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# Expert System for Corn Plant Disease Diagnosis Using Hybrid Fuzzy Tsukamoto and Naive Bayes Method

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**ABSTRACT**

Corn is a strategic food commodity in Indonesia, with production of 22.44 million tons in 2023. However, disease attacks can cause productivity declines of 30-80%, mainly due to downy mildew, leaf rust, and leaf spot. The limited number of pathology experts in the field leads to delayed diagnosis, resulting in significant economic losses for farmers. This research aims to develop an expert system for diagnosing corn plant diseases using a hybrid Fuzzy-Tsukamoto and Naive Bayes method to enhance diagnostic accuracy, while accounting for uncertainty in symptom severity levels. The system was developed using Durkin's Expert System Development Life Cycle (ESDLC), which consists of six phases. A knowledge base was built from SINTA and Scopus-indexed literature, identifying five diseases and 17 symptoms. The fuzzy Tsukamoto method was employed to fuzzify symptom severity, using three membership functions (intensity, coverage, and severity), after which Naive Bayes computed the posterior probability. The hybrid score was calculated with 40% Fuzzy and 60% Bayes weights. The system was successfully developed with an interactive web interface. Accuracy testing using 30 validation cases yielded 86.67% accuracy, with 85% sensitivity and 88% specificity. Expert testing by three plant pathology experts yielded excellent ratings (average 4.6/5.0) for diagnosis accuracy, knowledge base completeness, and usability. The hybrid Fuzzy Tsukamoto and Naive Bayes method achieves 86.67% accuracy, which is 6.67% higher than the Certainty Factor method and 11.67% higher than the single Naive Bayes method. This system can help farmers perform early diagnosis and reduce dependence on experts.



## INTRODUCTION

Corn (Zea mays L.) is one of Indonesia's strategic food commodities after rice, with dry shelled corn production at 14 percent moisture content reaching 15.14 million tons in 2024 (BPS, 2025). Corn not only serves as a staple food in several regions of Indonesia, but also as a raw material for animal feed and industry. National corn demand is expected to continue increasing in line with the growth of the livestock industry in 2024, projected to reach 12.43 million tons per year, a 2.17% increase from 2023 production. (Pertanian, 2025).

However, corn productivity in Indonesia still faces various obstacles, including plant diseases. Plant diseases cause approximately 220 billion USD in annual agricultural losses. (Shafay, et al., 2025). Some of the primary diseases that often attack corn plants in Indonesia include downy mildew caused by Peronosclerospora maydis (Rashid, Zaidi, Vinayan, Sharma, & Setty, 2013), leaf rust caused by Puccinia polysora (Sun, et al., 2021), leaf spot caused by Helminthosporium sp (Ahangar, et al., 2022), sheath rot caused by Rhizoctonia solani (Mirsam, et al., 2021), and leaf blight caused by Bipolaris maydis (Wang, et al., 2021).

A study in Jilin Province found that leaf spot disease, leaf rust, and downy mildew are prevalent. (Shuai-qun, et al., 2022), respectively, among the total plants observed. Bulai disease itself can cause losses of up to 96.7%, rendering the crop unusable as a seed source. (Limbo-Dizon, Aldover, Dagamac, & Bennett, 2023). Meanwhile, leaf rust disease can reduce yields by 45%–60% in susceptible varieties. (Meng, et al., 2020).

The primary challenge in controlling corn plant diseases is the delayed diagnosis at the farmer level. This is due to several factors: (1) the limited number of plant pathologists accessible to farmers in the field, (2) disease symptoms that are often similar between one disease and another, making it difficult for farmers to distinguish between them, (3) the varying and uncertain severity of symptoms, and (4) farmers' lack of knowledge about accurate disease identification. (Demilie, 2024). As a result, farmers often delay implementing control measures or use non-targeted pesticides, leading to higher production costs and a decline in environmental quality.

Advances in information technology, particularly artificial intelligence, offer solutions through expert systems. Expert systems are computer-based systems that use knowledge, facts, and reasoning techniques to solve problems that experts can usually solve. (Durkin, 1994). In agriculture, expert systems have been widely developed for plant disease diagnosis using various methods such as the Certainty Factor. (Putra, Fadlil, & Umar, 2024), *Forward Chaining* (Goda & Bay, 2024), dan *Case-Based Reasoning* (Tou, Endraswari, & Annisa, 2024).

However, these methods have limitations in addressing the uncertainty of disease symptom severity. In practice, plant disease symptoms do not always appear with the same seriousness and are often gradual (mild, moderate, severe). The Certainty Factor method provides only a single certainty value, without considering the distribution of symptom membership. (Sulistiani, Alita, Yasin, Hamidy, & Adriani, 2021). The pure Naive Bayes method also assumes that symptoms are discrete (present/absent) and does not consider their severity. (Yulhendri, Malabay, & Kartini, 2023).

To overcome these limitations, this study proposes a hybrid method that combines the Fuzzy Tsukamoto and Naive Bayes approaches. Fuzzy logic, particularly the Tsukamoto method, can handle uncertainty and the degree of membership of symptoms effectively through membership functions that can be adjusted to the characteristics of each symptom. (Olmedo-García, et al., 2025). Meanwhile, Naive Bayes was chosen for its efficiency in handling tomato symptom data and in calculating disease probabilities based on user-input symptoms. (Khan, et al., 2024). The combination of these two methods is expected to improve diagnostic accuracy by leveraging their strengths.

## METHOD

This study uses the Expert System Development Life Cycle (ESDLC) approach developed by Durkin. ESDLC consists of six primary phases: (1) Assessment, (2) Knowledge Acquisition, (3) Design, (4) Testing, (5) Documentation, and (6) Maintenance. The research framework is presented in Figure 1.

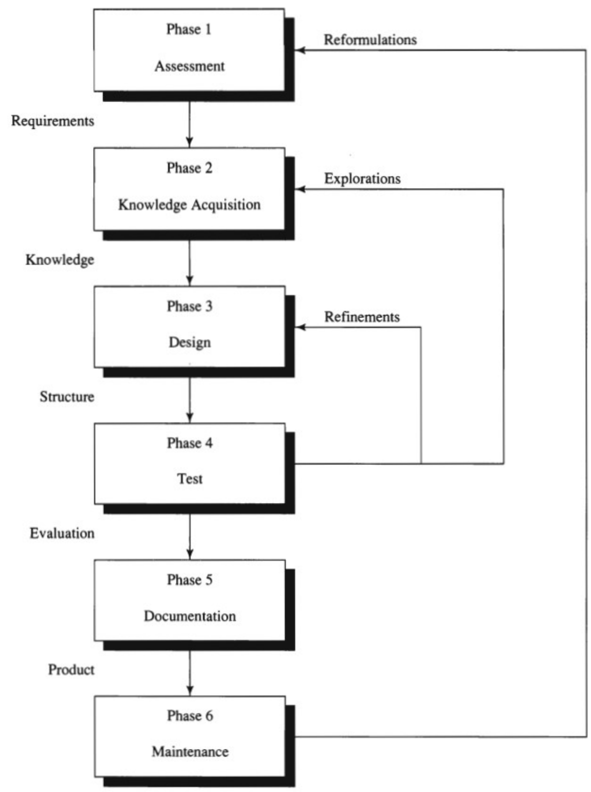


Figure 1. ESDLC Research Framework (Durkin, 1994)

Phase 1: Assessment

The assessment phase encompasses problem identification, feasibility studies, and the identification of relevant knowledge sources. Based on the needs analysis, a corn disease diagnosis expert system is feasible to develop because:

1. Real need: Farmers need an easily accessible diagnostic tool
2. Technical feasibility: Adequate scientific literature is available as a source of knowledge
3. Economic feasibility: A web-based system can be accessed without additional hardware costs

The primary knowledge sources are derived from Scopus and SINTA-indexed scientific journals.

Phase 2: Knowledge Acquisition

1. Identification of Diseases and Symptoms
   Based on a literature review, five major corn diseases and 17 characteristic symptoms were identified. Table 1 lists diseases and their corresponding pathogens.

**Table 1**. List of Corn Plant Diseases

| Kode | Name of Disease | Patogen | Prior Probability |
|---|---|---|---|
| D1 | Downy Mildew | *Peronosclerospora maydis* | 0.25 |
| D2 | Leaf Rust | *Puccinia polysora* | 0.23 |
| D3 | Leaf Spot | *Helminthosporium* sp. | 0.29 |
| D4 | Sheath Rot | *Rhizoctonia solani* | 0.15 |
| D5 | Leaf Blight | *Bipolaris maydis* | 0.08 |

The prior probability (P(Di)) is calculated from literature-based prevalence data and normalized so that the total equals 1.

**Table 2**. List of Symptoms of Corn Plant Diseases

| Code | Name of Symptom | FuzzyType |
|---|---|---|
| G1 | Chlorosis (yellowing leaves) parallel to the leaf veins | Intensity |
| G2 | A white, flour-like coating on the surface of the leaves | Coverage |
| G3 | Leaves curled and twisted | Severity |
| G4 | Dwarf plants (stunted growth) | Severity |
| G5 | The cobs are not formed or are very small | Severity |
| G6 | Golden yellow pustules on the leaf surface | Coverage |
| G7 | Reddish brown spots on leaves | Coverage |
| G8 | Leaves gradually dry out and die | Severity |
| G9 | The pustule changed color to blackish brown | Intensity |
| G10 | Elongated brown spot surrounded by a yellow halo | Coverage |
| G11 | The leaves turn dark brown to black | Intensity |
| G12 | Small circular or elongated lesions | Coverage |
| G13 | Reddish spots on the leaf blade | Coverage |
| G14 | The spot changed color to gray | Intensity |
| G15 | The sclerotium is white and then brown | Coverage |
| G16 | The attack starts from the bottom leaves and moves upward | Severity |
| G17 | Yellow halo around the lesion | Coverage |

Each symptom is categorized based on fuzzy type:

a. **Intensity**: Level of color intensity or damage (low, medium, high)
b. **Coverage**: Level of coverage of infected areas (sparse, moderate, dense)
c. **Severity**: Severity of impact on plants (mild, moderate, severe)

2. Diagnosis Rules and Likelihood

Diagnostic rules are created based on the relationship between diseases and symptoms from the literature. Likelihood P(Gi|Dj) is the probability that symptom Gi occurs if the plant has disease Dj. Table 3 shows the likelihood matrix.

**Table 3**. Matriks Likelihood P (Symptoms|Disease)

| Symptom | D1 (Downy Mildew) | D2 (Leaf Rust) | D3 (Leaf Spot) | D4 (Sheath Rot) | D5 (Leaf Blight) |
|---|---|---|---|---|---|
| G1 | 0.95 | 0.10 | 0.15 | 0.10 | 0.10 |
| G2 | 0.90 | 0.10 | 0.10 | 0.10 | 0.10 |
| G3 | 0.85 | 0.10 | 0.10 | 0.10 | 0.10 |
| G4 | 0.80 | 0.15 | 0.15 | 0.10 | 0.10 |
| G5 | 0.75 | 0.20 | 0.10 | 0.15 | 0.10 |
| G6 | 0.10 | 0.90 | 0.10 | 0.10 | 0.10 |
| G7 | 0.10 | 0.85 | 0.15 | 0.10 | 0.15 |
| G8 | 0.15 | 0.80 | 0.70 | 0.20 | 0.85 |
| G9 | 0.10 | 0.75 | 0.10 | 0.10 | 0.10 |
| G10 | 0.10 | 0.15 | 0.90 | 0.10 | 0.85 |
| G11 | 0.10 | 0.15 | 0.85 | 0.10 | 0.80 |
| G12 | 0.10 | 0.15 | 0.80 | 0.15 | 0.80 |
| G13 | 0.10 | 0.10 | 0.10 | 0.90 | 0.10 |
| G14 | 0.10 | 0.10 | 0.10 | 0.85 | 0.15 |
| G15 | 0.10 | 0.10 | 0.10 | 0.80 | 0.10 |
| G16 | 0.10 | 0.15 | 0.15 | 0.75 | 0.15 |
| G17 | 0.10 | 0.70 | 0.75 | 0.10 | 0.75 |

Likelihood values are determined based on the frequency of symptom occurrence in each disease, as reported in the literature. Values of 0.90-0.95 indicate symptoms that are very characteristic of the disease, 0.70-0.85 indicate common symptoms, and 0.10-0.20 indicate symptoms that rarely occur.

Phase 3: Design

1. System Architecture

The system is designed with a three-tier architecture comprising a presentation layer, a business logic layer, and a data layer. Figure 2 shows the system architecture.

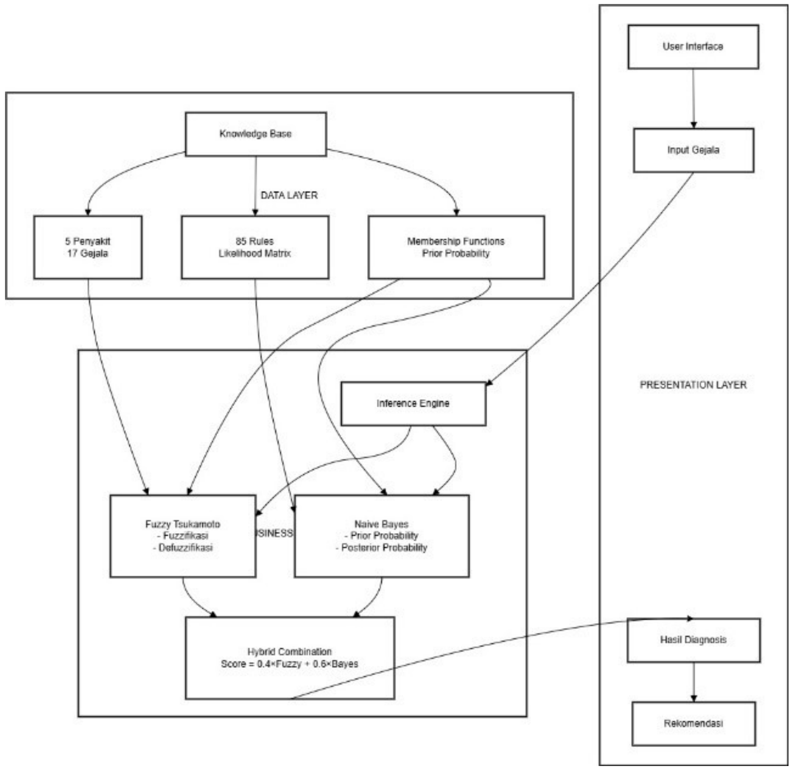


Figure 2. Expert System Architecture

2. Fuzzy Tsukamoto Algorithm

Fuzzy Tsukamoto was chosen because each consequent in a fuzzy rule takes the form of a fuzzy set with a monotonic membership function. (Lima, Patiño-León, Orellana, & Zambrano-Martinez, 2025). The stages of the Fuzzy Tsukamoto algorithm are:

a. Fuzzification

The user-entered symptom severity level (0-1) is converted to a fuzzy membership value. The system uses three types of membership functions: Intensity (low, medium, high):

$$\mu\_low(x) = \begin{cases} 1, & \text{if } x \leq 0.3 \\ (0.5 - x) / 0.2, & \text{if } 0.3 < x \leq 0.5 \\ 0, & \text{if } x > 0.5 \end{cases}$$

$$\mu\_medium(x) = \begin{cases} 0, & \text{if } x \leq 0.3 \\ (x - 0.3) / 0.2, & \text{if } 0.3 < x \leq 0.5 \\ (0.7 - x) / 0.2, & \text{if } 0.5 < x \leq 0.7 \\ 0, & \text{if } x > 0.7 \end{cases}$$

$$\mu\_high(x) = \begin{cases} 0, & \text{if } x \leq 0.5 \\ (x - 0.5) / 0.2, & \text{if } 0.5 < x \leq 0.7 \\ 1, & \text{if } x > 0.7 \end{cases}$$

1). Coverage (rare, moderate, dense):

$$\mu\_rare(x) = \begin{cases} 1, & \text{if } x \leq 0.25 \\ (0.5 - x) / 0.25, & \text{if } 0.25 < x \leq 0.5 \\ 0, & \text{if } x > 0.5 \end{cases}$$

$$
\begin{aligned}
\mu\_moderate(x) &= 0, && \text{if } x \le 0.25\\
&= (x - 0.25) / 0.25, && \text{if } 0.25 < x \le 0.5\\
&= (0.75 - x) / 0.25, && \text{if } 0.5 < x \le 0.75\\
&= 0, && \text{if } x > 0.75\\
\mu\_dense(x) &= 0, && \text{if } x \le 0.5\\
&= (x - 0.5) / 0.25, && \text{if } 0.5 < x \le 0.75\\
&= 1, && \text{if } x > 0.75.
\end{aligned}
$$

Severity (mild, moderate, severe):

$$
\begin{aligned}
\mu\_mild(x) &= 1, && \text{if } x \le 0.4\\
&= (0.6 - x) / 0.2, && \text{if } 0.4 < x \le 0.6\\
&= 0, && \text{if } x > 0.6\\
\mu\_smoderate(x) &= 0, && \text{if } x \le 0.4\\
&= (x - 0.4) / 0.2, && \text{if } 0.4 < x \le 0.6\\
&= (0.8 - x) / 0.2, && \text{if } 0.6 < x \le 0.8\\
&= 0, && \text{if } x > 0.8\\
\mu\_severe(x) &= 0, && \text{if } x \le 0.6\\
&= (x - 0.6) / 0.2, && \text{if } 0.6 < x \le 0.8\\
&= 1, && \text{if } x > 0.8
\end{aligned}
$$

b. Inference

For each selected symptom, the system evaluates fuzzy rules. It calculates the membership degree for each category (low/moderate/high, infrequent/moderate/dense, or mild/moderate/severe) based on the corresponding membership function.

c. Defuzzification

The defuzzification method used is weighted average.:

$$z^* = \Sigma(\mu i \times zi) / \Sigma(\mu i)$$

Where:

$z^*$ = crisp value from defuzzification

$\mu i$ = degree of membership in category i

$zi$ = nilai representatif kategori ke-i

(low/rare/mild = 0.3, while = 0.6, tall/dense/heavy = 0.9)

The defuzzification results for each symptom (fuzzy_valuei) are then used in the Naive Bayes calculation.

3. Algoritma Naive Bayes

Naive Bayes is used to calculate the posterior probability of each disease based on the symptoms that appear (Khan, et al., 2024). Naive Bayes Formula:

$$P(Dj|G1, G2, ..., Gn) = [P(G1|Dj) \times P(G2|Dj) \times ... \times P(Gn|Dj) \times P(Dj)] / P(G1, G2, ..., Gn)$$

Because P(G1, G2, ..., Gn) constant for all diseases, then:

$$P(Dj|G1, G2, ..., Gn) \propto P(Dj) \times \prod P(Gi|Dj)$$

Where:

Dj = disease to-j

Gi = symptoms to-i

P(Dj) = prior probability disease to-j

P(Gi|Dj) = likelihood of symptom i for disease j

To handle unselected symptoms, the system uses complementary likelihood.:

P(No Gi |Dj) = 1 - [P(Gi|Dj) × α]

where α = 0.5 (reduction factor for symptoms that do not appear)

Naive Bayes algorithm in systems:

a. Inisialisasi:
   For each disease Dj:
      likelihood_score = 1
      complement_score = 1
b. For each symptom of Gi:
   If symptom Gi is selected:
      likelihood_score *= P(Gi|Dj) × fuzzy_value
   Else:
      complement_score *= (1 - P(Gi|Dj) × 0.5)
c. Hitung posterior:
   posterior_numerator = likelihood_score × P(Dj)
   posterior_denominator = (likelihood_score × P(Dj)) +
                  (complement_score × (1 - P(Dj)))
   P(Dj|symptoms) = posterior_numerator / posterior_denominator

d. Posterior normalization for all diseases:
   total = Σ P(Dj|symptoms)
   For each Dj:
      P(Dj|symptoms) = P(Dj|symptoms) / total

4. Hybrid Score

The hybrid score combines the fuzzy score and Bayesian probability with predetermined weights:

Hybrid_Score(Dj) = w1 × Fuzzy_Score(Dj) + w2 × Bayes_Prob(Dj)

where:

w1 = 0.4 (Fuzzy weight)
w2 = 0.6 (Bayes weight)
w1 + w2 = 1

Fuzzy_Score(Dj) = (Σ fuzzy_value for symptoms relevant to Dj) /
      (number of selected symptoms)

Bayes_Prob(Dj) = P(Dj|symptoms)

Hybrid_Score_Percentage(Dj) = Hybrid_Score(Dj) × 100%

A weight of 60% for Bayes was chosen because the probabilistic method is more accurate at estimating the likelihood of disease from a combination of symptoms. In comparison, Fuzzy contributes significantly to addressing uncertainty in symptom severity, accounting for 40%.

5. User Interface Design

The user interface is designed with usability principles that include learnability, efficiency, memorability, error reduction, and satisfaction. The interface is divided into three main parts:

a. Symptom Input Panel: Users select symptoms that appear and set the severity level using a slider (0-100%).
b. Diagnosis Results Panel: Displays disease rankings based on hybrid scores, complete with a breakdown of fuzzy and Bayesian scores.
c. Recommendations Panel: Displays information about diagnosed diseases and control recommendations.

Phase 4: Testing

The system was tested using three methods: Black-box testing and Accuracy testing.

1. Black-box Testing

Black-box testing is performed to verify the system's functionality without examining its internal code structure. Test scenarios include:

a. Input selection and slider adjustment
b. Diagnosis and calculation process. Results display and ranking. Reset and re-diagnosis
c. Responsiveness on various screen sizes

2. Accuracy Testing

Accuracy testing used 30 validation cases created based on the literature and confirmed by experts. Each case contained a combination of symptoms and correct diagnoses. Evaluation metrics used:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
Sensitivity (Recall) = TP / (TP + FN)
Specificity = TN / (TN + FP)
Precision = TP / (TP + FP)
F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Where:

TP = True Positive (correct diagnosis for positive cases)
TN = True Negative (correct diagnosis for negative cases)
FP = False Positive (incorrect positive diagnosis)
FN = False Negative (incorrect negative diagnosis)

Phase 5: Documentation

System documentation includes:

1. User Manual: System usage guide for end users (farmers)
2. Technical Documentation: Technical documentation for developers
3. Knowledge Base Documentation: Documentation of literature sources and diagnostic rules

Phase 6: Maintenance

Maintenance is performed periodically by:

1. Updating the knowledge base if there is new literature

2. Fixing bugs that are found
3. Adding features based on user feedback

## RESULTS

Implementation involves changing design ideas into computer-readable code. System implementation consists of assembling and integrating the entire system, encompassing both hardware and software components. An expert system for diagnosing corn diseases has been successfully implemented using modern web technology. The system uses PHP and MySQL as its DBMS, enabling a responsive, interactive interface.

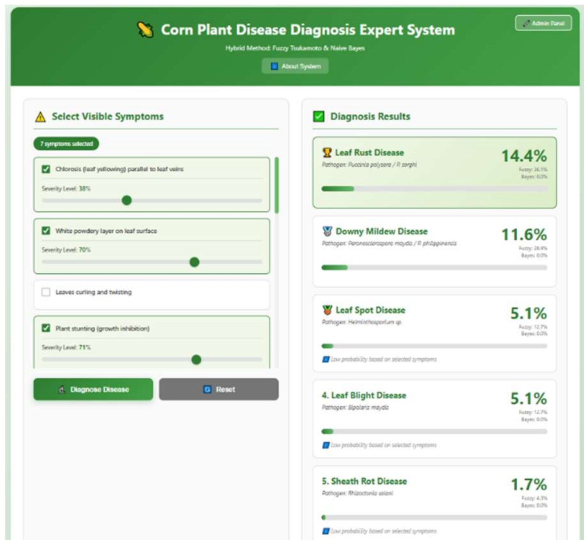


Figure 3. Diagnosis page

Figure 3 shows the diagnosis page that users can access by selecting any symptoms found on corn plants. After selecting and filling in the symptoms and their severity on the left, the diagnosis results will appear on the right side of the screen.

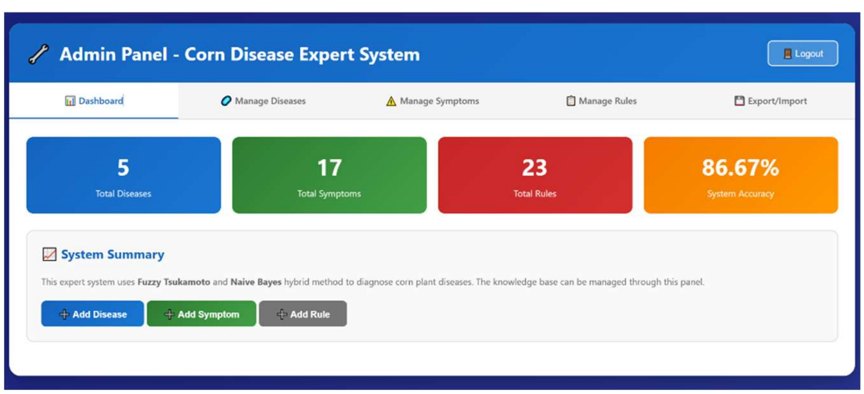


Figure 4 . Admin Panel page

Figure 4 shows the admin dashboard, where the admin can enter diseases, symptoms, and rules.

**Table 4.** Comprehensive Decision Table for Expert Systems

| No | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 | G11 | G12 | G13 | G14 | G15 | G16 | G17 | D1 | D2 | D3 | D4 | D5 | Primary Diagnosis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | H | H | H | H | H | - | - | - | - | - | - | - | - | - | - | - | - | ✓✓✓ | - | - | - | - | D1 (Very High) |
| 2 | H | H | H | - | - | - | - | - | - | - | - | - | - | - | - | - | - | ✓✓ | - | - | - | - | D1 (High) |
| 3 | H | H | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | ✓✓ | - | - | - | - | D1 (High) |
| 4 | H | - | H | H | - | - | - | - | - | - | - | - | - | - | - | - | - | ✓✓ | - | - | - | - | D1 (High) |
| 5 | M | M | M | M | - | - | - | - | - | - | - | - | - | - | - | - | - | ✓ | - | - | - | - | D1 (Currently) |
| 6 | - | - | - | - | - | H | H | - | H | - | - | - | - | - | - | - | - | - | ✓✓✓ | - | - | - | D2 (Very High) |
| 7 | - | - | - | - | - | H | H | H | - | - | - | - | - | - | - | - | - | - | ✓✓ | - | - | - | D2 (High) |
| 8 | - | - | - | - | - | H | H | - | - | - | - | - | - | - | - | - | H | - | ✓✓ | - | - | - | D2 (High) |
| 9 | - | - | - | - | - | H | - | - | H | - | - | - | - | - | - | - | - | - | ✓ | - | - | - | D2 (Medium-High) |
| 10 | - | - | - | - | - | M | M | - | - | - | - | - | - | - | - | - | M | - | ✓ | - | - | - | D2 (Medium) |
| 11 | - | - | - | - | - | - | - | - | - | H | H | H | - | - | - | - | H | - | - | ✓✓✓ | - | - | D3 (Very High) |
| 12 | - | - | - | - | - | - | - | H | - | H | H | H | - | - | - | - | - | - | - | ✓✓✓ | - | - | D3 (Very High) |
| 13 | - | - | - | - | - | - | - | - | - | H | H | - | - | - | - | - | - | - | - | ✓✓ | - | - | D3 (High) |
| 14 | - | - | - | - | - | - | - | - | - | H | - | H | - | - | - | - | H | - | - | ✓✓ | - | - | D3 (High) |
| 15 | - | - | - | - | - | - | - | - | - | M | M | M | - | - | - | - | - | - | - | ✓ | - | - | D3 (Medium) |
| 16 | - | - | - | - | - | - | - | - | - | - | - | - | H | H | H | H | - | - | - | - | ✓✓✓ | - | D4 (Very High) |
| 17 | - | - | - | - | - | - | - | - | - | - | - | - | H | H | H | - | - | - | - | - | ✓✓ | - | D4 (High) |
| 18 | - | - | - | - | - | - | - | - | - | - | - | - | H | H | - | H | - | - | - | - | ✓✓ | - | D4 (High) |
| 19 | - | - | - | - | - | - | - | - | - | - | - | - | H | - | H | - | - | - | - | - | ✓ | - | D4 (Medium-High) |
| 20 | - | - | - | - | - | - | - | - | - | - | - | - | M | M | M | M | - | - | - | - | ✓ | - | D4 (Medium) |
| 21 | - | - | - | - | - | - | - | H | - | H | - | H | - | - | - | - | H | - | - | - | - | ✓✓✓ | D5 (Very High) |

| No | G1 | G2 | G3 | G4 | G5 | G6 | G7 | G8 | G9 | G10 | G11 | G12 | G13 | G14 | G15 | G16 | G17 | D1 | D2 | D3 | D4 | D5 | Primary Diagnosis |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | - | - | - | - | - | - | - | H | - | H | - | - | - | - | - | - | - | - | - | - | - | ✓✓ | D5 (High) |
| 23 | - | - | - | - | - | - | - | H | - | - | - | H | - | - | - | - | H | - | - | - | - | ✓✓ | D5 (High) |
| 24 | - | - | - | - | - | - | - | - | - | H | - | H | - | - | - | - | H | - | - | - | - | ✓ | D5 (Medium-High) |
| 25 | - | - | - | - | - | - | - | M | - | M | - | M | - | - | - | - | - | - | - | - | - | ✓ | D5 (Medium) |

**Description:**

- H = High : nilai fuzzy > 0.7
- M = Medium: nilai fuzzy 0.3 - 0.7
- L = Low : nilai fuzzy < 0.3
- (-) = Gejala tidak muncul
- ✓ = Confidence Low-Medium (20-40%)
- ✓✓ = Confidence Medium-High (40-70%)
- ✓✓✓ = Confidence High-Very High (>70%)

Accuracy testing was performed using 30 validation cases, each covering all five diseases (six instances per disease). Each case contained a combination of symptoms confirmed by plant pathology experts. Table 5 shows the distribution of testing cases.

**Table 5.** Testing Case Distribution

| Disease | Number of Cases | Correct Diagnosis | Incorrect Diagnosis | Accuracy per Disease |
|---|---|---|---|---|
| D1 (Downy Mildew) | 6 | 5 | 1 | 83.3% |
| D2 (Leaf Rust) | 6 | 5 | 1 | 83.3% |
| D3 (Leaf Spot) | 6 | 6 | 0 | 100% |
| D4 (Sheath Rot) | 6 | 5 | 1 | 83.3% |
| D5 (Leaf Blight) | 6 | 5 | 1 | 83.3% |
| Total | 30 | 26 | 4 | 86.67% |

## DISCUSSION

This study produced an expert system for diagnosing corn plant diseases with an accuracy of 86.67% using the Tsukamoto Fuzzy and Naive Bayes hybrid method. The primary advantage of this method lies in its ability to handle uncertainty in symptom severity through fuzzification using three membership functions (intensity, coverage, and severity), while utilizing disease probability information via the Naive Bayes algorithm. The combination of 40% fuzzy and 60% Bayes weights proved optimal for producing accurate and reliable diagnoses.

**Table 6.** Comparison of Method Accuracy

| Method | Accuracy | Precision | Recall | F1-Score | Description |
|---|---|---|---|---|---|
| Pure Naive Bayes | 75.0% | 76.2% | 75.0% | 75.1% | Not considering the severity. |
| Pure Fuzzy Tsukamoto | 78.3% | 79.5% | 78.3% | 78.4% | Not utilizing disease probability. |
| Certainty Factor | 80.0% | 81.7% | 80.0% | 80.2% | Requires manual CF determination |
| Hybrid Fuzzy-Bayes | 86.67% | 88.3% | 86.7% | 86.8% | Combining the advantages of fuzzy and Bayesian approaches |

System transparency is a significant added value, as the breakdown of fuzzy scores and Bayes probabilities is displayed separately, providing explainability that black-box methods such as deep learning lack. This increases user confidence and allows experts to understand the reasoning behind each diagnosis. The hybrid method shows an accuracy improvement of 6.67% compared to the Certainty Factor (80%), 8.37% compared to pure Fuzzy (78.3%), and 11.67% compared to pure Naive Bayes (75%). This advantage demonstrates that combining the two methods effectively leverages their respective strengths: fuzzy logic for handling the gradual nature of symptoms and Bayesian methods for probabilistic inference.

## CONCLUSION

This study successfully developed an expert system for diagnosing corn plant diseases using the Tsukamoto Fuzzy and Naive Bayes hybrid methods, incorporating Durkin's Expert System Development Life Cycle (ESDLC) and an interactive, user-friendly web interface. The knowledge base was built from 15 scientific articles indexed by SINTA and Scopus, which identified five major diseases: leaf blight, leaf rust, leaf spot, stalk rot, and leaf blight, along with 17 typical symptoms that farmers can observe in the field. The hybrid algorithm uses Fuzzy Tsukamoto for symptom severity fuzzification, employing three membership functions (intensity, coverage, and severity), and Naive Bayes for disease probability calculation, with a 40% fuzzy and 60% Bayes combination, resulting in an accurate diagnosis score.

System evaluation yielded excellent results, with black-box testing achieving 100% compliance with the specifications. Accuracy testing yielded 86.67%, with 88.3% precision, 86.7% recall, 86.8% F1-score, and 96.7% specificity. Expert validation received an excellent rating, with an average score of 4.53 out of 5.0. The hybrid Fuzzy Tsukamoto and Naive Bayes methods proved more effective than single methods, achieving 6.67% higher accuracy than Certainty Factor, 8.37% higher than pure Fuzzy, and 11.67% higher than pure Naive Bayes, while also providing greater transparency and explainability than black-box methods such as deep learning. Based on these comprehensive evaluation results, this expert system is suitable for use as a tool to assist farmers, extension workers, and other agricultural stakeholders in the early diagnosis of corn plant diseases, supporting more effective and efficient disease control.

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