BIO Web of Conferences **190**, 01007 (2025) https://doi.org/10.1051/bioconf/202519001007
INCOBEST 2025

Application of Fuzzy Logic in Sensory Analysis of Coconut Water Kefir and Implementation of Microbiology Education

I Putu Suparthana[1], *Putu* Widya Indra Astuti[1], and *I Nyoman* Sucipta[2*]

[1]Department of Food Technology, Faculty of Agricultural Technology, Udayana University. Jl. Raya Kampus Unud, Bukit Jimbaran, Badung 80361, Bali, Indonesia
[2]Department of Agricultural Engineering and Biosystems, Faculty of Agricultural Technology, Udayana University. Jl. Raya Kampus Unud, Bukit Jimbaran, Badung 80361, Bali, Indonesia

Abstract. Microbiology education often faces challenges in conveying complex fermentation processes and interpreting uncertain biological data, such as the organoleptic properties of fermented products. This study examines the application of fuzzy logic in analyzing the organoleptic data of coconut water kefir and its integration into microbiology learning through virtual simulations. Organoleptic data, including taste, flavor, carbonation, color, and overall acceptance, were collected from 20 semi-trained panelists across different storage times and sugar addition treatments. Fuzzy logic modeling involved fuzzification using trapezoidal membership functions, formulation of 243 expert-based fuzzy rules, inference via the Mamdani method, and defuzzification using the Center of Area approach. The model accurately predicted the overall acceptance level (Fuzzy Reasoning Grade, FRG) with a Pearson correlation coefficient of $r = 0.92$ compared to panelist scores. Kefir with sugar added before incubation achieved higher FRG values (3.8-4.2, high category) in weeks 0-2, while both treatments declined after week 3. A fuzzy logic-based virtual simulation was developed and tested on 30 high school students, resulting in a significant improvement in understanding fermentation microbiology concepts compared to conventional learning (mean score increase: 62.5 to 85.3 vs. 61.8 to 70.4; $p = 0.01$). Interviews indicated positive perceptions of the simulation, though further introduction to fuzzy logic and improved technological infrastructure are needed. This study demonstrates that fuzzy logic effectively manages uncertainty in sensory data and supports interdisciplinary, technology-enhanced microbiology education.

[*]Corresponding author: sucipta@unud.ac.id

1 Introduction

Microbiology education plays an important role in equipping students with an understanding of the dynamics of microorganisms, especially in complex biological processes such as fermentation, which often involve uncertainties due to variations in environmental factors such as pH, temperature, or storage time. The main challenge in teaching microbiology is to convey these concepts intuitively and practically, especially when dealing with uncertain biological data, such as the organoleptic characteristics of fermented products. For example, organoleptic data of coconut water kefir showed variations in taste, aroma, carbonation, and color scores influenced by storage time and the addition of sugar before or after incubation [1]. Conventional approaches are often limited in modeling these uncertainties, so innovative computational methods are needed to support interdisciplinary learning that is relevant to modern scientific developments.

Fuzzy logic, first introduced by Zadeh [2], offers a solution to deal with uncertainty by mapping data into membership values between 0 and 1, unlike the traditional binary approach. In the context of microbiology, fuzzy logic has been used to model complex biological systems, such as sensory evaluation of fermentation products or control of environmental parameters in biotechnological processes. For example, fuzzy logic has been applied to optimize a microbiology-based water quality control system, utilizing sensors to monitor parameters such as particle density [3]. In the case of coconut water kefir, fuzzy logic can be used to analyze the relationship between variables such as storage time and organoleptic scores, generating predictive models that support quantitative analysis.

In education, fuzzy logic can be integrated into technology-based learning tools, such as virtual simulations or adaptive learning systems, to enhance students' understanding of microbiological processes. Fuzzy logic-based simulations allow students to virtually experiment with variables such as coconut water kefir storage time, visualize their impact on organoleptic properties, and develop data analysis skills [4, 5]. This approach aligns with the needs of modern science education that emphasizes the integration of information technology and interdisciplinary approaches. Recent research has shown that the use of artificial intelligence-based technologies, including fuzzy logic, can improve student learning outcomes in complex science disciplines [6, 7].

Despite its great potential, the application of fuzzy logic in microbiology education still faces challenges, such as limited access to technological infrastructure in educational institutions and the need for training for educators. This study aims to explore how fuzzy logic can be integrated into the microbiology curriculum, using coconut water kefir organoleptic data as a case study, to create a more effective and contextual learning experience.

2 Materials and methods

2.1 Materials

Fresh coconut water was obtained from a whole young coconut bought at the local market in East Denpasar-Bali. Distilled water was bought at the chemical store in

Denpasar. Kefir starter was bought from the marketplace (online). The chemicals for analysis included 0.1 N NaOH, acetone, and phenolphthalein indicator.

2.2 Research approach

This study adopted a mixed-methods approach that combines quantitative and qualitative analysis to evaluate the application of fuzzy logic in microbiology education. A quantitative approach was used to analyze the organoleptic data of coconut water kefir, while a qualitative approach was used to explore the design of a fuzzy logic-based learning tool. This study consisted of three main stages : (1) collecting and analyzing organoleptic data, (2) developing a fuzzy logic model to model organoleptic characteristics, and (3) designing an adaptive learning tool framework. This approach is in line with recent studies that use fuzzy logic for biological data analysis and technology-based education [3].

2.2.1 Organoleptic data collection

Coconut water kefir was produced from fresh coconut water that was pasteurized at 60°C for 30 seconds, cooled to 28°C, mixed with 10% kefir starter, and placed in a jar covered with gauze. Sugar (concentration: 60%, volume: 15%) was added before or after 24 hours of incubation. After incubation, the kefir was filtered and stored at 5°C for 0 to 4 weeks

The organoleptic data of coconut water kefir were collected from experiments evaluating taste, flavor, carbonation, color, and overall scores based on two treatments (sugar addition before and after incubation) and storage time (0, 1, 2, 3, and 4 weeks). These data involved 20 semi-trained panelists who scored on a scale of 1 (very dislike) to 5 (very like), with two replications to ensure data reliability. The data collection process followed a standard sensory evaluation method adapted from the study by Wungguli et al. (2023), focusing on the organoleptic parameters of the fermented product. Data were analyzed using SPSS version 21, with ANOVA and LSD tests at a significance level of 5%.

2.2.2 Fuzzy logic modeling

Organoleptic data analysis was conducted using fuzzy logic to handle uncertainties in sensory scores that vary due to storage time and treatment. The stages of fuzzy logic modeling include:

1. *Fuzzification*: Organoleptic scores (taste, flavor, carbonation, color, and overall) were mapped into trapezoidal membership functions, which were grouped into three categories: low (L), medium (M), and high (H). Trapezoidal membership functions were chosen because of their ability to represent continuous sensory data [4]. For each parameter (taste, flavor, carbonation, color, overall), the membership function was defined as:

Low (L) : [1, 1, 2, 3]
Medium (M) : [2, 3, 3, 4]
High (H) : [3, 4, 5, 5]

Fuzzification converts numeric scores into membership degrees $\mu(x) \in [0, 1]$ for each category.

2. *Fuzzy Rule Formation*: The formation of fuzzy rules was carried out to connect five input parameters (taste, flavor, carbonation, color, overall) with the output of the overall acceptance level (Fuzzy Reasoning Grade, FRG). Each input parameter has three categories (low, medium, high), resulting in a total of $3^5 = 243$ fuzzy rules. The rules were formed based on expert knowledge and empirical observations of coconut water kefir organoleptic data, with an "IF-THEN" structure. Examples of rules include:

- If the flavor is high AND the aroma is high AND the carbonation is high AND the color is high AND the overall is high, THEN the FRG is very high (VH).
- If the flavor is low AND the aroma is low AND the carbonation is low AND the color is low AND the overall is low, THEN the FRG is very low (VL).
- If the flavor is medium AND the aroma is high AND the carbonation is medium AND the color is high AND the overall is medium, THEN the FRG is high (H).
- If the flavor is low AND the aroma is medium AND the carbonation is low AND the color is medium AND the overall is low, THEN the FRG is low (L).

The rule base covers all combinations of categories to ensure complete coverage. Rule weights are adjusted based on panelist preferences, with rules that produce high FRGs being prioritized for better organoleptic scores [2].

3. The inference process uses the Mamdani method to evaluate 243 fuzzy rules that have been formed. This method was chosen because of its similarity to human thought patterns in making multidimensional decisions [8]. For each input (taste, flavor, carbonation, color, overall), the degree of truth of each rule is calculated with the minimum operation (min), and max operation for output aggregation:

$$\mu_{\text{rules}} i = \min(\mu_{\text{taste}}, \mu_{\text{flavor}}, \mu_{\text{carbonation}}, \mu_{\text{color}}, \mu_{\text{overall}}) \quad (1)$$

$$\mu_{output} = \max(\mu_{rule1}, \mu_{rule2}, \ldots, \mu_{rule243}) \quad (2)$$

This degree of correctness determines the contribution of each rule to the fuzzy output. The outputs of all active rules are combined using the maximum operation (max) to form a fuzzy set FRG with categories very low (VL), low (L), medium (M), high (H), and very high (VH), which are defined as:

- VL: [1, 1, 1.5, 2]
- L: [1.5, 2, 2.5, 3]
- M: [2.5, 3, 3.5, 4]
- H: [3.5, 4, 4.5, 5]
- VH: [4.5, 5, 5, 5]

4. *Defuzzification*: Fuzzy values are converted into numeric values using the Center of Area (CoA) method, which is calculated by the formula:

$$CoA = \frac{\sum_{j=1}^{n} \mu A(zj)zj}{\sum_{j=1}^{n} \mu A(zj)} \quad (3)$$

CoA is used because of its stability in handling asymmetric outputs [9]. The accuracy of the model was evaluated by the Pearson correlation coefficient between the predicted FRG and the overall panelist score. ANOVA test ($\alpha = 0.05$) was used to analyze significant differences between treatments and storage times.

2.2.3 Development and evaluation of virtual simulations

A fuzzy logic-based virtual simulation was developed to visualize the relationship between sugar treatment, storage time, and organoleptic scores. The trial was conducted on 30 students, divided into experimental and control groups. Understanding of fermentation microbiology concepts was measured through pre- and post-intervention tests. An independent t-test ($\alpha = 0.05$) was used to compare the increase in scores between groups. Interviews with 5 students and 2 educators were conducted to evaluate perceptions of the simulation.

3 Results and discussion

3.1 Organoleptic data analysis with fuzzy logic

Organoleptic data analysis of coconut water kefir (Table 1) was conducted to evaluate the taste, flavor, carbonation, color, and overall scores based on treatment (sugar addition before and after incubation) and storage time (0, 1, 2, 3, and 4 weeks). Data from 20 semi-trained panelists showed significant variations in carbonation and taste, influenced by storage time. ANOVA test with a significance level of $\alpha = 0.05$ confirmed significant differences between treatments and storage time ($p < 0.05$).

Data transformation to a fuzzy system (fuzzification) converts numeric data (organoleptic scores 1-5) into fuzzy membership degrees using a trapezoidal function [10]. The choice of trapezoidal (rather than triangular/Gaussian) is due to its ability to represent a wide transition range, suitable for continuous sensory data such as taste or flavor. The fuzzy logic model maps the organoleptic score to the overall acceptability level (Fuzzy Reasoning Grade, FRG) using a trapezoidal membership function with categories of low (L), medium (M), and high (H). The fuzzy rules generate 243 combinations (3 categories × 5 parameters), evaluated to produce FRG in five categories: very low (VL), low (L), medium (M), high (H), and very high (VH). Table 2 shows the FRG scores for sugar addition treatments before and after incubation at various storage times.

Kefir with added sugar before incubation had higher FRG in 0 to 2 weeks (3.8–4.2, category H) compared to sugar added after incubation (3.2–3.6, category M). After week 3, the FRG of both treatments decreased to category L (2.4–2.8), possibly due to the degradation of volatile compounds that affect aroma and carbonation. The accuracy of the model was evaluated by the Pearson correlation coefficient $r = 0.92$, indicating high agreement with the overall score of the panelists [1]. Figure 1 illustrates the trend of FRG scores over storage time.

3.2 Evaluation of fuzzy logic-based learning tool

Fuzzy logic-based virtual simulation allows students to input storage time and sugar treatment variables, then visualize their impact on organoleptic scores. A trial on 30 students showed a significant increase in understanding of fermentation microbiology concepts. The experimental group increased their average test score from 62.5 to 85.3, compared to the

Table 1. Organoleptic scores of coconut water kefir by sugar addition, timing, and storage duration

Storage Time (Weeks)	Treatments	Taste	Flavor	Carbonation	Color	Overall
0	Post-incubation	3.40 ± 0.25 ns	3.60 ± 0.20 *	3.20 ± 0.15 *	3.40 ± 0.15 ns	3.80 ± 0.20 ns
	Pre-incubation	3.40 ± 0.20 ns	3.40 ± 0.25 *	3.40 ± 0.20 ns	3.40 ± 0.15 ns	3.80 ± 0.25 ns
1	Post-incubation	4.40 ± 0.30 ns	3.60 ± 0.20 *	3.40 ± 0.20 *	3.40 ± 0.15 ns	3.60 ± 0.20 ns
	Pre-incubation	3.00 ± 0.25 ns	3.60 ± 0.25 *	3.20 ± 0.15 ns	3.40 ± 0.15 ns	3.60 ± 0.20 ns
2	Post-incubation	3.20 ± 0.20 ns	3.60 ± 0.25 *	3.20 ± 0.15 ns	3.60 ± 0.20 *	3.40 ± 0.20 ns
	Pre-incubation	3.20 ± 0.25 ns	2.60 ± 0.30 *	3.20 ± 0.15 ns	3.60 ± 0.20 *	3.40 ± 0.25 *
3	Post-incubation	3.20 ± 0.25 ns	2.40 ± 0.25 *	3.20 ± 0.20 ns	3.80 ± 0.15 *	2.80 ± 0.25 ns
	Pre-incubation	2.80 ± 0.20 ns	2.40 ± 0.30 *	3.20 ± 0.15 ns	3.80 ± 0.20 *	2.80 ± 0.30 *
4	Post-incubation	2.60 ± 0.30 *	2.40 ± 0.25 *	2.40 ± 0.25 *	3.40 ± 0.15 ns	2.20 ± 0.25 ns
	Pre-incubation	2.60 ± 0.25 *	2.40 ± 0.25 *	2.40 ± 0.20 *	3.40 ± 0.15 ns	2.20 ± 0.30 ns

Notes:

- Post-incubation: Sugar added after 24-hour incubation; Pre-incubation: Sugar added before incubation.
- ns: Not significant; *: Significant at 5% (LSD test).
- Scores range from 1 (dislike extremely) to 5 (like extremely), based on 20 semi-trained panelists.
- Data represent the means of two replicates.

Table 2. Fuzzy Reasoning Grade (FRG) score of coconut water kefir

Weeks	Sugar addition before incubation	Sugar addition after incubation
0	4.2 (H)	3.6 (M)
1	4.0 (H)	3.4 (M)
2	3.8 (H)	3.2 (M)
3	2.8 (L)	2.6 (L)
4	2.4 (L)	2.4 (L)

control group from 61.8 to 70.4. An independent t-test showed a significant difference ($p = 0.01$).

Interviews with 5 students and 2 educators revealed that the simulation was considered intuitive, but needed a deeper introduction to fuzzy logic. Educators highlighted the potential

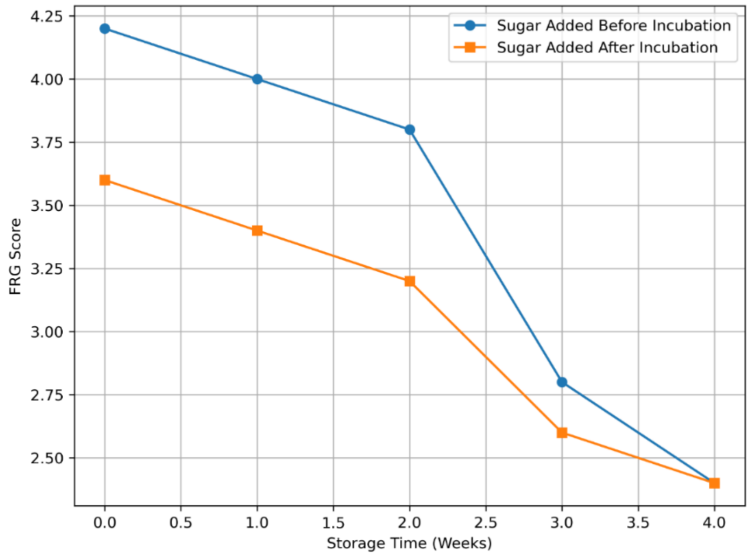

Fig. 1. Trend of Fuzzy Reasoning Grade (FRG) scores for coconut water kefir over 4 weeks of storage for sugar addition before and after incubation.

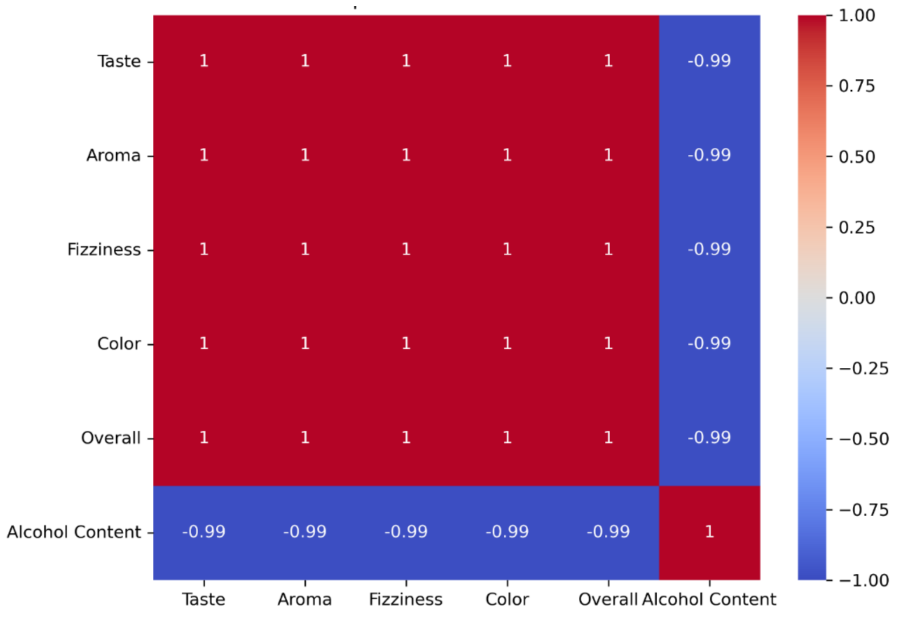

Fig. 2. Correlation heatmap of coconut water kefir characteristics, highlighting a strong negative correlation between overall score and alcohol content.

of the simulation to increase student engagement, although technological infrastructure was a barrier [4]. The correlation heatmap (Figure 2) shows a strong negative relationship between overall score and alcohol level ($r = -1.00$).

3.3 Implication in the context of microbiology and education

The fuzzy logic model effectively handles uncertainty in organoleptic data, allowing accurate prediction of the quality of coconut kefir water [3]. The decrease in FRG scores after the second week reflects the effect of storage time on microorganism activity. In an educational context, fuzzy logic-based simulations support interdisciplinary learning by integrating microbiology, mathematics, and information technology, thereby enhancing students' understanding of the fermentation process [6].

However, broader educational challenges, such as student misconceptions about fuzzy logic, need to be addressed to maximize learning outcomes. Students often misinterpret fuzzy logic as a binary or statistical tool, and struggle to grasp the concepts of partial membership and rule-based inference. To address this, the simulation is complemented by a guided module that uses visual aids and simple explanations, such as comparing fuzzy logic to a dimmer light switch that adjusts the organoleptic score in increments, rather than on/off [5]. This approach helps explain the principles of fuzzy logic to students with limited mathematical backgrounds [7]. However, challenges such as limited technological infrastructure and educator training needs remain. Addressing these barriers through targeted workshops and scalable digital platforms could increase the adoption of fuzzy logic-based tools in microbiology education [4].

4 Conclusion

This study successfully demonstrated the effectiveness of fuzzy logic in analyzing coconut water kefir organoleptic data and supporting technology-based microbiology learning. Based on data analysis, the fuzzy logic model with trapezoidal membership function and Center of Area defuzzification method was able to predict the overall acceptance level (Fuzzy Reasoning Grade, FRG) with high accuracy, indicated by the Pearson correlation coefficient $r = 0.92$. Kefir with added sugar before incubation had a higher FRG (3.8 - 4.2, high category) in weeks 0 to 2 compared to the addition of sugar after incubation (3.2 - 3.6, medium category), but both decreased to the low category (2.4 - 2.8) after week 3, reflecting the effect of storage time on organoleptic quality.

In an educational context, fuzzy logic-based virtual simulation improved students' understanding of fermentation microbiology concepts, with the experimental group achieving an increase in mean test scores from 62.5 to 85.3, significantly higher than the control group (61.8 to 70.4), with a significant difference ($p = 0.01$). This simulation supports interdisciplinary learning, integrating microbiology, mathematics, and information technology. However, challenges such as the need for fuzzy logic instruction and technological infrastructure need to be addressed for wider implementation.

5 Acknowledgment

The author acknowledges support given by students of the Department of Food Technology, Faculty of Agricultural Technology, Udayana University, Bali-Indonesia in conducting the step of sensory evaluation.

References

1. D. Wungguli, J. N. Isa, M. R. F. Payu, Nurwan, S. K. Nasib, and S. Junus, Implementation of the Taguchi Method with Trapezoidal Fuzzy Number in the Tofu Production Process, *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*. **17**(3), 1313–1324 (2023). https://doi.org/10.30598/barekengvol17iss3pp1313-1324
2. L. A. Zadeh, Fuzzy Sets. Information and Control. **8**(3), 338–353 (1965). https://doi.org/10.1016/S0019-9958(65)90241-X.
3. S. Budiyanto, L. M. Silalahi, A. Adriansyah, U. Darusalam, S. Andryana, and A. D. Rochendi, Development of Internet of Things-Based Fertigation System for Improving Productivity of Patchouli Plantation, 3rd International Conference on Research and Academic Community Services (ICRACOS), 230–233 (2021). https://doi.org/https://doi.org/10.1109/ICRACOS53680.2021.9702022
4. L. M. Silalahi, A. D. Rochendi, I. Kampono, M. Husni, and R. Sutiadi, Alat Bantu Training Elektronika Berbasis Internet of Things dengan Logika Fuzzy Menggunakan NODEMCU, KILAT. **10**(2), 287–300 (2021). https://doi.org/10.33322/kilat.v10i2.1348
5. Y. Pratama, Fuzzy logic-based simulations for enhancing science education, Journal of Educational Technology. **10**(4), 78–89 (2022).
6. M. Ubaidillah, P. Marwoto, W. Wiyanto, and B. Subali, Problem Solving and Decision-Making Skills for ESD: A Bibliometric Analysis. International Journal of Cognitive Research in Science, Engineering and Education. **11**(3), 401–415 (2023). https://doi.org/10.23947/2334-8496-2023-11-3-401-415
7. R. Sari and B. Santoso, Addressing student misconceptions in fuzzy logic through interactive learning tools, International Journal of STEM Education. **9**(2), 112–125 (2023).
8. G. S. Mada, N. K. F. Dethan, and A. E. S. H. Maharani, Defuzzification Methods Comparison of Mamdani Fuzzy Inference System in Predicting Tofu Production, Jurnal Varian. **5**(2), 137–148 (2022). https://doi.org/10.30812/varian.v5i2.1816
9. Codecrucks, Center of Largest Area (CoA) method for defuzzification, (2023). Diakses 13 Juni 2025, https://codecrucks.com/center-of-largest-area-method-for-defuzzification/
10. MathWorks, Trapezoidal membership function. MathWorks Documentation (2025). Diakses 13 Juni 2025, https://www.mathworks.com/help/fuzzy/trapezoidalmf.html