---|---|
| 1 | The presence of bite marks on the leaves, damaged roots due to grub bites, the presence of bite marks on the trunk | Grasshopper | Grasshopper |
| 2 | Plants become dwarfs fruitless, the cob is not normal, plants wither | Downy mildew | Downy mildew |
| 3 | The stem is broken near the ground; bite marks on the trunk damage young plant leaves. | Grayak caterpillar | Grayak caterpillar |
| 4 | Leaves are green and interspersed with yellow lines, the lower and upper leaves are held without feeling the presence of spore powder, and plants become dwarfs. | Dwarf Mosaic Virus | Dwarf Mosaic Virus |
| 5 | Rotten stem: are plants easily collapsed, the top withers and dry, and is the outer bark thin? Broken cob | Rotten Stems and Cobs | Rotten Stems and Cobs |
| 6 | Seeds will be damaged and rotten; even cobs can fall. The brown leaf surface of the seeds is covered with mycelium, gray to black. | Rust Disease | Rust Disease |
| 7 | With short, dotted lines on the leaf bones, plants become dwarfs, and leaves look long, yellow, and | Stem Borer | Stem Borer |

| | | | |
|---|---|---|---|
| | striped. | | |
| 8 | Little holes in the leaf, broken tassel pile, slit hole in the trunk, fragile rod and tassel | Stem Borer | Stem Borer |
| 9 | Leaf color from normal green to yellowish, the top wither and dry, damaged young plant leaves, leaves look long yellow striped | Aphids | Aphids |
| 10 | Broken cob, there is a caterpillar on the cob of corn, and there is dirt in corn cobs. | Cob Borer | Cob Borer |
| 11 | Leaves become transparent, broken leaf bone, hollowed, even only bones | Grayak caterpillar | Grayak caterpillar |
| 12 | The presence of bite marks on the leaves, the presence of bite marks on the trunk, broken leaf bone | grasshopper | grasshopper |
| 13 | Plants wither, withered leaves become dwarfs, leaves look yellow striped, leaves look long yellow striped. | Corn Planthopper (Horn Beetle) | Corn Planthopper (Horn Beetle) |
| 14 | The brown leaf surface has a yellow-brown powder and red-brown dots like rust. | Rust Disease | Rust Disease |
| 15 | Black swollen corn, there are red-brown dots like rust, bite marks on the trunk, cob wrapping broken. | Swollen Burn Disease | Swollen Burn Disease |
| 16 | Damaged roots due to grub bites, plants wither, leaves look yellow-striped | Stem Borer | Stem Borer |
| 17 | The lower and upper leaves are held without feeling the presence of spore powder, and plants become dwarfed, rotten stems. | Dwarf Mosaic Virus | Dwarf Mosaic Virus |
| 18 | With short, dotted lines on the leaf bones, plants become dwarfs, rotten stems. | Downy mildew | Downy mildew |
| 19 | Is the outer bark thin? Broken cobs have a brownish-yellow powder, seeds will be damaged and rotten, and even cobs can fall. | Rotten Stems and Cobs | Rotten Stems and Cobs |
| 20 | Bite marks on the trunk damaged young plant leaves, and plants wither. | Aphids | Aphids |

Table 5 lists plant symptoms and expert identifications of the diseases or pests causing them. Each row details observed symptoms and expert identifications, supplemented by identifications from other methods. Columns include No (serial number), Symptom (observed symptoms), and Expert Identification (diseases or pests identified by experts). The analysis involved 20 tests, yielding 18 correct and 2 erroneous identifications, resulting in a qualification appraisal of 90% (18/20 x 100%). This indicates the system's high accuracy and feasibility for use.

The research findings indicate that the expert system developed using the Naive Bayes algorithm achieved high accuracy in diagnosing corn diseases, with an overall accuracy rate of 90%. This system's performance was validated by comparing its diagnostic outcomes with those of human experts, demonstrating its reliability and potential for real-world application. Key Findings: High Accuracy and Reliability: The system correctly identified diseases in 18 out of 20 test cases, showing its potential to assist farmers in timely disease management. Efficiency in Disease Detection: The Naive Bayes algorithm's computational simplicity enabled rapid diagnosis, which is crucial for large-scale agricultural operations.

## 4. CONCLUSION

In conclusion, the developed expert system utilizing the Naive Bayes algorithm demonstrated high accuracy and effectiveness in diagnosing diseases in corn plants. The study highlighted the importance of feature selection, algorithm optimization, and model evaluation in enhancing diagnostic capabilities for agricultural applications. Future research could explore expanding the model's diagnostic capabilities to cover additional plant diseases, optimizing computational efficiency, and conducting field validation studies to assess its performance in real-world farming scenarios. Overall, This research contributes to the field of agricultural technology by validating the effectiveness of the Naive Bayes method for disease diagnosis in corn. It underscores the potential of probabilistic models to simplify and accelerate the diagnostic process while maintaining high accuracy. For farmers and agricultural stakeholders, the developed expert system offers a practical tool for early disease detection, enabling more informed and timely interventions. This can lead to better crop management, reduced losses, and increased productivity, contributing to sustainable agricultural practices. The system's high accuracy and efficiency make it a valuable asset in regions with limited access to expert diagnostic services, democratizing access to advanced farming technology. Future studies should aim to expand the diagnostic capabilities of the system to cover a broader range of diseases and pests. Field validation studies are essential to assess the system's performance in diverse agricultural settings and under varying environmental conditions. Additionally, integrating this system with other advanced technologies, such as remote sensing and IoT devices, could further enhance its diagnostic accuracy and usability, paving the way for more comprehensive and automated crop management solutions.

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