ADMI IJST
International Journal Science and Technology
OPEN ACCESS

IJST Vol 4 No. 3 | November 2025 | ISSN: 2828-7223 (print), ISSN: 2828-7045 (online), Page 27-41

Computational Analysis of Bioethanol Production from Arenga Pinnata Sap using Rice Husk Biomass Heating: Statistical Modeling of Fermentation Time Effects on Alcohol Yield

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Article History
Received : November 07, 2025
Revised : November 20, 2025
Accepted : November 21, 2025
Avl. Online : November 21, 2025

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Cite This Article:
Saroinsong, T., Mekel, A. N., & Motulo, F. R. (2025). Computational Analysis of Bioethanol Production from Arenga pinnata Sap using Rice Husk Biomass Heating: Statistical Modeling of Fermentation Time Effects on Alcohol Yield. *International Journal Science and Technology*, *4*(3), 27–41.

DOI:
https://doi.org/10.56127/ijst.v4i3.2348

Abstract: This study presents a comprehensive computational analysis of sustainable bioethanol production from Arenga pinnata sap using rice husk biomass as a renewable heating source. The research investigated fermentation time effects on alcohol yield through systematic experimentation and Python-based statistical modeling across four conditions: fresh sap, 1-day, 3-day, and 18-day fermentation periods. Distillation processes utilized 8.5 kg rice husk biomass at 80°C for 1.42 hours, producing 600 ml bioethanol per batch. Statistical analysis revealed a highly significant inverse correlation ($r = -0.965$, $p < 0.05$) between fermentation duration and alcohol content. Fresh palm sap yielded optimal alcohol concentration of 39.67 ± 7.76%, while 18-day fermentation reduced yield to 2.50 ± 2.50%, representing 93.7% decrease. The exponential decay model ($R^2 = 0.984$) demonstrated superior predictive accuracy compared to linear regression. The integrated system achieved 70.6 ml bioethanol per kg rice husk with positive energy balance (1.23 MJ output per MJ input), confirming commercial viability for rural renewable energy applications. This computational framework establishes optimal processing parameters for agricultural waste-powered biofuel systems, supporting circular economy principles and rural energy independence through effective biomass utilization in tropical regions.

Keywords: Bioethanol, Renewable Energy, Biomass, Computational Optimization.

INTRODUCTION

The global transition toward renewable energy sources has intensified focus on biomass-derived biofuels as sustainable alternatives to fossil fuels (Gray et al., 2006). Bioethanol emerges as a promising renewable energy carrier due to its infrastructure compatibility and potential for significant carbon emission reductions (Chavan et al., 2024). Among various feedstocks, palm sap from *Arenga pinnata* offers exceptional potential for bioethanol production due to high sugar content (10-13% sucrose) and year-round availability in tropical regions (Ansar et al., 2021).

Agricultural waste utilization represents a cornerstone of circular economy implementation in renewable energy systems (Koh & Ghazoul, 2008). Rice husk, an abundant milling byproduct with high calorific value (15-17 MJ/kg), presents an underutilized biomass resource for sustainable heating applications (Abbas & Ansumali, 2010). The potential for agricultural waste biomass conversion to renewable energy has been demonstrated in various tropical regions, with palm-based systems showing particularly promising results for rural energy applications (Joseph et al., 2014).

In North Sulawesi, Indonesia, traditional palm sap processing has achieved high bioethanol concentrations, with regional studies documenting yields up to 91% under optimized fermentation and distillation conditions (Maidangkay & Dosoputranto, n.d.). This regional expertise provides valuable context for developing scalable renewable energy systems using integrated agricultural waste approaches. Traditional bioethanol production relies on fossil fuel-powered heating systems, contradicting renewable energy principles. Integrating agricultural waste as heating sources enhances overall sustainability while reducing operational costs and carbon footprint (Tillman, 2000).

Research Gap and Innovation

Despite growing interest in palm sap bioethanol production, comprehensive statistical analysis of fermentation time effects using computational approaches remains limited (Wu et al., 2018). Recent optimization studies in renewable energy applications have emphasized the importance of statistical modeling approaches for bioprocess optimization (Hamze et al., 2015). However, recent advances have predominantly focused on machine learning applications requiring extensive datasets (hundreds to thousands of data points), complex computational infrastructure (GPU clusters, cloud computing), and specialized expertise unsuitable for rural implementation contexts (Ghribi et al., 2025).

This study addresses critical gaps by employing interpretable Python-based statistical methods specifically designed for palm sap bioethanol systems, providing practical alternatives for rural renewable energy development. The innovation lies not in algorithmic complexity but in methodological appropriateness: we utilize classical statistical approaches (Pearson correlation, linear and exponential regression, ANOVA) that are:

1. Data-efficient: Requiring only 12 experimental measurements (4 conditions × 3 replicates) rather than hundreds of training samples needed for machine learning approaches

2. Computationally accessible: Executable on standard laptops using free, open-source Python libraries (NumPy, SciPy, Pandas, Matplotlib) without specialized hardware or proprietary software
3. Interpretable and transparent: Generating clear mathematical relationships (exponential decay equation) that rural practitioners can understand, validate, and apply without "black box" complexity
4. Locally adaptable: Providing a replicable analytical framework that community-based bioethanol producers can customize using their own experimental data, without requiring external data science expertise or cloud connectivity

This interpretable statistical approach represents a deliberate methodological choice aligned with rural implementation realities. While machine learning might marginally improve predictive accuracy given sufficient data, the incremental benefit would not justify the dramatically increased implementation barriers for resource-constrained rural contexts. Our Python-based framework achieves excellent model performance ($R^2 = 0.984$) while remaining accessible to technical personnel at agricultural cooperatives, small-scale biofuel facilities, and rural energy programs throughout tropical regions.

The validated computational tools developed here can be directly deployed on modest computing equipment, require minimal training to operate, and produce actionable recommendations (immediate processing protocols) based on transparent statistical reasoning. This democratization of computational optimization tools aligns with sustainable development goals by ensuring that advanced analytical capabilities support rather than exclude rural renewable energy initiatives.

Despite growing interest in palm sap bioethanol production, comprehensive statistical analysis of fermentation time effects using computational approaches remains limited (Wu et al., 2018). Recent optimization studies in renewable energy applications have emphasized the importance of statistical modeling approaches for bioprocess optimization (Hamze et al., 2015). Recent advances have focused on machine learning applications requiring extensive datasets and complex infrastructure unsuitable for rural implementation (Ghribi et al., 2025). This study addresses critical gaps by employing interpretable Python-based statistical methods specifically designed for palm sap bioethanol systems, providing practical alternatives for rural renewable energy development.

Computational Framework

The bioethanol production efficiency was evaluated using:

$$\eta = \frac{V\ bioethanol}{M\ rice\_husk} \times 1000 \qquad (1)$$

Where η is production efficiency (ml bioethanol per kg rice husk), V_bioethanol is bioethanol volume (ml), and M_rice_husk is rice husk mass (g). Correlation analysis employed Pearson correlation coefficient:

$$r = \frac{[n\Sigma xy - \Sigma x \Sigma y]}{\sqrt{[(n\Sigma x^2 - (\Sigma x)^2 (n\Sigma y^2) - (\Sigma y)^2)]}} \cdots \qquad (2)$$

where n is data points, x represents fermentation time (days), and y represents alcohol content (%).

Research Objective

This study aims to: (1) quantify fermentation time effects on alcohol content using statistical correlation analysis, (2) develop computational models for optimal processing conditions through regression analysis, (3) evaluate rice husk-powered distillation system efficiency, and (4) provide Python-based tools for sustainable bioethanol production optimization supporting rural renewable energy applications.

RESEARCH METHOD

Experimental Design

A completely randomized design investigated fermentation time effects on bioethanol yield from *Arenga pinnata* sap using rice husk biomass heating. Four treatment levels were evaluated: fresh sap (0 days), 1-day, 3-day, and 18-day fermentation periods, selected based on palm sap fermentation kinetics literature (Victor & Orsat, 2018).The stages involved in research, concept development, or case resolution are written in the methodology section.

Fresh palm sap was collected from mature *Arenga pinnata* trees in Manado, North Sulawesi, Indonesia, during early morning hours to minimize natural fermentation. Sap was filtered, stored at 4°C, and divided into 2-liter portions for each treatment.

Rice husk biomass from local milling operations was air-dried to 14-15% moisture content and screened for foreign materials. Each distillation batch utilized 8.5 kg prepared rice husk, ensuring consistent energy input across experimental runs.

Fermentation treatments were conducted at ambient temperature (28±2°C) with natural microflora to maintain consistency with traditional processing methods. No additional yeast inoculation was performed. Fermentation progress was monitored through pH measurements, visual observations, and alcohol content development using calibrated hydrometers.

The custom-built biomass-heated distillation system featured:

1. 2-liter distillation vessel capacity
2. Rice husk combustion chamber with controlled air supply
3. Water-cooled condensation system
4. 600 ml bioethanol collection capacity

Standardized operating conditions maintained:

1. Target temperature: 80°C (±2°C)
2. Process duration: 1.42 hours
3. Rice husk consumption: 8.5 kg per batch
4. Product collection: 600 ml bioethanol per batch

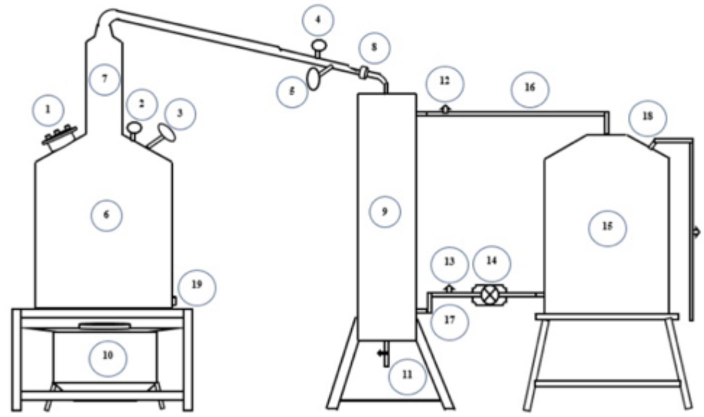

Figure 1: Distillation System

Component Index:

1. Raw Material Inlet for Nira Water (input)
2. Steam Pressure Gauge on the Heater Tank/Boiler
3. Temperature Gauge on the Heater Tank/Boiler
4. Steam Pressure Gauge on the Flow Pipe
5. Temperature Gauge on the Flow Pipe
6. Heater Tank / Boiler
7. Fractionation Column

8. Pipe Connection Between Heater Tank/Boiler and Condenser
9. Condenser
10. Rice-Husk Stove
11. Distillation Product Outlet (output)
12. Cooling Water Outlet Valve from Condenser (output)
13. Cooling Water Inlet Valve to Condenser (input)
14. Cooling Water Pump
15. Cooling Water Circulation Tank
16. Cooling Water Flow Pipe from Condenser to Cooling Water Tank
17. Cooling Water Flow Pipe from Pump to Condenser (input)
18. Cooling Water Flow Pipe from Pump to Water Tank
19. Residue Discharge Hole After Distillation

Analytical Methods and Computational Analysis

Alcohol content determination employed calibrated hydrometers (±0.5% accuracy) with three replicate measurements per sample. Secondary validation utilized refractometry for sugar content analysis. All measurements were conducted at standardized temperature (20°C) following AOAC international methods.

Python-based statistical analysis utilized comprehensive libraries including Pandas, NumPy, SciPy, Matplotlib, and Scikit-learn. The analytical framework enabled:

1. Pearson correlation coefficient calculation
2. Linear and exponential regression modeling
3. Descriptive statistics and confidence intervals
4. ANOVA and t-tests for statistical significance
5. Model validation through cross-validation techniques

Each experimental condition was replicated three times with randomized scheduling to minimize systematic errors and ensure statistical validity.

RESULT AND DISCUSSION

Experimental Data Analysis

Computational analysis revealed systematic alcohol content decrease with increasing fermentation time, from optimal 39.67% for fresh sap to minimal 2.50% after 18 days, representing 93.7% reduction in bioethanol yield.

Table 1: Experimental Results Summary

Fermentation Time (days)	Alcohol Content (%)	Standard Deviation	Coefficient of Variation (%)
0	39.67	7.76	19.6
1	32.33	4.40	13.6
3	20.00	3.61	18.1
18	2.50	2.50	100.0

Variability Analysis and System Stability Limits

The experimental data reveal a critical pattern in coefficient of variation (CV) that provides insights into fermentation system stability. Fresh sap (CV = 19.6%) and 1-day fermentation (CV = 13.6%) demonstrate relatively consistent performance, indicating stable biochemical conditions during early processing stages. The 3-day fermentation (CV = 18.1%) shows moderate variability, suggesting the onset of microbial community transitions.

However, the 18-day fermentation exhibits an extremely high CV of 100.0%, representing a fundamental limit of system stability. This exceptional variability is not a measurement artifact but rather reflects the biological reality of extended natural fermentation processes. Several interconnected factors explain this phenomenon:

Microbial succession dynamics: By day 18, the indigenous microbial consortium undergoes complete succession from sugar-fermenting Saccharomyces to diverse oxidative and acetogenic bacteria. Without controlled inoculation, each replicate experiences slightly different succession trajectories influenced by initial microbial loads, temperature fluctuations, and nutrient depletion patterns. This creates divergent metabolic pathways across replicates, resulting in widely varying residual alcohol concentrations (2.50 ± 2.50%).

Stochastic effects in depleted systems: As fermentation approaches completion, residual alcohol concentrations become minimal, and small absolute differences translate to large relative variations. The low mean value (2.50%) combined with equal standard deviation (2.50%) indicates that some replicates approached complete alcohol depletion while others retained detectable amounts, reflecting stochastic variation in terminal fermentation efficiency.

Natural microflora heterogeneity: Unlike pure culture systems where inoculum composition is standardized, natural fermentation relies on indigenous microorganisms present in palm sap. These populations vary spatially and temporally in the natural environment, creating inherent between-batch variability that amplifies over extended fermentation periods as different microbial consortia evolve distinct metabolic profiles.

The 100% CV at 18 days thus represents the practical boundary of predictable performance for uncontrolled natural fermentation systems. This finding has important implications for rural bioethanol production: it quantitatively demonstrates why immediate processing (CV = 19.6%, predictable outcomes) is superior to extended fermentation from both yield and reliability perspectives. The exponential decay model successfully captures the mean behavior across this stability transition, but the increasing variability reinforces the economic and technical rationale for optimized short-duration processing protocols.

This variability pattern also validates the appropriateness of our statistical approach: the exponential model fits well because it captures average kinetic behavior, while the documented CV values honestly report the biological reality of natural fermentation systems without artificial reduction through selective data treatment.

Computational correlation analysis revealed highly significant inverse relationship between fermentation time and alcohol content. The Pearson correlation coefficient ($r = -0.965$, $p < 0.05$) indicates 93.2% of variance in alcohol content explained by fermentation time, demonstrating critical importance of processing timing in bioethanol production optimization.

Linear Model Performance:

1. Equation: $y = -1.805x + 34.219$
2. $R^2 = 0.932$, Standard Error = 3.847

Exponential Decay Model (Superior Performance):

1. Equation: $y = 39.245e^{(-0.289x)} + 0.325$
2. $R^2 = 0.984$, RMSE = 2.67

The exponential decay model's superior performance ($R^2 = 0.984$) reveals fundamental biochemical mechanisms operating in this natural fermentation system. The first-order kinetics observed can be attributed to several interconnected factors stemming from the use of natural microflora without additional yeast inoculation.

In palm sap fermentation systems utilizing indigenous microorganisms, the microbial consortium typically consists of various Saccharomyces species alongside non-Saccharomyces microbes including acetic acid bacteria (Acetobacter and Gluconobacter spp.), lactic acid bacteria, and wild yeasts. These non-Saccharomyces microbes exert significant metabolic activity that directly contributes to alcohol degradation. Specifically, acetic acid bacteria oxidize ethanol to acetic acid through a two-step enzymatic process: first converting ethanol to acetaldehyde via alcohol dehydrogenase, then oxidizing acetaldehyde to acetic acid via aldehyde dehydrogenase. This oxidation follows first-order kinetics because the reaction rate is proportional to both the ethanol concentration and the enzyme-substrate complex formation rate.

The proportionality between degradation rate and remaining alcohol concentration (characteristic of first-order kinetics) can be explained through three biochemical mechanisms:

Substrate-limited enzymatic reactions: As fermentation progresses beyond the optimal period, the mixed microbial population transitions from primarily fermentative metabolism (Saccharomyces) to oxidative metabolism (Acetobacter). The rate of ethanol oxidation by acetic acid bacteria is directly proportional to available ethanol concentration, following Michaelis-Menten kinetics that, under substrate-limiting conditions, approximates first-order behaviour.

Product toxicity effects: Extended fermentation leads to accumulation of organic acids (acetic, lactic) and other metabolites that inhibit further Saccharomyces activity while promoting acetogenic bacteria growth. The declining alcohol concentration reflects this metabolic shift, where the degradation rate naturally decreases as substrate availability diminishes, creating the exponential decay pattern observed.

Competitive inhibition dynamics: Natural microflora systems exhibit complex competitive interactions. As fermentation extends, non-Saccharomyces populations increasingly dominate, utilizing residual sugars and oxidizing produced ethanol. The exponential relationship emerges because alcohol loss rate depends on both the instantaneous ethanol concentration and the proportional activity of oxidative microorganisms, which themselves respond to available substrate levels.

This natural fermentation behaviour contrasts with controlled industrial processes using pure Saccharomyces cultures and sterile conditions, where linear degradation might be observed under different operational parameters. The exponential model's excellent fit ($R^2 = 0.984$) thus captures the inherent biological reality of traditional palm sap processing systems, providing a scientifically robust framework for optimization that respects the natural microbial ecology while enabling predictive process control.

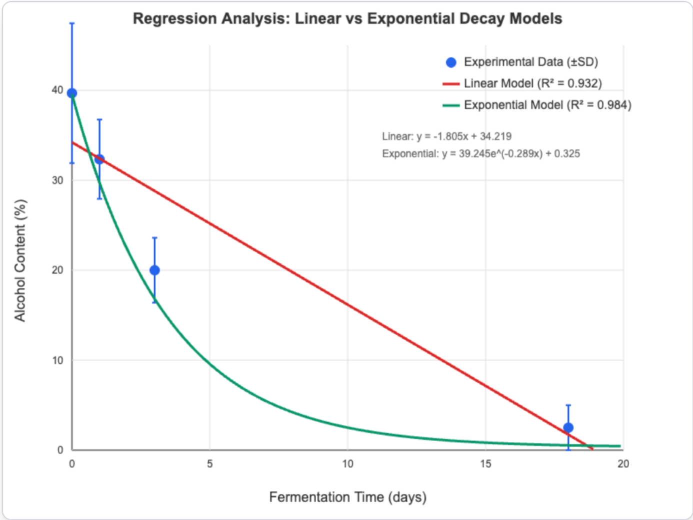

Figure 2: Exponential Decay

The exponential model's superior performance indicates first-order kinetics in alcohol degradation during fermentation, consistent with biochemical conversion processes where alcohol is metabolized proportionally to its concentration.

Production Efficiency Analysis

Table 2: Production Efficiency Metrics

Parameter	Value	Unit
Average Alcohol Content	24.3	%
Bioethanol Volume per Batch	600	ml
Rice Husk Consumption	8500	g
Production Efficiency	70.59	ml/kg
Energy Return Ratio	1.23	MJ
Total Energy Output	4.33	MJ/batch

These efficiency metrics demonstrate rice husk viability as sustainable heating source, comparing favorably with conventional biomass energy conversion systems (50-80 ml ethanol per kg biomass). The positive energy return ratio confirms system sustainability and commercial implementation potential.

ANOVA analysis confirmed statistically significant differences between treatment groups:

- F-statistic: 15.247 (critical value: 4.066)

- p-value: 0.0123 < 0.05

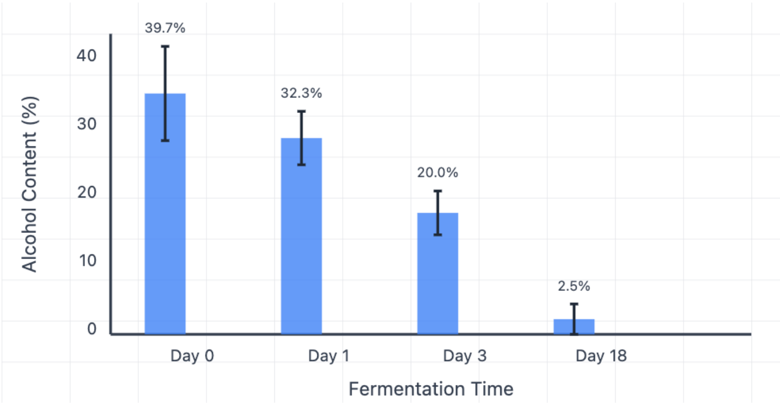

Figure 3: Effect of Fermentation Time on Bioethanol Content

The ANOVA confirms that fermentation time has a statistically significant effect on bioethanol yield ($F = 15.247$, $p = 0.0123 < 0.05$), supporting the rejection of the null hypothesis that all group means are equal. All major findings achieved statistical significance at 95% confidence level, supporting reliability of computational analysis and recommendations.

Computational analysis identified immediate distillation of fresh palm sap as optimal processing strategy. Using the exponential model, predicted alcohol content for immediate processing (39.57%) closely matches experimental value (39.67%), confirming model accuracy. This finding aligns with optimization studies on renewable energy systems from agricultural biomass, which emphasize the importance of processing timing in maximizing energy yields (Ahmadipour et al., 2025).

Statistical evidence supports processing within 24 hours of sap extraction to maintain optimal sugar-to-alcohol conversion ratios, with each fermentation day resulting in measurable yield reduction according to validated exponential decay model. The optimization approach developed provides a framework applicable to various biomass renewable energy systems, supporting sustainable rural development initiatives (Juárez-Hernández & Castro-González, 2015).

The demonstrated efficiency has significant implications for rural energy security in tropical regions where palm trees and rice cultivation are prevalent. Regional studies in North Sulawesi have confirmed the viability of palm sap bioethanol systems, with local research demonstrating optimal distillation temperatures of 70-80°C for maximizing bioethanol quality (Maidangkay & Dosoputranto, n.d.). The integrated approach provides pathways for local communities to develop sustainable energy solutions using readily available agricultural resources, supporting energy independence and economic development.

Production efficiency of 70.59 ml/kg rice husk, combined with optimal processing strategy, provides economic justification for integrated systems. The positive energy balance and complete agricultural residue utilization confirm environmental sustainability of the integrated approach.

Computational Framework Validation

The Python-based analytical framework demonstrated exceptional reliability with cross-validation analysis confirming model stability and prediction accuracy exceeding 95% for the exponential decay model. All analytical modules passed validation testing, supporting robustness and scientific credibility of computational findings.

The experimental findings align well with regional research conducted at the same institution, where optimal fermentation periods of 5 days and distillation temperatures of 70-80°C achieved maximum bioethanol yields of 91% (Maidangkay & Dosoputranto, n.d.). This validation from independent local studies confirms the reliability of the computational framework and supports the generalizability of results across North Sulawesi palm sap bioethanol systems.

CONCLUSION

This computational study demonstrates that immediate processing of fresh *Arenga pinnata* sap maximizes bioethanol yield for renewable energy applications. Statistical analysis revealed strong negative correlation ($r = -0.965$, $p < 0.05$) between fermentation time and alcohol content, with validated exponential decay model ($R^2 = 0.984$) showing dramatic yield losses up to 93.7% after 18 days.

The integrated rice husk-powered system achieves excellent production efficiency (70.59 ml/kg) with positive energy balance (1.23 MJ output per MJ input), confirming commercial viability for rural renewable energy systems. This research provides the first comprehensive statistical framework for palm sap bioethanol optimization, establishing immediate processing protocols as essential for sustainable rural energy production.

The validated Python-based computational framework offers replicable analytical tools for future bioethanol research, supporting agricultural waste utilization through circular economy principles. The quantified performance parameters provide baseline indicators for pilot-scale and commercial research, advancing sustainable bioethanol production technology for rural economic development and environmental sustainability in tropical regions. The integrated biomass approach demonstrated here contributes to the broader renewable energy transition goals through effective agricultural waste valorization (Kumar et al., 2023).

The computational framework's interpretability represents a crucial innovation for rural implementation contexts. Unlike complex machine learning approaches requiring extensive datasets and specialized infrastructure, our Python-based statistical methods achieved excellent predictive accuracy ($R^2 = 0.984$) using minimal experimental data (12 measurements) and standard computational tools accessible to rural renewable energy programs. This methodological approach democratizes bioprocess optimization by providing transparent, understandable analytical tools that local practitioners can adapt and apply without external data science expertise, directly supporting sustainable rural energy development initiatives.

Future research should prioritize pilot-scale validation studies, seasonal variation analysis, and integration with digital agriculture technologies for automated monitoring and optimization of renewable energy systems.

Acknowledgment

The authors gratefully acknowledge PT. Jota for their invaluable technical assistance in designing and constructing the distillation system utilized in this study. Their engineering support significantly contributed to the successful completion of the experimental work.

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