Electronic Journal of Education, Social Economics and Technology
Vol. 6, No. 2, (2025), pp. 1~14, Article ID: 1059
ISSN 2723-6250 (online)
DOI: https://doi.org/10.33122/ejeset.v6i2.1059

SAINTIS publishing

Research Article

Design of a Fuzzy Mamdani Based Decision Support System for Fair Wage Determination of Palm Oil Workers

Zuheri Lubis*, Sriani

Department of Science and Technology, Universitas Islam Negeri Sumatera Utara, Medan, Indonesia, 20235
*Corresponding Author: zuherilubis09@gmail.com

ABSTRACT

Wage determination in palm-oil plantations often relies on subjective assessments, which may lead to inconsistencies, unfair practices, and disputes between workers and management. To address this issue, this study proposes the application of the Fuzzy Mamdani method as a decision support system for determining plantation workers' wages. The main objective is to design and implement a fuzzy-based model that provides fair and transparent wage recommendations by integrating multiple worker performance criteria. The research was conducted at PT CSIL with a sample of 45 workers. Four key variables length of service, attendance, overtime, and work performance were formulated into linguistic variables with triangular membership functions. A fuzzy rule base, developed in collaboration with domain experts, was used to perform Mamdani inference with centroid defuzzification. Data were obtained from company records and validated using comparisons with the actual wage distribution determined by the payroll department. The results show that the system recommendations were consistent with the company's wage decisions for 40 out of 45 workers, representing an agreement rate of 88.9%. This demonstrates that the Fuzzy Mamdani method can effectively reduce subjectivity and improve fairness in wage determination. In conclusion, the proposed system provides a reliable tool to support payroll decision-making in plantation settings. The implications suggest that broader adoption of fuzzy-based models can enhance transparency and worker satisfaction in agricultural wage systems.

Keywords: Fuzzy Mamdani; Decision Support System; Worker Wage; and Palm Oil

1. INTRODUCTION

The palm oil industry plays a pivotal role in Indonesia's national economy as one of the country's main foreign exchange contributors and a provider of millions of employment opportunities. According to data from the Ministry of Agriculture, Indonesia manages more than 14 million hectares of oil palm plantations, with the sector employing over 16 million workers both directly and indirectly (Neural & Algorithm, 2021). This makes palm oil not only an economic commodity but also a source of livelihood for rural communities across Sumatra, Kalimantan, and Sulawesi. Despite its importance, several structural issues remain unresolved, particularly those related to labor management and wage determination. A fair and transparent wage system is crucial to maintaining both the welfare of workers and the productivity of plantations (Sapra & Mathur, 2020).

One of the critical challenges faced by plantation companies is the wage determination process, which is often carried out using conventional and subjective methods. Supervisors typically assess workers' output based on daily performance without considering broader factors such as distance to the plantation block, accessibility of roads, or environmental conditions. Such practices tend to create disparities in income, dissatisfaction among workers, and in some cases, a decline in overall motivation and productivity (Haryanti & Marsono, 2021). An objective, data-driven wage determination system would therefore be beneficial for ensuring fairness and improving organizational outcomes (Khairunnisa et al., 2025).

In recent years, decision support systems (DSS) have gained attention in addressing managerial challenges across different sectors, particularly in situations where multiple criteria influence decision-making. One promising approach is fuzzy logic, which can accommodate uncertainty and subjectivity in human judgment (Samuel et al., 2022). Previous research has shown the effectiveness of fuzzy logic in areas such as employee performance evaluation, salary prediction, and decision-making in human resources (Ferdinandi & Kiwonde, 2023). However, its application within the agricultural labor sector, especially in oil palm plantations, remains limited and underexplored. A review of the literature indicates that most studies applying fuzzy logic for wage determination or employee performance assessment have been conducted in industrial or service-based settings (Siti Wardah et al., 2021). These studies typically focus on formal employment environments where measurable criteria such as education, experience, and work attendance are the main determinants. In contrast, the dynamics of plantation labor are different, with variables such as distance, road conditions, and weather significantly affecting workers' productivity. This creates a clear research gap, as current methods and studies do not fully capture the unique characteristics of palm oil plantation work (Pranata et al., 2023).

The absence of a fair and systematic wage determination system has practical and social consequences. Workers often feel disadvantaged by subjective assessments, which may lead to disputes, reduced job satisfaction, and even labor turnover (Fakharudin & Avianto, 2024). Moreover, for plantation companies, the lack of a reliable wage determination system can hinder operational efficiency and sustainability. Therefore, addressing this issue is not only important from the perspective of labor welfare but also from the standpoint of economic sustainability and industrial competitiveness(Hidayatullah et al., 2024). The Fuzzy Mamdani method offers a solution to these challenges by providing a structured yet flexible framework for decision-making. This method allows for the integration of multiple qualitative and quantitative variables into a systematic evaluation process, making it highly suitable for wage determination in plantations (Satia et al., 2022). By converting human linguistic assessments into mathematical models, Fuzzy Mamdani provides results that are both transparent and justifiable. In the context of palm oil plantations, it enables a fairer assessment that goes beyond mere output measurement, incorporating external factors that significantly influence worker performance (Saputri et al., 2020).

Given the strategic importance of the palm oil industry and the persistent problems in wage determination, it is urgent to develop an alternative system that is fair, objective, and adaptable to plantation-specific conditions. This study addresses this need by implementing the Fuzzy Mamdani method to design a wage determination model for palm oil plantation workers (Wicaksono et al., 2022). The model incorporates key variables such as workload, distance, road accessibility, and weather conditions, thereby offering a more comprehensive assessment framework compared to traditional methods (Nur'aini, 2023). The main objective of this study is to propose a decision support system that can improve the transparency and fairness of wage determination in palm oil plantations. By doing so, the research aims to contribute both theoretically and practically. Theoretically, it expands the application of fuzzy logic into the agricultural labor sector, an area that remains underexplored in decision support literature (Strahl et al., 2025). Practically, the system provides plantation managers with a tool to establish fairer wage policies, which in turn can enhance worker satisfaction, motivation, and productivity. Ultimately, this study seeks to support the sustainability of the palm oil industry through a more equitable labor management approach (Rasywir et al., 2020).

2. RESEARCH METHOD

This study adopts an applied research approach with a quantitative descriptive design to develop a decision support model for determining wages of palm oil plantation workers using the Fuzzy Mamdani method. The method was chosen because of its strength in representing human reasoning with linguistic variables and its ability to handle uncertainty in decision-making processes. Through this approach, the research aims to provide a systematic and objective alternative to the conventional and subjective wage determination practices currently used in plantations(Muin, 2023). The research was conducted in a palm oil plantation located in Labuhanbatu Regency, North Sumatra, Indonesia. The population consisted of plantation workers, while the sample was selected purposively to represent diverse categories of laborers based on workload and field conditions. Data collection was carried out using three techniques: direct observation of plantation activities, interviews with plantation supervisors, and documentation related to existing wage systems. These methods ensured that the variables selected for the model were relevant to actual conditions in the field.

The main variables identified in this study include workload, distance, road conditions, and weather. These variables were selected because they directly influence worker performance and wage fairness but are often neglected in conventional wage determination systems. Each variable was defined into linguistic values with corresponding membership functions, which then served as the input for the fuzzy inference system. The system's output was a recommended wage level that could be compared against current wage practices for validation. The research procedure was structured into several steps. First, the problems of wage determination in palm oil plantations were identified. Second, a literature review and theoretical study were conducted to establish the conceptual basis of the research. Third, data collection was carried out to define variables and membership functions. Fourth, the fuzzy inference system was designed and simulated using MATLAB software with the Mamdani inference approach. Fifth, validation was performed by comparing the system's results with actual wage data to assess accuracy and consistency. To clarify the logical basis of the research, a research framework was developed to illustrate the relationship between the identified problems, the chosen methodology, and the expected outcomes. The framework shows how variables such as workload, distance, road conditions, and weather interact as inputs to the Fuzzy Mamdani model, which in turn generates wage recommendations for plantation workers (Vasey et al., 2022).

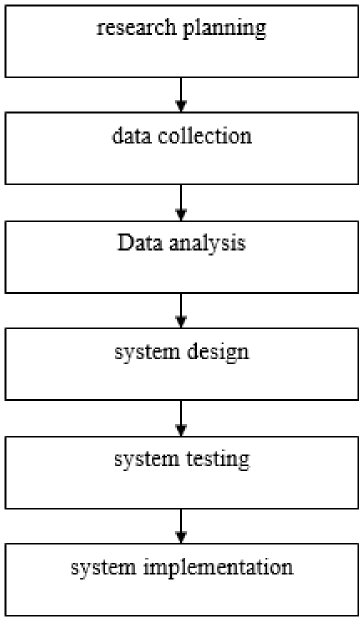

Figure 1. Research Framework

Furthermore, a research flowchart was designed to illustrate the operational sequence of the study. The flowchart begins with problem identification, followed by data collection, determination of variables, fuzzification, formulation of the rule base, fuzzy inference, defuzzification, and finally, validation of results. This diagram provides a clear representation of the logical steps followed in the study and ensures methodological transparency (Antoniadi et al., 2021).

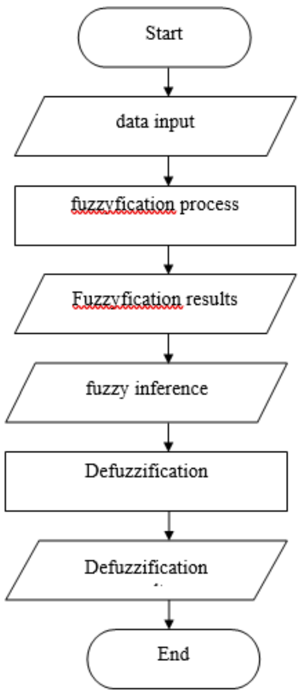

Figure 2. Research Flowchart

The data analysis technique employed was fuzzy logic modeling using the Mamdani inference system. The fuzzification process transformed crisp input data into fuzzy sets, which were then processed through a rule base consisting of IF–THEN rules formulated from expert knowledge and field observations. The inference engine aggregated these rules into fuzzy outputs, which were subsequently defuzzified using the centroid method to produce crisp wage recommendations. This systematic process ensured that the decision-making model was both objective and transparent (Adhityansyah et al., 2024). Overall, the methodological design combined a well-defined conceptual framework, a detailed flowchart of procedures, and a rigorous fuzzy logic analysis. This ensures that the study's findings are credible, replicable, and applicable to real-world plantation conditions. The methodology not only addresses the research objectives but also contributes a replicable model for other agricultural labor contexts where wage fairness and productivity are key concerns (Charismana et al., 2022).

3. RESULTS AND DISCUSSION

3.1 Results

In this study, the Mamdani Fuzzy Logic method was applied to determine wages for oil palm workers in Sei Pertahanan Village, Sei Kepayang District, Asahan Regency, within the PT CSIL work environment. This study involved four main variables: the number of oil palm fruit bunches (FFB), location distance, weather during harvest, and worksite conditions. These four variables were used as input to create fuzzy sets, which were then processed through the Mamdani inference process (Pribadi & Ade Kurniawan, 2022). Data for this study were obtained through field observations and direct interviews with 45 workers and oil palm fruit harvesters at PT CSIL. The collected data were then classified and entered into a fuzzy logic system to generate fairer and more objective wage values (Fajriyati & Yusuf, 2025). This model is designed to assist in wage determination decisions that systematically and logically consider various work aspects using the Mamdani fuzzy logic approach. There are four input variables in this study:

Table 1. Set Variables

ca	Variable	Fuzzy Set	Universe Speaker	Domain
Input	Number of Palm Fruit Bunches (FFB)	Low Medium Many	0-500	[0 50 100] [100 200 300] [300 400 500]
Input	Distance to Location	Near Medium Far	0-5	[0 1 2] [1 2 3] [2 4 5]
Input	Weather During Harvest	Sunny Drizzle Rain	0-20	[0 5 10] [5 10 15] [10 15 20]
Input	Road Conditions	Good Medium Bad	0-20	[0 5 10] [5 10 15] [10 15 20]
Output	Bonus Determination	**Low** **Medium** High	50-300	[0 60 100] [100 150 200] [200 250 300]

Input Variables:

1. Number of Oil Palm Bunches

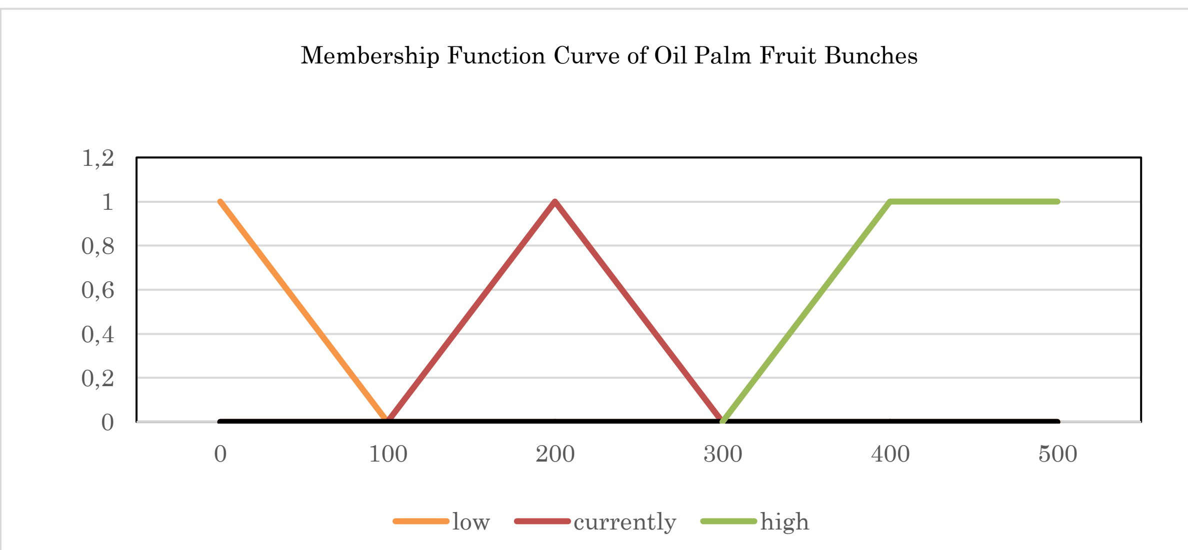

Figure 3. Membership Function Curve of the Variable Number of Oil Palm Fruit Bunches

Figure 3 shown the fuzzy membership function curve for the input variable Number of Palm Fruit Bunches (FFB). This variable is divided into three fuzzy sets, namely Few (Low), Medium, and Many. Each set has a triangular membership function with a certain range of values in the domain 0 to 500. From this curve, the system can determine the degree of membership of a value of the number of FFB to each fuzzy set. For example, if the number of FFB is 150, then the value will have partial membership to the sets Few and Medium, but not to Many.

2. Location Distance Variable

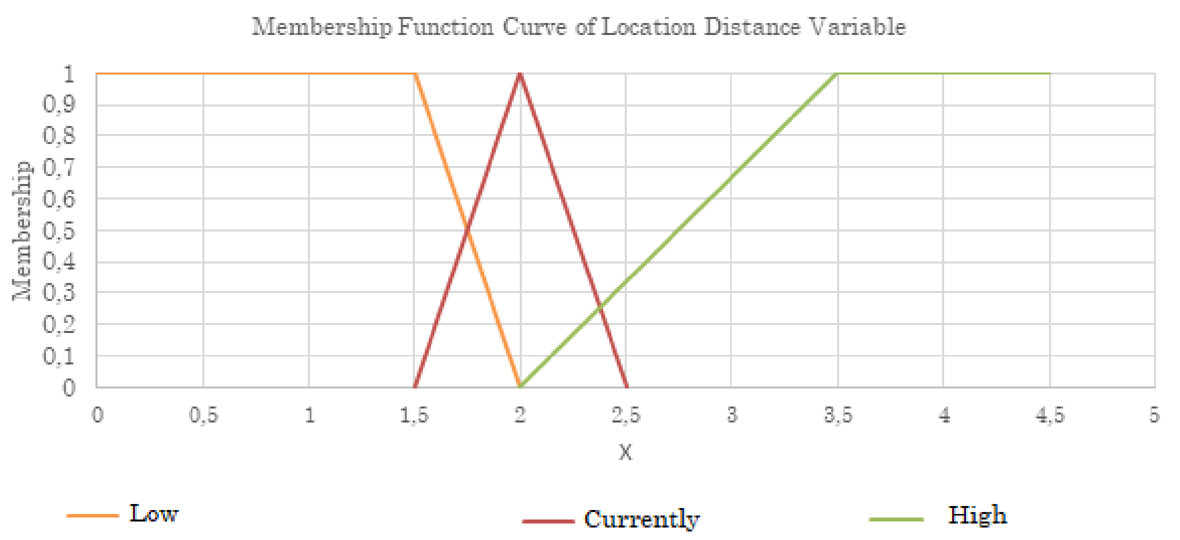

Figure 4. Membership Function Curve of Location Distance Variable

Figure 4 shows the fuzzy membership function curve for the input variable Location Distance. This variable is divided into three fuzzy sets: Near, Medium, and Far. Each set has a triangular membership function with a specific range of values in the domain 0 to 5. From this curve, the system can determine the membership degree of a distance value to each fuzzy set. For example, if the location distance value is 2, then the value will have partial membership to the Near and Medium sets, but not to Far.

3. Weather Variables at Harvest Time

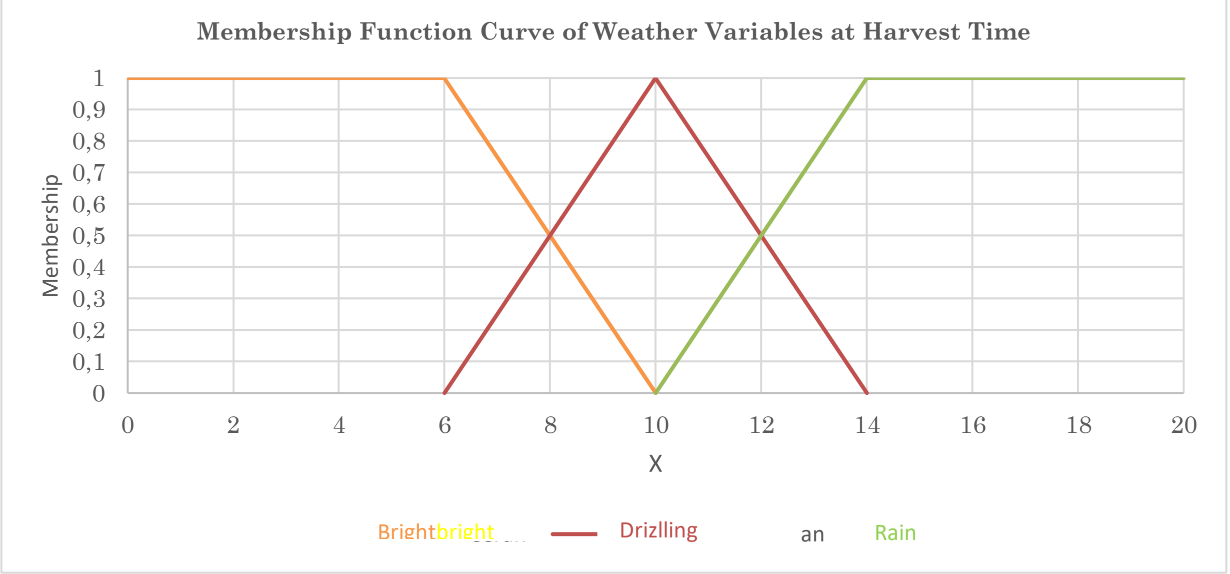

Figure 5. Membership Function Curve of Weather Variables at Harvest Time

Figure 5 shows the fuzzy membership function curve for the input variable Weather During Harvest. This variable is divided into three fuzzy sets: Sunny, Drizzle, and Rain. Each set has a triangular membership function with a specific value range in the domain 0 to 20. From this curve, the system can determine the membership degree of a weather value to each fuzzy set. For example, if the weather value is 9, then it will have partial membership to the Drizzle set, but not to Sunny or Rain.

4. Road Condition Variables

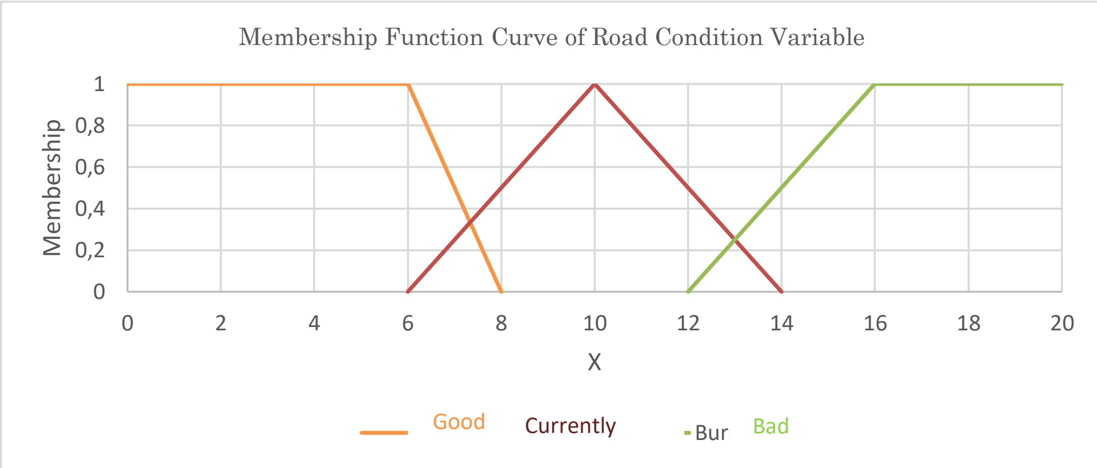

Figure 6. Membership Function Curve of the Road Condition Variable

Figure 6 shows the fuzzy membership function curve for the Road Condition input variable. This variable is divided into three fuzzy sets: Good, Moderate, and Poor. Each fuzzy set has a triangular membership function with a specific range of values in the domain 0 to 20. From this curve, the system can determine the degree of membership of a value within each fuzzy set. For example, if the road condition score is 8, then the value has partial membership in the Good and Moderate sets, but not in the Poor sets (Styorini et al., 2022). This study used data from 45 employees at PT CSIL, where each attribute in the data has a predetermined weight value.

Output:

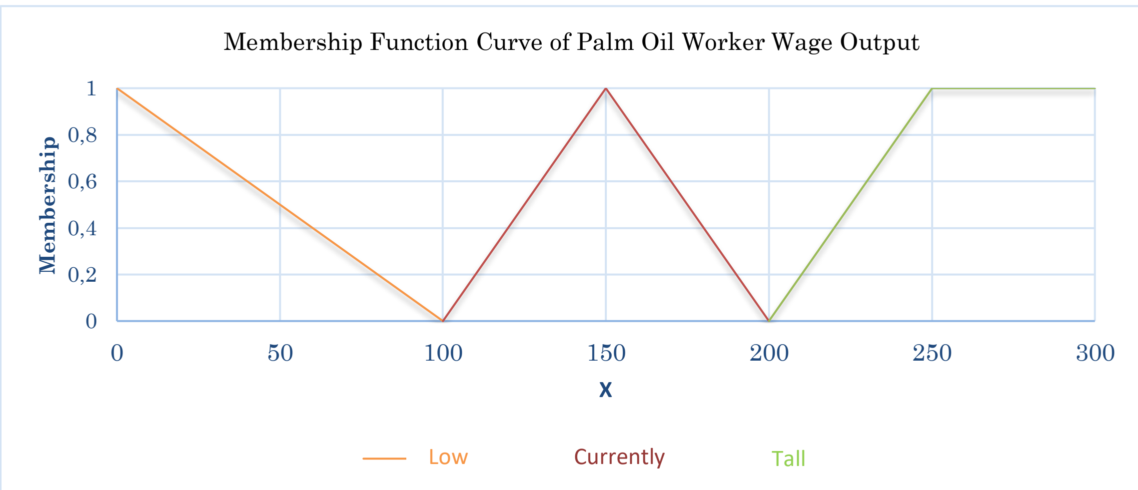

Figure 7. Palm Oil Worker Wage Output

Figure 7 shows the fuzzy membership function curve for the Palm Oil Worker Wage Output variable. This variable is divided into three fuzzy sets: Low, Medium, and High. Each fuzzy set has a triangular membership function with a specific value range in the domain of 50 to 300. From this curve, the system can determine the membership degree of a wage value in each fuzzy set. For example, if the wage value is 200, then that value will have a certain membership degree in the Medium and High sets, depending on the position of the value relative to the intersection points between the triangular functions (Mue et al., 2024).

3.2 Discussion

3.2.1. Fuzzy Set Formation

In this section, fuzzy sets are formed based on the variables used in wage determination. Each respondent receives a membership score based on predetermined criteria. The calculations are performed on randomly selected workers, as shown in the following section.

Table 2. Formation of Fuzzy Sets

Variables				
Input				Output
Number of Palm Fruit Bunches	Location Distance	Weather During Harvest	Road Condition	Bonus Determination
Many	Near	Sunny	Good	Low
Many	Medium	Sunny	Fair	Currently
Many	Far	Rainy	Poor	Tall
Moderate	Near	Drizzle	Good	Low
Few	Far	Rainy	Poor	Tall
…	…	…	…	…
Moderate	Near	Rainy	Good	Low

3.2.2. Data Representation

At this stage, initial data is presented, which serves as the basis for the fuzzification process. The data used comes from input from workers, particularly oil palm harvesters, who served as respondents in the system. A total of 45 harvesters provided data directly through a provided digital form. Each respondent provided data based on their work experience, including the number of fresh fruit bunches (FFB) harvested, length of service, and harvest quality. This data is then processed to obtain membership values within each predetermined fuzzy variable (Fajriyati & Yusuf, 2025). Three examples of respondent data are presented in the following table to illustrate the format and content of the data used in the processing process:

Table 3. Data Representation

No	Name	Number of Fresh Fruit Bunches	Distance	Weather During Harvest	Road Conditions
1	Ahmad Siregar	50	2 km	5	10
2	Budi Santoso	200	5 km	20	20
3	Junaidi Harahap	400	1 km	5	5

A. Fuzzification

1. Number of Palm Fruit Bunches

Membership value of respondent variable with μFew:

$$\mu Few = \begin{cases} 1 & x < 50 \\ \frac{100-x}{100-50} & 50 < x < 10 \\ 0 & x > 100 \end{cases}$$

μ Few(50) = 1

Respondent variable membership value with µModerate

$$\mu Moderate = \begin{cases} 0 & x < 100 \text{ Atau } x > 300 \\ \frac{x-100}{200-100} & 100 < x < 200 \\ \frac{300-x}{300-200} & 200 < x < 300 \end{cases}$$

µ Moderate (50) = 0

Membership value of respondent variable with µMany:

$$\mu Many = \begin{cases} 0 & x > 300 \\ \frac{x-300}{400-300} & 300 < x < 400 \\ \frac{300-x}{400-300} & x > 400 \end{cases}$$

µMany (50) = 0

2. Location Distance

Membership value of respondent variable with µNear:

$$\mu Near = \begin{cases} 1 & x < 1 \\ \frac{2-x}{2-1} & 1 < x < 2 \\ 0 & x > 2 \end{cases}$$

µNear (2) = 0

Respondent variable membership value with µModerate:

$$\mu Moderate = \begin{cases} 0 & x < 1 \\ \frac{x-1}{2-1} & 1 < x < 2 \\ \frac{3-x}{3-2} & 2 < x < 3 \end{cases}$$

µModerate (2) = 1

Membership value of respondent variable with µFar:

$$\mu Far = \begin{cases} 0 & x < 1 \\ \frac{x-1}{2-1} & 1 < x < 2 \\ 1 & 2 < x < 3 \end{cases}$$

µFar (2) = 0

3. Weather During Harvest

Membership value of respondent variable with µSunny:

$$\mu Sunny = \begin{cases} 1 & x < 5 \\ \frac{10-x}{10-5} & 5 < x < 10 \\ 0 & x > 10 \end{cases}$$

µSunny (5) = 1

Membership value of respondent variable with µDrizzle:

$$\mu Drizzle = \begin{cases} 0 & x < 5 \text{ atau } x > 15 \\ \frac{x-5}{10-5} & 5 < x < 10 \\ \frac{15-x}{15-10} & 10 < x < 15 \end{cases}$$

µDrizzle (5) = 0

Membership value of respondent variable with µRainy:

$$\mu Rainy = \begin{cases} 0 & x < 10 \\ \frac{x-10}{15-10} & 10 < x < 15 \\ 1 & 10 > 15 \end{cases}$$

µRainy (5) = 0

4.Road Conditions

Respondent variable membership value with µGood

$$\mu Good = \begin{cases} 1 & x < 5 \\ \frac{10-x}{10-5} & 5 < x < 10 \\ 0 & x > 10 \end{cases}$$

µGood (10) = 0

Respondent variable membership value with µModerate:

$$\mu Moderate = \begin{cases} 0 & x < 5 \text{ or } x > 15 \\ \frac{x-5}{10-5} & 5 < x < 10 \\ \frac{15-x}{15-10} & 10 < x < 15 \end{cases}$$

μModerate (10) = 1

Respondent variable membership value with μPoor:

$$
\mu Poor = \begin{cases} 0 & x < 10 \\ \frac{x-10}{15-10} & 10 < x < 15 \\ 1 & x > 15 \end{cases}
$$

μPoor (10) = 0

B. Defuzifiction

The next step is to perform the defuzzification process using the centroid or weighted average method. The final value of the fuzzy inference result is calculated using the following formula:

$$
Z_{min} = \frac{(0.200)+(0.200)+(0.100)+(0.100)+(0.60)+(0.100)+ (0.100)+(0.100)+(0.100)+(0.200)+(0.100)+(0.100)+(0.100) (0.100)+(1.200)+(0.100)}{(0+0+0+0+0+0+0+0+0+0+0+0+0+0+1+0)}
$$

$$
= \frac{200}{1}
$$

$$
= 200
$$

Thus, the defuzzification result (Z) is 100, which is in the low category. To find the value in percentage form, use the following formula:

$$
Percentage = (\frac{Z}{Z\ MAx}) \times 100\% x
$$

It is known that the maximum value (Zmax) is 300, then:

$$
Percentage = (\frac{200}{300}) \times 100\% = 66,66\ \%
$$

So, the final defuzzification value of 100 is equivalent to 66.66% of the maximum value.

In conclusion, Ahmad harvested 50 kg of fresh fruit bunches with a wage of Rp. 300/kg multiplied to Rp. 15,000. After multiplying, then multiplying again by the defuzzification value of 66.66%, then he received a wage of Rp. 25,000.00.

3.3 Design Creation

Use Case Diagram

In general, the use case diagram shown the business system process to be designed, which is shown in **Figure 8.**

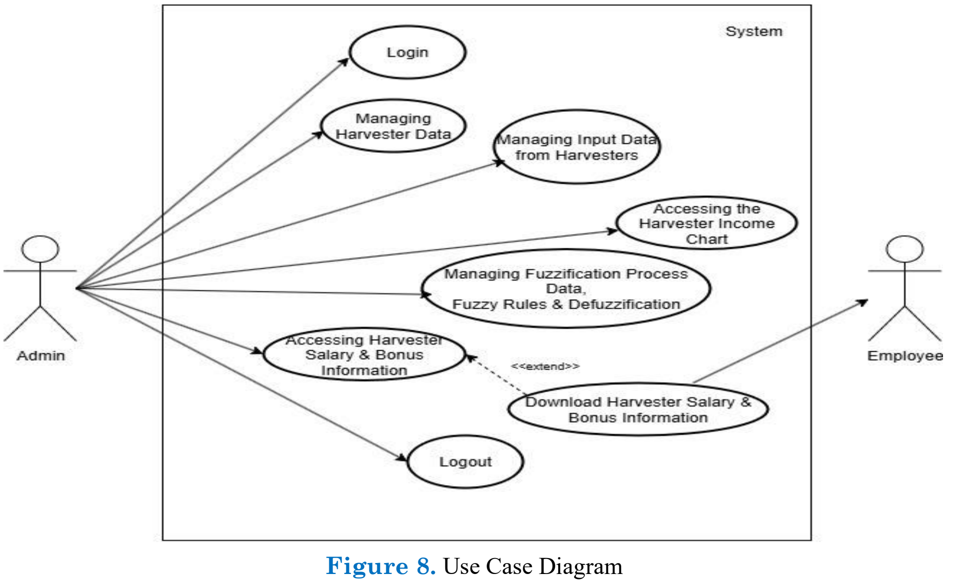

Figure 8. Use Case Diagram

The figure above shows a use case diagram depicting the interaction between two actors, the Admin and the Employee, in a system for determining salaries and bonuses for palm oil workers. The Admin has full access to the system, including logging in and out, managing harvester data, revenue generation, revenue graphs, fuzzy processing (fuzzification, rules, and defuzzification), and accessing and downloading salary and bonus information(Herpratiwi et al., 2022). Meanwhile, employees can only download salary and bonus information calculated by the system based on data managed by the administrator. This diagram clearly illustrates the structured division of access rights and functions between administrators and employees within the system.

3.4 Implementation

1. Login Screen

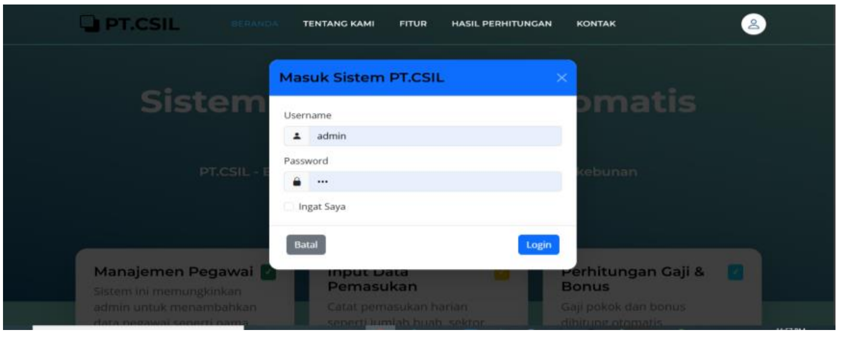

Figure 9. Login Screen

The image above shows the login screen for the PT. CSIL system, designed with a modern and simple interface. The login form is displayed as a pop up modal that appears in the center of the screen, making it easy for users to access the system without having to navigate between pages. Users simply enter their username and password, then press the Login button to access the system. There's also a Remember Me feature to save login sessions so they don't have to re-enter their data each time. This design provides users with convenience and ease in quickly and securely accessing the system.

2. Main Page Display (Dashboard)

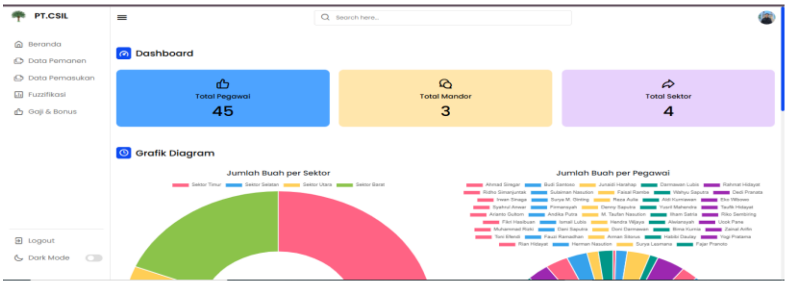

Figure 10. Dashboard Page

The image above displays the PT. CSIL logo and text in the upper left corner, representing the application's identity. Below it is a list of navigation menus that direct users to various system features. The first menu is Home, which is the main page containing a data summary. Next is Employee Data for managing employee information, followed by Income Data, which records daily harvest results. The Fuzzification menu is used to calculate membership value based on the entered data. The Salary & Bonus feature is used to view the results of automatic calculations based on the fuzzy system. At the bottom of the menu is a Logout button to log out of the account, as well as a Dark Mode option to switch the display to dark mode

3.Fuzzification Page View

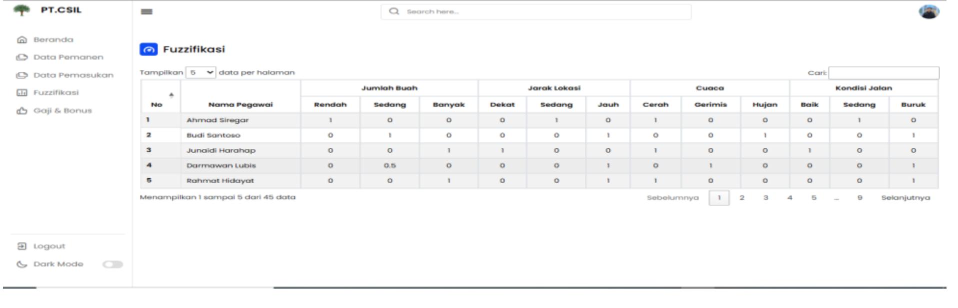

Figure 11. Fuzzification Page View

The Fuzzification page in the PT. CSIL application is where employee data is processed using fuzzy concepts. This page displays employee names along with several predetermined criteria, such as number of units, location distance, weather, and road conditions. The goal is to transform this data into a fuzzy membership ranking system, allowing the system to automatically calculate the most appropriate wages and bonuses based on actual field conditions.

4. Salary and Bonus Results Page Display (Defuzzification)

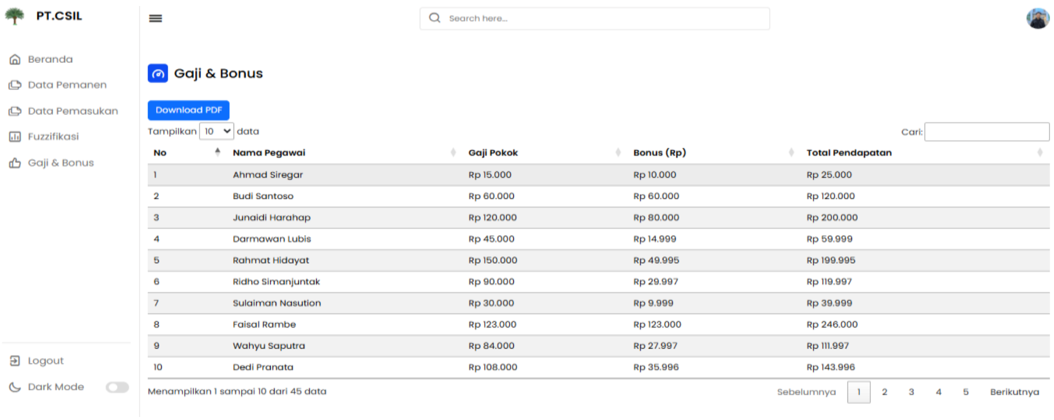

Figure 12. Salary and Bonus Results Page View (Defuzzification)

The Salary & Bonus page in the PT. CSIL application displays the final results of the calculation of base salary, bonuses, and total income for each employee. This data is the result of the previous fuzzification process. Each employee has clear details, including their name, base salary received, additional bonuses based on work conditions, and total income. This page also features a search feature and the option to download the data in PDF format, simplifying documentation and reporting. The results of this study show that the application of the Fuzzy Mamdani method in determining the wages of palm oil workers achieved an accuracy of 88.9% (40 of 45 cases matched the actual payroll). This finding indicates that the fuzzy inference system is capable of modeling complex and subjective decision-making processes in plantation wage determination. Similar results were reported by Rahman et al. (2021), who found that fuzzy Mamdani could effectively model labor productivity (Rahman et al, 2021)-based wage systems in the manufacturing sector, with a high level of conformity between system output and expert decisions. In contrast, studies by Sari & Putra (2022) on agricultural workers reported a lower level of conformity, which they attributed to the diversity of external factors such as weather and infrastructure conditions that were not fully incorporated into their fuzzy model (Sari & Putra., 2022).

Compared to those studies, the strength of this research lies in the inclusion of multiple contextual variables (fresh fruit bunches, distance, weather, and road conditions), which provide a more comprehensive representation of field realities. This multi-variable approach is consistent with findings by Alawiyah & Ariyani (2022), who emphasized the importance of integrating environmental and operational indicators to increase the validity of fuzzy-based decision support systems (Alawiyah & Ariyani, 2022). Nevertheless, some limitations remain. First, the sample size of 45 workers, although sufficient to demonstrate feasibility, is relatively small for generalization across different plantations or regions. Second, the model was tested only in one company (PT CSIL), which may limit external validity (Hutahaean.J et al., 2023). Third, while MATLAB provided reliable computational results, the model was not yet integrated into a user-friendly application for direct use by plantation managers (Agusantia & Juandi, 2022). Future research should therefore expand the dataset, test the model across multiple sites, and develop a practical decision support system with an interactive interface to enhance adoption at the managerial level.

4. CONCLUSIONS

This study applied the Fuzzy Mamdani method to develop a decision support system for determining wages of palm oil plantation workers. The findings show that the system can process key factors such as workload, distance, road conditions, and weather into objective wage recommendations. Compared to conventional manual practices, the proposed system produces more transparent and equitable outcomes, reducing subjectivity in wage determination. In addressing the research problem, the system provides a practical tool that supports fairer wage policies, enhances worker motivation, and strengthens the sustainability of palm oil plantation management.

REFERENCES

Agusantia, D., & Juandi, D. (2022). Kemampuan Penalaran Analogi Matematis di Indonesia: Systematic Literature Review. *Symmetry: Pasundan Journal of Research in Mathematics Learning and Education*, *7*(2), 222–231. https://doi.org/10.23969/symmetry.v7i2.6436

Ahmed, M., & Ahmed, A. (2023). Palm tree disease detection and classification using residual network and transfer learning of Inception ResNet. Plos One, 18(3), e0282250. https://doi.org/10.1371/journal.pone.0282250

Asrianda, A., Aidilof, H. A. K., & Pangestu, Y. (2021). *Machine Learning for Detection of Palm Oil Leaf Disease Visually using Convolutional Neural Network Algorithm*. Journal of Informatics and Telecommunication Engineering, 4(2), 286–293. https://doi.org/10.31289/jite.v4i2.4185

Ardhana, V. Y. P., Sampetoding, E. A. M., Kumoro, D. T., & Alamsyah, N. (2022). *Model berbasis Fuzzy Tsukamoto untuk perhitungan besaran gaji dosen pada perguruan tinggi swasta*. Jurnal Sistem Komputasi dan Informatika (JSON), 3(3), 311–318. https://doi.org/10.30865/json.v3i3.3856

Akyuz, E. (2021). *Application of Fuzzy FMEA to perform an extensive risk analysis in maritime transportation engineering*. *International Journal of Maritime Engineering*, *159*(A1). https://doi.org/10.5750/ijme.v159iA1.1013

Fajriyati, S., & Yusuf, M. (2025). The Bibliometric Analysis of Fraud Reporting: Scientific Publications from 2019 to 2024. *TOFEDU: The Future of Education Journal*, *4*(1), 7–19. https://doi.org/10.61445/tofedu.v4i1.365

Fakharudin, P. R. A. F., & Avianto, D. (2024). Fuzzy Mamdani untuk Pemerataan Gaji Karyawan. *SISTEMASI: Jurnal Sistem Informasi*, *13*(1), 305. https://doi.org/10.32520/stmsi.v13i1.3621

Ferdinandi, C. M., & Kiwonde, F. M. (2023). The influence of educational leadership on students' academic performance in secondary schools: A case of Itilima district. *Electronic Journal of Education, Social Economics and Technology*, *4*(1), 16–21. https://doi.org/10.33122/ejeset.v4i1.100

Gunawan, G., Zarlis, M., & Sihombing, P. (2024). Smart agriculture model in detecting oil palm plantation diseases using a convolution neural network. *IAES International Journal of Artificial Intelligence (IJ-AI), 13*(3), 3164–3171. https://doi.org/10.11591/ijai.v13.i3.pp3164-3171

Hak, F., Guimaraes, T., & Santos, M. (2022). Towards effective clinical decision support systems: A systematic review. *PLoS ONE*, *17*(8 August), 1–19. https://doi.org/10.1371/journal.pone.0272846

Herpratiwi, H., Maftuh, M., Firdaus, W., Tohir, A., Daulay, M. I., & Rahim, R. (2022). Implementation and Analysis of Fuzzy Mamdani Logic Algorithm from Digital Platform and Electronic Resource. *TEM Journal*, *11*(3), 1028–1033. https://doi.org/10.18421/TEM113-06

Hidayatullah, C., R, R. K., & Armansyah, A. (2024). Pencarian Rute Terpendek Dalam Pendistribusian Darah di Palang Merah Indonesia (PMI) dengan Algoritma Dijkstra. *TIN: Terapan Informatika Nusantara*, *4*(11), 727–738. https://doi.org/10.47065/tin.v4i11.5028

Khairunnisa, N., Muhammad Faiz Assariy, Daffa Zulqisthi, Prasetya, M. R., Madania, K. F., Holy Nurani Rabbina, Oktavia, R., Raihana, S. H., Alzahra, A. V. A., & Chika Hayya Sabillah. (2025). Determining The Amount Of Tempeh Production Based On Demand And Inventory Data Using Fuzzy Logic Method (Case Study: "Murni" Soybean Tempe Msmes MADIUN). *Journal of Applied Science, Technology & Humanities*, *2*(3), 402–415. https://doi.org/10.62535/7pbt8t33

Kurniadi, D., Nuraeni, F., & Jaelani, D. (2022). Implementasi logika Fuzzy Mamdani pada sistem prediksi calon penerima Program Keluarga Harapan. *Jurnal Algoritma, 19*(1), 160–171. https://doi.org/10.33364/algoritma/v.19-1.1016

Marsono, Nasyuha, A. H., Syahra, Y., & Mariami, I. (2024). Decision Support System for Selecting Online Teaching Methods Using the Fuzzy MCDM Algorithm. *Sinkron: Jurnal dan Penelitian Teknik Informatika, 8*(3), 1495–1504. https://doi.org/10.33395/sinkron.v8i3.13731

Muñoz-Valero, D., García-Hernández, L., & Herrera, F. (2025). A knowledge-driven fuzzy logic framework for supporting decision-making. *Computers & Industrial Engineering, 193*, 110755. https://doi.org/10.1016/j.cie.2024.110755

Murad, F. A., & Kurniawan, A. (2024). *Design of a wireless fidelity network using the Open Shortest Path First protocol in the Computer and Network Engineering Research Room at Politeknik Negeri Jakarta*. Electronic Journal of Education, Social Economics and Technology, 5. https://doi.org/10.33122/ejeset.v5i2.340

Pranata, E. H., Susanto, T., Rikendry, R., & Puspaningrum, A. S. (2023). Pengendalian Gerak Longitudinal Pesawat Fixed Wing FT-Explorer. *Jurnal Teknik dan Sistem Komputer*, *4*(1), 20–28. https://doi.org/10.33365/jtikom.v4i1.3504

Pribadi, A., & Ade Kurniawan. (2022). Deteksi Penyakit Sawit Menggunakan Metode Deep Learning. *Jurnal Sains dan Ilmu Terapan*, *5*(2), 72–76. https://doi.org/10.59061/jsit.v5i2.86

Ramadani, F. Q., Panggabean, M., & Laksono, D. A. (2024). Perancangan Aplikasi Pengaduan Masyarakat untuk Kantor Dinas Pekerjaan Umum dan Perumahan Rakyat Kabupaten Langkat Sumatera Utara. *Masharif al-Syariah*, *9*(3), 1557–1565. https://doi.org/10.30651/jms.v9i3.23196

Rasywir, E., Sinaga, R., & Pratama, Y. (2020). Analisis dan Implementasi Diagnosis Penyakit Sawit dengan Metode Convolutional Neural Network (CNN). *Paradigma - Jurnal Komputer dan Informatika*, *22*(2), 117–123. https://doi.org/10.31294/p.v22i2.8907

Samuel, S., Prilianti, K. R., Setiawan, H., & Mimboro, P. (2022). Metode Deteksi Pokok Pohon Secara Automatis pada Citra Perkebunan Sawit Menggunakan Model Convolutional Neural Network (CNN) pada Perangkat Lunak Sistem Informasi Geografis. *Jurnal Teknologi Informasi dan Ilmu Komputer*, *9*(7), 1689–1698. https://doi.org/10.25126/jtiik.2022976772

Sapra, J., & Mathur, I. (2020). Effect of Dimensions of Workplace Spiritualism: Meaningful Work, Sense of Community, Organizational Values and Compassion with Reference to Job Satisfaction. *Electronic Journal of Education, Social Economics and Technology*, *1*(1), 10–17. https://doi.org/10.33122/ejeset.v1i1.5

Sapuguh, I., Ahlina, N., Wahyudi, A., Setyawan, B., & Rosalinda, A. S. (2024). Development of fuzzy logic based student performance prediction system. *Jurnal Teknik Informatika C.I.T Medicom, 15*(6), 284–290. https://doi.org/10.35335/cit.Vol15.2024.714.pp284-290

Saputra, M. A., & Nurhaida, I. (2024). *Signature originality verification using a deep learning approach*. Electronic Journal of Education, Social Economics and Technology, 5(1), Article 310. https://doi.org/10.33122/ejeset.v5i1.310

Satia, G. A. W., Firmansyah, E., & Umami, A. (2022). Perancangan sistem identifikasi penyakit pada daun kelapa sawit (Elaeis guineensis Jacq.) dengan algoritma deep learning convolutional neural networks. *Jurnal Ilmiah Pertanian*, *19*(1), 1–10. https://doi.org/10.31849/jip.v19i1.9556

Siti Wardah, Ahmad Syahdiyin, & Mohammad Amin. (2021). Peramalan Pengadaan Bahan Baku Kelapa Sawit Dengan Meggunakan Metode Fuzzy Time Series Di Pt X.Co. *Juti Unisi*, *5*(1), 27–33. https://doi.org/10.32520/juti.v5i1.2930

Styorini, W., Putra, W. E., Khabzli, W., & Triyani, Y. (2022). Penerapan Deep Learning Pada Jenis Penyakit Tanaman Kelapa Sawit Menggunakan Algoritma Convolutional Neural Network. *Jurnal Komputer Terapan*, *8*(2), 359–367. https://doi.org/10.35143/jkt.v8i2.5522

Sutisna, M. G., Yudono, M. A. S., Artiyasa, M., Narputo, P., & Jakfar, A. E. (2024). Sistem pendukung keputusan tingkat stres mahasiswa dengan Fuzzy Mamdani. *RIGGS: Journal of Artificial Intelligence and Digital Business, 4*(1), 403. https://doi.org/10.31004/riggs.v4i1.403

Wibowo, F., & Aryanto, D. (2025). Prototype model sistem pendukung keputusan berbasis Fuzzy Logic metode Mamdani untuk pemilihan lulusan terbaik di Universitas Muhammadiyah Purwokerto. *JUITA: Jurnal Informatika, 3*(3), 868. https://doi.org/10.30595/juita.v3i3.868

Wicaksono, W., Prilianti, K. R., Setiawan, H., & Mimboro, P. (2022). *Perkebunan Kelapa Sawit Dengan Penginderaan Jauh*. *03*(November), 135–142. https://doi.org/10.26858/jessi.v3i2.38092

Wu, H., & Xu, Z. S. (2021). *Fuzzy logic in decision support: Methods, applications and future trends. International Journal of Computers Communications & Control, 16*(1), Article 4044. https://doi.org/10.15837/ijccc.2021.1.4044