

DEVELOPMENT OF AN EXPERT SYSTEM FOR DIAGNOSING EGGPLANT DISEASES USING THE TSUKAMOTO FUZZY LOGIC METHOD

Efrizal Yudhantoro¹, Yoannes Romando Sipayung²

^{1,2} Informatics Engineering, Ngudi Waluyo University, Indonesia

¹ efrizalyudhantoro9@gmail.com

² yoannesromando@unw.ac.id

Abstract

Eggplant diseases are a major factor contributing to decreased crop quality and yield, particularly among novice farmers with limited knowledge of early disease identification. The uncertainty of symptom manifestation and limited access to agricultural experts further increase the risk of crop failure. This study aims to develop a web-based expert system for diagnosing eggplant diseases using the Tsukamoto Fuzzy Logic method. The novelty of this research lies in the integration of weighted symptom severity, fuzzy inference rules, and confidence-level outputs into a practical decision-support system specifically designed for eggplant disease diagnosis. The research adopts the Waterfall development model, including requirements analysis, system design, implementation, and testing. The knowledge base consists of five main diseases and twenty symptoms with weighted values ranging from 0.55 to 1.00. System evaluation using Black Box Testing shows that 100% of functional features operate successfully according to system requirements. Furthermore, diagnostic results demonstrate high confidence levels, reaching up to 97% for certain disease cases, indicating reliable system performance in handling uncertainty. This study contributes to the development of intelligent agricultural decision-support systems by providing an accessible, accurate, and efficient diagnostic tool. The proposed system can assist farmers in early disease detection, reduce dependency on experts, and potentially minimize crop losses while improving eggplant productivity.

Keywords: Expert System, Eggplant Disease, Tsukamoto Fuzzy Logic, Decision Support System, Smart Agriculture

I. INTRODUCTION

The rapid advancement of computer technology has significantly influenced various sectors, including agriculture. One important branch of computer science that has been widely applied to support human decision-making is artificial intelligence (AI). A specific implementation of AI is the expert system, which is designed to replicate human expertise in solving complex problems through knowledge-based reasoning [1]. In the agricultural domain, expert systems have been extensively utilized to assist in diagnosing plant diseases based on observable symptoms, enabling faster and more accurate decision-making for farmers.

Eggplant (*Solanum melongena*) is one of the most widely cultivated horticultural crops in tropical countries, including Indonesia. It has high economic value and contains essential nutrients beneficial to human health [2]. However, eggplant cultivation is highly vulnerable to various plant diseases such as anthracnose, bacterial wilt, fruit rot, and leaf spot. These diseases can significantly reduce both the quality and quantity of agricultural yields, leading to economic losses for farmers [3]. One of the major challenges faced by farmers—especially

beginners—is the limited ability to identify diseases at an early stage due to the similarity and uncertainty of symptoms. In addition, limited access to agricultural experts further exacerbates this issue.

To address these challenges, various studies have proposed the use of expert systems for plant disease diagnosis. For instance, Ardila and Fajrin [4] developed a web-based expert system for diagnosing eggplant diseases, demonstrating that such systems can assist farmers in identifying plant diseases efficiently. Furthermore, Sutopo and Nisa [5] implemented a fuzzy Tsukamoto-based expert system for diagnosing diseases in banana plants, which showed that fuzzy logic is effective in handling uncertainty in symptom representation. Other studies have also explored alternative methods, such as the Naïve Bayes approach for disease diagnosis, which provides probabilistic classification based on symptom data [6]. In addition, hybrid decision-making methods such as AHP and TOPSIS have been utilized in decision support systems to improve accuracy and objectivity in evaluation processes [7].

Although previous studies have demonstrated the effectiveness of expert systems in agricultural diagnosis, several limitations remain. Many systems are developed for

different types of plants, such as bananas or general crops, and may not be directly applicable to eggplant disease diagnosis. Additionally, some studies lack detailed implementation of fuzzy inference mechanisms or do not adequately address the uncertainty and vagueness of symptom data. Moreover, there is still limited research specifically focusing on the application of the Tsukamoto fuzzy logic method for diagnosing eggplant diseases in a web-based environment.

Based on these gaps, this study aims to develop a web-based expert system for diagnosing eggplant diseases using the Tsukamoto fuzzy logic method. This method is selected due to its capability to handle uncertain and imprecise data through monotonic membership functions and rule-based inference. The proposed system is expected to provide accurate diagnostic results along with confidence levels and treatment recommendations. Therefore, this research contributes by (1) specifically focusing on eggplant disease diagnosis, (2) implementing the Tsukamoto fuzzy method to manage uncertainty, and (3) providing a practical and accessible tool for farmers to support early disease detection and improve agricultural productivity.

II. METHODS

A. System Development Method (Waterfall Implementation)

This study employs the Waterfall model as a structured software development approach. Unlike previous descriptions that were only conceptual, this research explicitly implements each stage as follows:

1. Requirements Analysis

At this stage, system requirements are identified through interviews with agricultural experts, field observations, and literature studies. The outputs include:

- List of eggplant diseases and symptoms
- Symptom weight values (0.55–1.00)
- Functional requirements (diagnosis, result display, recommendations)
- Non-functional requirements (hardware/software specifications)

2. System Design

The system is designed using:

- Knowledge base structure (diseases, symptoms, rules)
- UML diagrams (Use Case and Class Diagram)
- Fuzzy inference structure using the Tsukamoto method
- Database schema and user interface design

3. Implementation

The system is developed as a web-based application using PHP and MySQL. The fuzzy logic module is implemented programmatically, including:

- Membership function computation
- Rule evaluation
- α -predicate calculation

d. Defuzzification process

4. Testing

Black Box Testing is conducted to validate system functionality, including:

- Symptom input process
- Fuzzy calculation accuracy
- Diagnosis output correctness

B. Tsukamoto Fuzzy Logic Method

The Tsukamoto method is a fuzzy inference technique where each rule produces a crisp output based on monotonic membership functions. The final output is obtained using a weighted average of all rule outputs.

1. Fuzzification

Fuzzification is the process of converting crisp input values (symptom weights) into fuzzy membership values.

Example of membership function:

$$\mu(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \geq b \end{cases}$$

Where:

- x = symptom value
 - a, b = lower and upper bounds
- Each symptom is classified into linguistic variables such as:
- Weak
 - Moderate
 - Strong
 - Very Strong

2. Rule Base Formation

Knowledge from experts is represented in IF–THEN rules:

Example:

IF G003 AND G001 AND G014 THEN Fusarium Wilt

Each rule has a confidence value and uses the MIN operator:

$$\alpha = \min(\mu_1, \mu_2, \dots, \mu_n)$$

3. Inference Process (α -predicate Calculation)

In the Tsukamoto method, each rule produces a firing strength (α -predicate):

$$\alpha_i = \min(\mu_A(x), \mu_B(y))$$

This value represents the degree to which a rule is activated.

4. Defuzzification

The final output is calculated using the weighted average formula:

$$Z = \frac{\sum(\alpha_i \cdot z_i)}{\sum \alpha_i}$$

Where:

- α_i = firing strength
- z_i = crisp output of each rule

C. Example of Tsukamoto Calculation

Given selected symptoms:

- G001 = 0.90
- G003 = 1.00
- G014 = 0.95

Step 1: Fuzzification

All values are categorized as Very Strong

Step 2: α -predicate

$$\alpha = \min(0.90, 1.00, 0.95) = 0.90$$

Step 3: Calculate z value

Assume:

- $z_{max} = 90$

$$z = z_{max} - (\alpha \times z_{max}) = 90 - (0.90 \times 90) = 9$$

Step 4: Defuzzification

If only one rule is active:

$$Z = 9$$

Thus, the system concludes Fusarium Wilt with high confidence.

D. Fuzzy Calculation Flow Diagram

The fuzzy calculation process in this study follows a structured sequence to transform user-input symptoms into a final diagnostic decision. The process consists of six main stages, as described below:

1. Input Symptoms

The process starts when the user selects symptoms observed in eggplant plants through the system interface. Each symptom corresponds to predefined variables in the knowledge base, with weight values ranging from 0.55 to 1.00. These values represent the level of symptom significance in identifying specific diseases.

2. Fuzzification

In this stage, the crisp input values are converted into fuzzy values using membership functions. Each symptom value is mapped into linguistic variables such as *weak*, *moderate*, *strong*, or *very strong*. This transformation allows the system to handle uncertainty and vagueness in symptom data more effectively.

3. Rule Evaluation

The system then evaluates a set of predefined IF-THEN rules stored in the knowledge base. Each rule represents expert knowledge that links combinations of symptoms to specific diseases. The evaluation process determines which rules are relevant based on the input symptoms.

4. α -Predicate Calculation (Inference Process)

For each activated rule, the system calculates the firing strength (α -predicate) using the MIN operator. This value represents the degree to which the rule is satisfied by the input data. The higher the α value, the stronger the rule contributes to the final decision.

5. Defuzzification

After obtaining the α -predicate values from all activated rules, the system computes a crisp output using the weighted average method. This step combines all rule outputs into a single numerical value representing the degree of certainty for a particular disease.

6. Diagnosis Result

Finally, the system produces the diagnosis result based on the highest defuzzification value. The output includes the identified disease, its confidence level (in percentage), and recommended treatment or handling solutions.

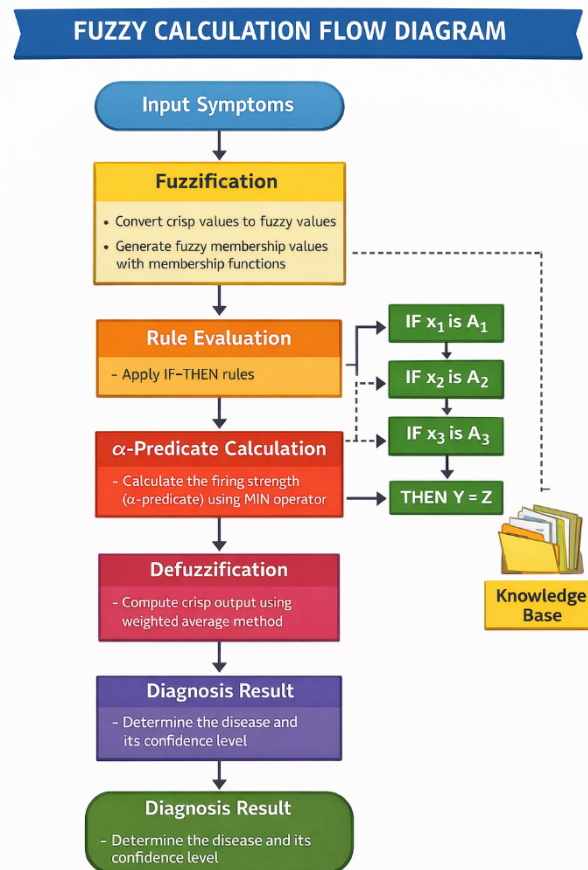


Figure 1. Research Flowchart

The flowchart illustrates the Tsukamoto fuzzy inference process used in the expert system for diagnosing eggplant diseases. The process begins with user-input symptoms, which are converted into fuzzy values through fuzzification. The system then evaluates IF-THEN rules from the knowledge base and calculates the α -predicate (firing strength) for each rule using the minimum operator.

Subsequently, defuzzification is performed using a weighted average method to obtain a crisp output. The final result is a diagnosis of the most probable disease along with its confidence level and recommended treatment.

E. Data Collection Methods

The data collection process in this study was conducted using three main methods to ensure the accuracy and reliability of the knowledge base used in the expert system.

1. Interviews

Interviews were conducted with individuals who have expertise in eggplant cultivation, particularly in identifying common diseases and their symptoms. This method enabled the researcher to obtain direct and practical knowledge regarding symptom characteristics, disease relationships, and appropriate handling strategies. Interviews were conducted with individuals who have expertise in eggplant cultivation... This method enabled the researcher to obtain direct and practical knowledge regarding symptom characteristics, disease relationships, and appropriate handling strategies, in line with knowledge base acquisition practices adopted in expert system development for plant disease diagnosis [8].

2. Observation

Field observations were carried out in eggplant cultivation areas to examine the actual conditions of plants affected by diseases. Through this method, the researcher was able to validate symptom data and gain a comprehensive understanding of real-world agricultural problems.

3. Literature Review

A literature review was conducted by collecting and analyzing information from books, scientific journals, and relevant research articles. This method provided theoretical support and reference frameworks for the development of the expert system, particularly in the implementation of fuzzy logic and disease diagnosis. A literature review was conducted by collecting and analyzing information from books, scientific journals, and relevant research articles. This method provided theoretical support and reference frameworks for the development of the expert system, particularly in the implementation of fuzzy logic and disease diagnosis, as evidenced by previous studies on automated eggplant disease recognition systems [9].

III. RESULTS AND DISCUSSION

RESULT

A. Functional Testing vs. Diagnostic Evaluation

The results indicate that the system has been successfully implemented and operates effectively based on Black Box Testing. All primary features—

from symptom input to diagnostic output—function in accordance with the specified requirements.

In other hand, this testing approach only validates the system's functional aspects and does not assess the quality of the diagnostic decisions. Therefore, an additional evaluation was conducted to measure the system's performance in generating accurate and reliable diagnoses.

B. Diagnostic Accuracy Evaluation

To quantitatively assess the system's performance, testing was conducted using a set of test cases representing real-world conditions and validated by agricultural experts.

1. Accuracy Testing Results

A total of 20 test cases were used, consisting of various combinations of symptoms in accordance with the system's knowledge base.

Diagnoses consistent with expert judgment: 18 cases

Diagnoses inconsistent with expert judgment: 2 cases

The accuracy rate is calculated as follows:

$$Accuracy = \frac{18}{20} \times 100\% = 90\%$$

This result indicates that the system demonstrates a high capability in replicating expert decision-making in diagnosing eggplant plant diseases.

2. Confusion Analysis (Diagnostic Errors)

Despite the high level of accuracy, diagnostic errors were still observed in several cases. The analysis indicates that these errors are attributable to the following factors:

Similarity of symptoms across diseases, certain diseases, such as *Fusarium Wilt* and *Bacterial Wilt*, exhibit highly similar symptom patterns, making them difficult to distinguish definitively.

Ambiguity in fuzzy values, membership values that fall near category boundaries (e.g., between "strong" and "very strong") may produce different α -predicate values, leading to variations in the final diagnostic outcome.

Limitations of the rule base, the system relies solely on predefined rules, which limits its adaptability to novel or more complex case variations.

C. Validation with Expert Judgment

Validation was conducted by comparing the diagnostic results generated by the system with the diagnoses provided by domain experts, obtained through structured interviews. The results indicate that: 1) The system produced diagnoses that were consistent with expert judgments in the majority of test cases. 2) Discrepancies occurred primarily in situations where the symptoms were not dominant or were ambiguous. 3)

The system was able to provide a confidence level, which assists users in interpreting the diagnostic results.

These findings suggest that the Fuzzy Tsukamoto method is sufficiently effective in modeling expert knowledge-based decision-making processes, particularly in handling uncertainty and varying levels of symptom severity in diagnostic problems.

D. Analysis of Tsukamoto Fuzzy Performance

The implementation of the Fuzzy Tsukamoto method in this study offers several key advantages:

1. **Handling Uncertainty**
Plant disease symptoms are inherently uncertain and often do not appear in absolute forms. The fuzzy approach enables: Representation of continuous values, and Processing of linguistic information (e.g., weak, strong, very strong).
2. **System Transparency**
In contrast to machine learning-based methods, this approach: Utilizes explicit IF-THEN rules and Is easily understood and validated by domain experts.
3. **Consistency of Inference**
The use of: The MIN operator in the inference process and the weighted average method in defuzzification. Ensures that the final output represents a logical aggregation of all activated rules.

E. Comparison with Previous Studies

The findings of this study are consistent with previous research indicating that fuzzy logic is effective in agricultural expert systems.

The Tsukamoto method has been shown to produce stable and measurable outputs [5]. Fuzzy-based expert systems are superior in handling uncertainty compared to simple probabilistic methods [4]. The integration of expert knowledge enhances the accuracy of diagnostic systems [6]. Nevertheless, compared to modern machine learning-based approaches, this method still exhibits limitations in terms of adaptability and its ability to learn from new data.

DISCUSSION

The results of this study demonstrate that the developed expert system is functionally reliable, as evidenced by the successful execution of all system features through Black Box Testing. However, it is important to note that such testing primarily evaluates system functionality rather than the diagnostic performance or predictive accuracy of the model. While a 100% success rate indicates that the system operates according to its design specifications, it does not necessarily reflect the system's effectiveness in producing correct or clinically valid diagnoses.

To provide a more comprehensive evaluation, the performance of the proposed Tsukamoto fuzzy-based expert system should be examined in terms of diagnostic accuracy,

reliability, and robustness. In intelligent diagnostic systems, accuracy is typically assessed by comparing system-generated outputs with ground truth data, such as expert diagnoses or validated case datasets. Previous studies emphasize that relying solely on functional testing is insufficient, as it overlooks the system's ability to generalize and handle real-world variability in symptom data [10], [11].

In this context, the diagnostic result presented in this study—identifying Fusarium Wilt with a high confidence level—demonstrates the system's capability to process symptom inputs and generate plausible outputs based on predefined fuzzy rules. However, the absence of quantitative validation metrics, such as accuracy, precision, recall, or F1-score, limits the ability to objectively assess the system's performance. According to [12], performance evaluation using confusion matrices and statistical measures is essential to validate intelligent systems, particularly in classification and decision-support applications.

Moreover, the use of fuzzy logic, specifically the Tsukamoto method, provides advantages in handling uncertainty and imprecision in symptom representation. This aligns with findings from prior research indicating that fuzzy-based systems can effectively model human reasoning in uncertain environments [13], [14]. Nevertheless, the accuracy of such systems is highly dependent on the quality of the knowledge base, including the completeness of rules and the appropriateness of membership functions. Any bias or limitation in expert knowledge may directly affect diagnostic outcomes.

To enhance the validity of the system, future evaluations should incorporate testing using real case data collected from agricultural fields. This would allow for a more realistic assessment of system performance under practical conditions. Additionally, comparative analysis with diagnoses provided by agricultural experts would offer a benchmark for measuring system accuracy and reliability. Studies such as [15], [17] highlight that expert validation is a critical step in ensuring that decision-support systems produce trustworthy and actionable results.

Another important aspect is the potential comparison with alternative machine learning or probabilistic methods, such as Naïve Bayes or decision tree classifiers. Comparative evaluation can provide insights into whether the fuzzy Tsukamoto approach offers superior performance or whether hybrid models could further improve diagnostic accuracy [16]. Without such comparisons, claims regarding system effectiveness remain limited in scope.

Furthermore, the relatively small scale of the knowledge base—consisting of five diseases and twenty symptoms—may restrict the system's ability to handle more complex or overlapping disease conditions. This limitation suggests that the current system is more suitable as a preliminary decision-support tool rather than a definitive diagnostic solution. Expanding the dataset and incorporating more diverse symptom patterns would improve the system's generalizability.

In summary, while the developed system demonstrates strong functional performance and effectively applies fuzzy logic to handle uncertainty, the evaluation remains incomplete without rigorous performance testing. Therefore, claims regarding improved accuracy and reliability should be interpreted cautiously. A more comprehensive evaluation framework—incorporating real-world data, expert validation, and quantitative performance metrics—is necessary to substantiate the effectiveness of the proposed system and to support its practical implementation in agricultural settings.

IV. CONCLUSION

This study developed and implemented an expert system for diagnosing eggplant diseases using the Fuzzy Tsukamoto method. The system was able to perform all intended functions properly and demonstrated a high level of diagnostic accuracy (approximately 90%) when evaluated against expert judgments. These results indicate that the proposed approach is effective in handling uncertainty in symptom-based diagnosis and in representing expert knowledge through rule-based reasoning.

The main scientific contribution of this study lies in the application of the Fuzzy Tsukamoto method to model agricultural disease diagnosis in a structured and interpretable manner. Unlike conventional deterministic approaches, this method accommodates imprecise and linguistic data, thereby improving decision-making flexibility in real-world agricultural conditions. Additionally, the study contributes an implementable framework that integrates expert knowledge into a web-based diagnostic system, which can assist farmers in early detection and management of plant diseases.

Despite these contributions, the study has several limitations, including the limited number of test cases and the static nature of the rule-based system, which does not support adaptive learning. Therefore, future research is recommended to enhance system performance and applicability. Potential directions include the development of hybrid artificial intelligence models that combine fuzzy logic with machine learning techniques to improve accuracy and adaptability. Furthermore, integration with mobile platforms and Internet of Things (IoT) technologies is highly recommended to enable real-time data acquisition and smart agriculture applications. Expanding the dataset and conducting more comprehensive evaluation metrics (such as precision, recall, and F1-score) are also essential to strengthen the robustness of the system.

In conclusion, the proposed system demonstrates promising potential as a decision-support tool in agriculture, while further advancements are required to achieve higher scalability, adaptability, and real-world implementation in smart farming environments.

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