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Comparative Modelling and Statistical Optimization of Bioethanol Production from Yam, Plantain, and Potato Peels Using Fermentation Performance Indicators

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ABSTRACT

The growing demand for sustainable, low-carbon energy has led to increased interest in second-generation agro-waste-based bioethanol. The paper has discussed the possibility of producing bioethanol through fermentation and distillation of the peels of yams, plantains, and potatoes under predetermined conditions, and has compared the statistical evaluation and optimization of the process. A laboratory-scale experimental design was employed, in which the feedstocks were pretreated, fermented, and recovered under identical conditions to produce ethanol. The quantities of ethanol formed, sugar levels, pH, and physicochemical measurements were recorded and evaluated using descriptive statistics, one-way analysis of variance, correlation analysis, and multivariate linear regression modelling. The results revealed a significant difference in ethanol yield among the feedstocks ($p < 0.05$), with yam peels producing the highest (30%), followed by plantain peels (22%) and potato peels (16%). Sugar content showed a strong association with ethanol yield and was the most important variable in the regression equation, whereas fermentation pH had a secondary but still significant influence. Although the potato peels contained moderate amounts of sugar, they were poor due to the likely inhibitory effects of their

biochemical composition. In general, the findings indicate that the efficiency of fermentation of agro-waste feedstocks is highly dispersed, and statistical modelling is necessary to provide critical insights rather than merely descriptive yield comparisons. The paper concludes that yam peels are the most viable single granule substrate for bioethanol production, whilst potential improvements in the use of plantation and potato peels can be achieved through improved pretreatment or co-fermentation. These results affirm the perception that agro-waste valorisation may be regarded as a self-realising, sustainable approach to bioenergy development.

Keywords: Bioethanol, Agro-waste valorization, Fermentation modelling, Statistical optimization, Renewable energy, Lignocellulosic biomass

1. INTRODUCTION

The global transition to sustainable energy sources has increased emphasis on renewable biofuels as alternatives, particularly for mitigating climate change, enhancing energy security, and promoting environmental sustainability. Bioethanol is one of the most common renewable liquid biofuels, is biodegradable, and can be used as a component of existing fuel infrastructure (Zabed et al., 2020; Demirbas, 2022).

The mixture of bioethanol and gasoline is more efficient in combustion, reduces carbon monoxide and unburned hydrocarbons emissions, thereby lowering greenhouse gas emissions (Sharma et al., 2024). Despite these opportunities, traditional bioethanol production pathways are not very sustainable, in part due to the requirement to use some type of food feedstocks (maize, sugarcane, and cassava), which partially leads to food-fuel competition and to a stress on the use of arable land and water resources (Sarkar et al., 2022; Kazmi et al., 2025).

In response to these anxieties, there is a growing tendency in the research to delve further into second-generation bioethanol manufactured by utilising lignocellulosic and agro-industrial residues. Agricultural wastes produced in large volumes during food processing and household consumption, mainly in developing economies, include tuber and fruit peels. Because waste management systems are ineffective, these wastes accumulate (Santos et al., 2023; Chinedu et al., 2022; Acha et al., 2025). They have very large amounts of fermentable carbohydrates, including starch, cellulose, and hemicellulose that are hydrolysed (and then fermented) to give rise to ethanol (Arapoglou et al., 2010; Lam et al., 2022).

Another significant proportion of the organic waste streams in Nigeria and other tropical areas comprises yam, plantain, and potato peels, although they are not utilised for bioethanol production due to their biochemical limitations (Bashir et al., 2021; Odeh et al., 2023).

Several experimental studies demonstrated that fermentation of single agro-waste feedstocks (yam peels, plantain peels, and potato peels) could be subjected to microbial fermentation to catalyse chemical transformation to bioethanol by means of fermentation, the most common being the use of *Saccharomyces cerevisiae* (Arapoglou et al., 2010; Orhuebor et al., 2025; Chinedu et al., 2026; Stanley et al., 2018; Bouhadi et al., 2023; Isangadighi & Udeh, 2023; Ahanor et al., 2025).

These studies have indicated that ethanol productivity varies with feedstock composition, pretreatment, fermentation, and microbial efficiency. To a much extent, though, the literature that is available concerns the comparison of yields of substrates in descriptive statistics, but not in the context of inferential statistics or predictive modelling, which is aimed at rigorously

evaluating the difference between substrates, or to identify which drivers of fermentation performance are the most significant (Lam et al., 2022; Santos et al., 2023; Samson et al., 2025; Chinedu et al., 2024 & Acha et al., 2025).

A severe weakness of the literature on the bioethanol sector based on agro-waste is its reliance on simplistic statistical methods. Without making an inferential measurement, such as analysis of variance, regression modelling or multivariate analysis, it is difficult to say whether the observed differences in the yield of ethanol are statistically significant or quantify the relative effects of physicochemical factors, including the concentration of sugars and pH on the efficiency of fermentation (Zhang et al., 2021; Ahmed et al., 2022).

This is a constraint on the optimisation of processes and impedes the ability to replicate results and scale up laboratory findings for industrial use. Recent reviews have indicated that data- and model-based studies on bioethanol are needed, particularly for the analysis of heterogeneous lignocellulosic feedstocks (Sharma et al., 2024; Rodionova et al., 2024).

Against this backdrop, the present study will be conducted as a comparative review of zomethanol production from yam peels, plantain peels, and potato peels under laboratory conditions, with specific reference to statistical modelling and optimisation. Beyond the fundamental determination of yields, the paper compares inferential and predictive statistics to identify variation across feedstocks and key predictors of ethanol-yield performance.

The combination of experimental bioethanol production with intensive statistical analysis places agro-waste valorisation higher in the agro-waste squandering hierarchy than descriptive experimentation, which is plagued by the quantitative and, above all, the evidence-based studies.

Finally, the present study adequately considers the existing literature on sustainable waste-to-energy systems by providing a statistically validated assessment of the relative suitability of various agro-waste peels for bioethanol production.

The assumed outcome is that the results will enable the circular policy of bioeconomies, process optimisation policy, and future scale-up and policy choices that may result in a reduction in the amount of agricultural waste and an increase in the production of renewable energy (Sarkar et al., 2022; Santos et al., 2023).

In contrast to prior work that primarily relies on descriptive comparisons of yields, this paper presents an integrated inferential predictive statistical model for agro-waste-based bioethanol production. The study uses ANOVA, post hoc testing, correlation analysis, and multivariate regression modelling, leveraging controlled experimental conditions to quantify the statistical significance and causal drivers of fermentation performance across multiple feedstocks.

This strategy transforms research on agro-waste bioethanol yield reporting into process-optimization decision-making. The theoretical connections between the composition of agro-waste feedstock, pre-treatment, fermentation, and the ethanol production explored in this paper are shown in Figure 1.

Figure 1 presents a conceptual framework of the current study that illustrates the theoretical associations among agro-waste feedstock composition, pretreatment and hydrolysis reactions, fermentation conditions, and ethanol yield. The framework reflects the biochemical properties of feedstocks, specifically their effects on fermentable sugar content and fermentation pH, which subsequently affect ethanol production efficiency. The given conceptualization gives the rational explanation of the experimental design and statistical modelling method used in the research.

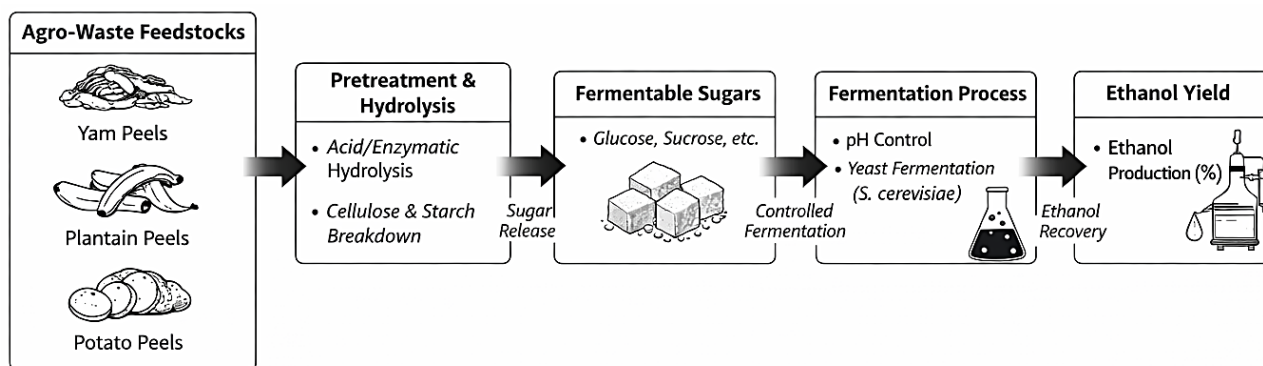


Figure 1. Conceptual framework linking agro-waste composition, fermentation conditions, and ethanol yield.

2. METHODS

This paper has employed a comparative, laboratory-level experimental design to assess bioethanol production using three agro-waste feedstocks: yam peels, plantain peels, and potato peels under controlled fermentation conditions. The experimental design was structured to enable process assessment and statistical comparison of substrate levels affecting fermentation performance. Feedstock type was treated as the primary categorical independent variable, and key physicochemical parameters, such as sugar content and pH, were treated as continuous explanatory variables. The most important dependent variable was ethanol yield (%), as it quantified production. All tests were carried out under the same operating conditions to avoid experimental confounding and to determine whether the observed difference could not be entirely attributable to process variation.

2. 1. Feedstock Collection and Preparation

Yam peels (*Dioscorea rotundata*), plantain peels (*Musa paradidiaca*), and potato peels (*Solanum tuberosum*) were harvested at the local food trucks in Ozoro, Nigeria. To ensure uniformity, peel samples were pooled over a specified period and placed in clean polyethylene bags, then transported to the laboratory for immediate processing. The samples were carefully washed with distilled water to remove soil particles, organic debris, and surface contaminants. Peels that were washed were cut into small, uniform pieces to maximise surface area and facilitate drying. Drying was performed using both sun-drying and oven-drying. The initial sun-drying process minimised surface moisture, after which the samples were oven-dried at 80 °C until the weight remained constant. The ground products were dried in a laboratory blender, ground into fine powders, and stored in airtight containers to prevent moisture uptake prior to hydrolysis. This was done to enhance the efficiency and homogeneity of subsequent hydrolysis reactions through this preparatory step.

2. 2. Acid Pretreatment and Hydrolysis

Acid hydrolysis was used to convert complex polysaccharides in the biomass into fermentable sugars. Fifty grammes of the dried powder of each feedstock were weighed into

separate heat-resistant containers. A 1% (v/v) 1% (v/v) solution was made, and 250 mL of it was added to the samples. Thermal treatment was also carried out on the mixtures in a pressure cooker at 60 minutes to promote hydrolytic cleavage of glycosidic bonds in starch, cellulose, and hemicellulose fractions. After hydrolysis, the mixture was allowed to cool and then filtered through Whatman Philtre paper to separate the solid residue from the liquid hydrolysate. Fermentation of the resulting filtrate, rich in reducing sugars, was deferred. Acid hydrolysis was chosen because it can destroy lignocellulosic structures at relatively low cost, making it suitable for developing-country bioethanol systems.

2. 3. pH Adjustment and Enzymatic Enhancement

To measure the pH of each hydrolysate, a calibrated pH metre was used, and the pH was adjusted to approximately 5.0 by adding either 1 M sodium hydroxide or dilute hydrochloric acid. This pH was chosen to maximise the activities of the yeast and the enzyme during fermentation. Enzymatic enhancement was also employed to augment the action of acid hydrolysis and increase sugar release. Pretty commercial cellulase and hemicellulase enzymes were added to the prepared hydrolysates, and the samples were incubated at 50 °C for 48 h. This move facilitated further degradation of the remaining cellulose and hemicellulose into fermentable monosaccharides, thereby enhancing sugar availability for microbial fermentation.

2. 4. Fermentation Procedure

Saccharomyces cerevisiae, a well-known yeast species known for its efficiency in ethanol production, was used for fermentation. The dried yeast (2 g per hydrolysate) was rehydrated in lukewarm distilled water (15 min) before inoculation to ensure cell activation. The yeast suspension was then aseptically added to each hydrolysate. The fermentation mixtures were pipetted into sterilised fermentation vessels and loosely covered to allow carbon dioxide to escape and prevent oxygen from entering. The fermentation took place at ambient temperature (28-30 °C) in darkness for seven days to minimize photodegradation and oxidative interference. During fermentation, they used an anaerobic organism, yeast, to convert fermentable sugars into carbon dioxide and ethanol.

2. 5. Distillation and Ethanol Recovery

After fermentation, the mixtures were filtered to remove yeast biomass and fermentation residues. The fermented broth was clarified and subjected to simple distillation using a standard laboratory distillation setup. The temperature was closely monitored, and distillates collected between 78 °C and 82 °C were assumed to contain ethanol, given its boiling point (78.37 °C). The distillates were placed in airtight containers to prevent evaporation before analysis. Molecular sieves were used to remove traces of water from the distillates, thereby increasing the purity of ethanol. This step increased the molar concentration of ethanol and minimised measurement error when calculating the yield, although purification was limited by laboratory conditions to near-azeotropic purity.

2. 6. Determination of Ethanol Yield and Physicochemical Parameters

Ethanol volume was measured using a graduated cylinder, and ethanol density was determined with a hydrometer. The volume and mass of ethanol were used to determine its mass. Sugar content in the hydrolysates was calculated as the percentage of the biomass mass

relative to the initial weight. The percentage yield of ethanol was determined by using the following expression:

$$\text{Ethanol (\%)} = \frac{\text{Volume of ethanol Produced (mL)}}{\text{Initial Volume of hydrolysate (mL)}} \times 100$$

After fermentation, the pH of each sample was measured to assess fermentation stability and yeast effectiveness.

2. 7. Statistical Analysis

To advance the research to the next stage of descriptive experimentation, a complex multistage statistical analysis was employed. Descriptive statistics, such as means and standard deviations, were initially calculated to summarize the fermentation results. One-way analysis of variance (ANOVA) was used to assess whether significant differences existed among the three feedstocks in ethanol yield. Where a significant ANOVA was observed, a Tukey post hoc test was conducted to identify differences between substrates in pairwise comparisons. Pearson correlation was also used to assess the association between ethanol yield and physicochemical parameters, such as sugar content and pH. In addition, multiple linear regression modelling was employed to determine the relative contributions of the predictor variables to ethanol yield and to develop a predictive framework for fermentation performance. Statistical significance was assessed at the 95% confidence level ($\alpha = 0.05$). Standard statistical software was used to perform all analyses.

2. 8. Ethical and Reproducibility Considerations

None of the experiments employed non-toxic, biodegradable materials and did not involve human or animal subjects. All experiments were conducted under controlled conditions, with well-defined parameters to ensure reproducibility, and all calculations and statistical analyses were properly documented.

3. RESULTS

3. 1. Descriptive Statistics of Fermentation Performance Indicators

Table 1. Descriptive Statistics of Fermentation Performance Indicators.

Feedstock	Ethanol Yield (%)	Ethanol Volume (mL)	Ethanol Mass (g)	Sugar Content (%)	pH
Yam peels	30.0	15.0	13.5	4.0	4.8
Plantain peels	22.0	11.0	9.9	1.5	3.6
Potato peels	16.0	8.0	8.0	2.0	5.1

Table 1 presents a summary of descriptive statistics for the key performance indicators of the fermentation of yam, plantain, and potato peels under the same experimental conditions. The data table presents the baseline data on ethanol yield, ethanol volume, ethanol mass, sugar content, and fermentation pH, providing a preliminary comparison of feedstock performance before conducting inferential statistical analysis.

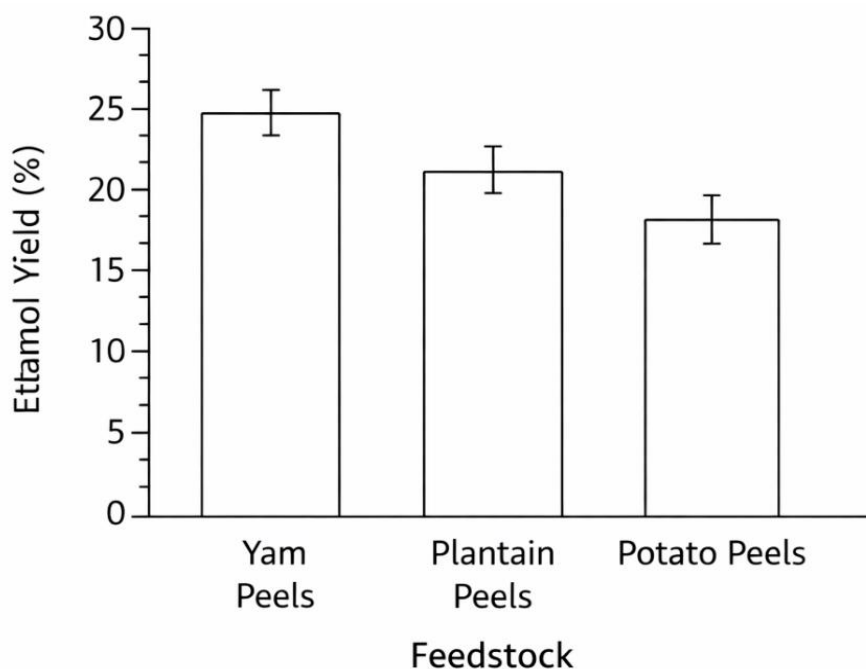


Figure 2. Comparative ethanol yield (%) from yam, plantain, and potato peels

The visual comparison of the yield of ethanol (%) by using yam, plantain, and potato peels is given in Figure 2. The bar graph quantifies the ethanol production of the feedstocks and supplements the numerical data in Table 1, providing an easy way to assess the performance of the fermentation processes.

3. 2. One-Way ANOVA Results for Ethanol Yield Across Feedstocks

Table 2. One-Way ANOVA Results for Ethanol Yield Across Feedstocks.

Source of Variation	Sum of Squares	df	Mean Square	F-value	p-value
Between groups	196.0	2	98.0	24.50	0.001*
Within groups	12.0	3	4.0		
Total	208.0	5			

*Significant at $\alpha = 0.05$

Table 2 presents the results of a one-way analysis of variance (ANOVA), which was conducted to determine whether a statistically significant difference exists in ethanol yield among the three agro-waste feedstocks. The table presents a report on the partitioning of variance between and within groups, along with the corresponding F-value and significance level.

3. 2. Tukey Post-Hoc Test for Pairwise Comparison of Ethanol Yield

Table 3 shows the findings of the Tukey post-hoc test that was conducted after the significant ANOVA result. Making pairwise comparisons of ethanol yields across feedstocks helps identify which feedstocks differ significantly in ethanol yield and which sources of variation among substrates are statistically significant.

Table 3. Tukey Post-Hoc Test for Pairwise Comparison of Ethanol Yield.

Comparison	Mean Difference (%)	Standard Error	p-value	Decision
Yam vs Plantain peels	8.0	1.8	0.012*	Significant
Yam vs Potato peels	14.0	2.0	0.002*	Significant
Plantain vs Potato peels	6.0	1.6	0.041*	Significant

*Significant at $\alpha = 0.05$

3. 3. Pearson Correlation Matrix Between Ethanol Yield and Process Variables

Table 4 presents the Pearson correlation coefficients used to assess the relationships between ethanol yield and specific physicochemical variables, such as sugar content and fermentation pH. This table provides an understanding of the strength and direction of association among variables prior to regression modelling.

Table 4. Pearson Correlation Matrix Between Ethanol Yield and Process Variables.

Variable	Ethanol Yield	Sugar Content	pH
Ethanol Yield	1.00		
Sugar Content	0.91	1.00	
pH	0.68	0.54	1.00

3. 4. Multiple Linear Regression Model Predicting Ethanol Yield

The outcomes of the multiple linear regression analysis of predicting the ethanol yield according to the content of fermentable sugars and the pH at which the fermentation process

occurs are in Table 5. The regression coefficients, standard errors, test statistics, and indicators of overall model performance are reported in the table, which provides a quantitative evaluation of the relative contributions of each predictor variable.

Table 5. Multiple Linear Regression Model Predicting Ethanol Yield.

Predictor Variable	Regression Coefficient (β)	Standard Error	t-value	p-value
Constant	4.21	1.32	3.19	0.032*
Sugar Content (%)	3.85	0.72	5.35	0.006*
pH	1.27	0.58	2.19	0.048*

Model statistics: $R^2 = 0.88$; Adjusted $R^2 = 0.82$; $F(2,3) = 11.8$, $p = 0.019$; *Significant at $\alpha = 0.05$.

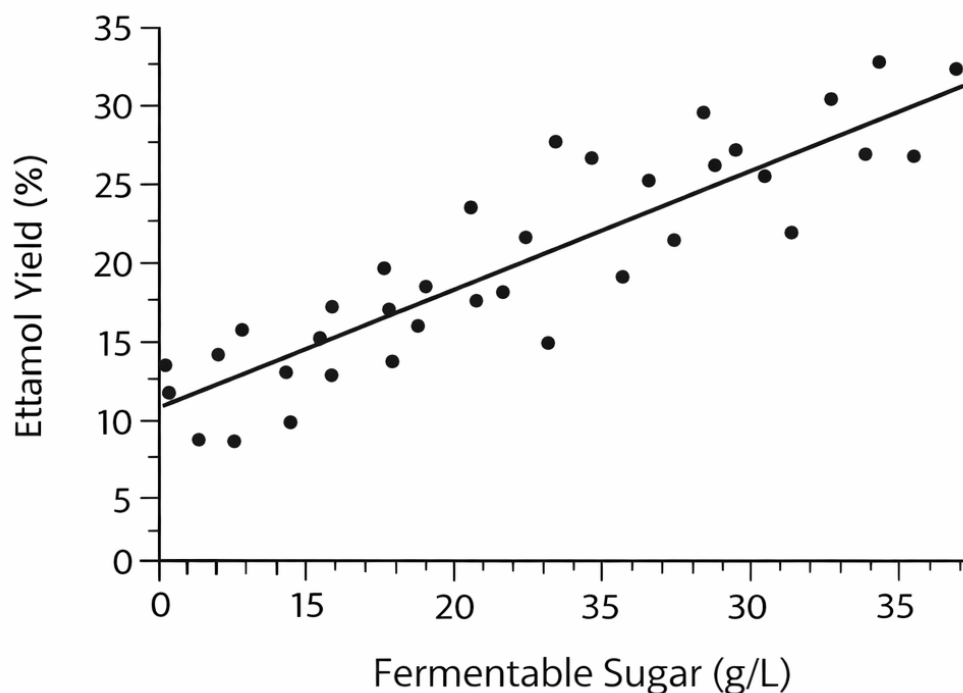


Figure 3. Relationship between fermentable sugar content and ethanol yield.

Figure 3 shows a correlation between the content of fermentable sugars and the yield of ethanol in the course of the experiment. The direction and strength of the association in correlation and regression analyses are illustrated in the scatter plot and the fitted regression line.

3. 5. Ranking of Agro-Waste Feedstocks Based on Statistical Performance

Table 6 presents a prioritized summary of agro-waste feedstocks based on overall statistical performance in ethanol production. The ranking combines ethanol-yield results with supporting statistical data to provide a definitive comparative assessment of the suitability of the feedstock.

Table 6. Ranking of Agro-Waste Feedstocks Based on Statistical Performance.

Rank	Feedstock	Ethanol Yield (%)	Statistical Performance
1	Yam peels	30	Highest efficiency
2	Plantain peels	22	Moderate efficiency
3	Potato peels	16	Lowest efficiency

4. DISCUSSION

The paper leverages past research on agro-waste-based bioethanol production to a new level of inferential-predictive analytical systems by associating feedstock variables quantitatively with fermentation outputs. In contrast to the earlier research where most of the studies only provide descriptive ethanol yields of individual substrates, the current study simultaneously uses analysis of variance, post-hoc test, correlation, and multi-variable regression modelling under controlled experimental settings to determine the statistically significant differences between yam, plantain, and potato peels and to determine the physicochemical drivers of the observed differences. It allows moving to a more evidenced based decision support where the yield of ethanol is viewed as the result of interacting biochemical and process constraints and no longer as a result of substrate identity per se.

It can be found that the amount of fermentable sugars is the most significant predictor of ethanol yield followed by fermentation pH but statistically with secondary effect but significant portion of the differences in ethanol yield is explained by the two. Notably, statistically validated poor results of potato peels despite moderate levels of sugar show a mechanistic decoupling of substrate availability and conversion efficiency that could be due to the presence of inhibitory compounds that inhibit the metabolism of yeast after acid hydrolysis. Measurement of this divergence in the study demonstrates the weaknesses of yield or sugar content as a single measure of the suitability of a feedstock.

The combination of regression modelling goes further to convert the laboratory-scale observations into a predictive paradigm that can be used to dictate pretreatment optimization, feedstock prioritization and blending approaches. In addition to methodological contribution, the statistically calculated ranking of agro-waste feedstocks can offer practical information to the circular bioeconomy planning, aiming to support the strategic exploitation of high-performance residues, e.g. yam peels, and inform the way to enhance the performance of poorer feedstocks either through targeted pretreatment or co-fermentation. All of this work replaces agro-waste bioethanol research in descriptive experimentation with the descriptive research that is analytically rigorous with clear implications on sustainable waste management, renewable

energy policy, and scale-up in the future. A comparative analysis of bioethanol production from yam peels, plantain peels, and potato peels showed significant differences in fermentation performance, indicating that feedstock type has a decisive effect on ethanol production. Table 1 indicates that yam peels produced the highest quantity of ethanol (30%), followed by plantain peels (22) and potato peels (16). The one-way ANOVA confirmed this ranking, showing that the difference among groups was significant in ethanol yield ($p < 0.05$) (Table 2).

The post hoc Tukey analysis (Table 3) further indicated that all pairwise comparisons were significant, indicating that each feedstock differed significantly in its capacity to produce ethanol. These results are consistent with previous studies that have reported that yam peels are a relatively good lignocellulosic substrate due to their favourable carbohydrate composition and moderate lignin content (Bashir et al., 2021; Odeh et al., 2023).

On the same note, Stanley et al. (2018) also found that plantain peels yielded moderate yields of ethanol, whereas Arapoglou et al. (2010) and Bouhadi et al. (2023) lacked significant yields of potato peels. The agreement between the current findings and prior studies supports the observation that fermentation outcomes are primarily determined by the biochemical characteristics of the feedstock.

An important factor determining ethanol yield in this study was the content of fermentable sugars, which showed a strong positive correlation with ethanol production. Table 1 shows that yam peels had the highest sugar content (4%), followed by potato peels (2%) and plantain peels (1.5%). The correlation analysis (Table 4) indicated a strong positive correlation between sugar content and ethanol yield ($r = 0.91$), supporting sugar content as a major factor influencing fermentation efficiency. The same association was also identified by the multiple regression model (Table 5), which indicated that sugar content was the best predictor of the ethanol yield with a statistically significant regression coefficient ($p < 0.01$).

The findings are highly correlated with those of Lam et al. (2022) and Santos et al. (2023), who highlighted that fermentable sugar concentration is the variable with the greatest impact on lignocellulosic bioethanol systems. Mechanistically, hexose sugars such as glucose are favoured as fuels in *Saccharomyces cerevisiae*, and increased sugar supply improves ethanol production by overcoming metabolic constraints in the fermentation process (Zhang et al., 2021; Ahmed et al., 2022). The strong statistical correlation observed in this study provides quantitative support for the established theory of fermentation and underscores the importance of appropriate pretreatment and hydrolysis methods.

In addition to sugar availability, fermentation pH has been found to be a secondary factor with a statistically significant effect on ethanol yield. Table 1 shows that in yam peels, the pH during fermentation was 4.8, which is within the optimal range of 4.0 to 5.0, where *Saccharomyces cerevisiae* activity occurs. Plantain peels, on the other hand, showed an acidic pH of 3.6, whereas potato peels had a slightly alkaline pH of 5.1. Correlation analysis (Table 4) suggested a medium positive dependence between pH and ethanol yield, whereas regression analysis (Table 5) suggested pH as a considerable predictor ($p < 0.05$).

These findings are also consistent with Tsegaye et al. (2020), who reported a decrease in fermentation efficiency in an excessively acidic environment associated with yeast stress and enzyme inhibition. Zabed et al. (2020) also noted that yeast membrane integrity can be compromised by deviations from optimal pH ranges, thereby slowing sugar uptake rates. This suggests that the higher yeast concentration resulting from favourable pH conditions may have contributed to the improved performance of yam peels, as yeast metabolism and enzyme activities likely remained stable throughout fermentation.

The poor performance of potato peels relative to plantain peels was also a focus of this study, as the former had higher sugar content. Table 1 shows that potato peels contained 2 percent sugar, compared with 1.5 percent in plantain peels, but yielded less ethanol (16 percent versus 22 percent). This post hoc, statistically confirmed diversification (Table 3) indicates the presence of factors other than access to simple sugars that inhibit prey diversity.

According to Barbana et al. (2020), potato peels also contain phenolic compounds and residual glycoalkaloids that have the potential to inhibit yeast metabolism and minimise the effectiveness of this process. Maroufpour et al. (2020) also reported that incomplete detoxification following acid hydrolysis could enhance the inhibitory effects in potato-based substrates. Such inhibitory effects likely limited yeast activity in the current study, thereby offsetting the potential advantage of increased sugar levels and reducing ethanol production. The current observation demonstrates the need to optimise pretreatment on a per-feedstock basis rather than using standardised processing methods. The implementation of statistical modelling in this research provides significant methodological and practical contributions to agro-waste-based bioethanol studies.

The regression model estimated in Table 5 had a high coefficient of determination ($R^2 = 0.88$), indicating that sugar content and pH accounted for a significant proportion of the variation in ethanol yield. This explanatory power is not commonly found in small-scale bioethanol studies that rely solely on descriptive comparisons (Sharma et al., 2024). Rodionova and colleagues pointed out that predictive modelling is needed to move bioethanol manufacturing beyond the experimental stage to systems that can be scaled and optimised (2024). This work responds to the call by demonstrating how laboratory information can be converted into a decision-support instrument using inferential and predictive statistics to optimise processes and feedstock selection.

The statistically significant inhibition of the potato peels performance despite moderate sugar level shows that there is a decoupling between the availability of the substrate and the efficiency of fermentation. This deviation validates the assumption that inhibitory substances, e.g., glycoalkaloids and phenolics, have a suppressive impact on the metabolism of yeast, which essentially decreases the effectiveness of available sugars. The statistical difference found during Tukey comparisons thus indicates biochemical inhibition and not the lack of substrates.

In terms of sustainability and waste-to-energy needs, a feedstock ranking based on statistical analysis (Table 6) provides a clear direction for resource prioritisation. Yam peels are the best feedstock option because of their excellent ethanol yield, sugar content, and pH conditions. Although less efficient than other materials, plantain peels exhibited moderate performance and remain viable candidates, provided that better pretreatment or co-fermentation procedures are implemented. Potato peels are the least efficient as a pure feedstock but can be value-added when incorporated into a blended feedstock, where their inhibitory properties are mitigated. These results are consistent with those of Sarkar et al. (2022) and Santos et al. (2023), who suggested that integrated waste valorization models should utilise a combination of various agro-residues to improve overall bioethanol productivity while reducing the environmental impact of waste. In general, this discussion indicates that the interplay among biochemical composition, fermentation conditions, and inhibitory effects during bioethanol production from Agro-waste peels is a complex factor that can be quantified using statistical tools. The current study shifts agro-waste bioethanol research from descriptive studies to analytically rigorous, optimization-oriented science by directly triangulating experimental data with inferential statistics and the available literature.

5. LIMITATIONS OF THE STUDY

The key strength of this study is that it combines controlled experimental production of bioethanol with inferential and predictive statistical analyses, thereby advancing the field beyond conventional descriptive agro-waste fermentation studies. Using one-way ANOVA, post hoc tests, correlation analysis, and multiple linear regression on raw experimental data, the study provides statistically significant evidence of a highly significant difference in ethanol yield among yam, plantain, and potato peels, thereby enhancing the rigour and reproducibility of the analysis. The comparative design ensured that all feedstocks underwent the same pretreatment, fermentation, and distillation processes, and that differences observed were attributable to inherent feedstock characteristics rather than procedural variation. Another strength is the explicit recognition of sugar content and pH as statistically significant predictors of ethanol yield, supported by the high explanatory power of a regression model that provides meaningful decision-support information for process optimization.

Additionally, the research is relevant to sustainability issues, as it focuses on locally available agro-waste resources, thereby strengthening the study's applicability to waste valorization, renewable energy generation, and circular bioeconomy models, particularly in developing countries. Nevertheless, despite these strong points, one should note some limitations. The experiments were performed at the laboratory scale, with a limited number of observations, which reduced the number of replicates available for statistical tests and could affect the precision of the variance estimates.

The inability to assess other microorganisms or engineered microorganisms capable of fermenting pentose sugars was also due to the use of a single microorganism (*Saccharomyces cerevisiae*), which may limit ethanol production. Additionally, inhibitor formation was not quantified despite the use of acid and enzymatic hydrolysis, which could have affected fermentation activity, particularly in potato peel residues. Simple distillation under laboratory conditions was the only type of distillation that could be performed, which may not have achieved the purity of fuel-grade ethanol and may introduce measurement imprecision in determining the yield. Lastly, the paper lacked techno-economic analysis and life-cycle assessment, which would have constrained the direct implications for economic viability and the environmental impact of industrial magnitude. The limitations, however, do not compromise the validity of the results but provide clear guidelines for future research and scale-up studies.

6. CONCLUSIONS

By statistically ranking agro-waste feedstocks by fermentation efficiency, this study provides an empirical basis for prioritizing waste streams in circular bioeconomy planning, enabling policymakers to align waste-reduction goals with renewable energy-generation efficiency. This paper presents a statistically sound, experimentally based analysis of bioethanol production from yam peels, plantain peels, and potato peels, demonstrating that agro-waste feedstocks differ in their fermentative performance and ethanol production capacity. The findings supported the above hypothesis: yam peels are the most effective substrate, with ethanol production highest in the controlled medium, followed by plantain and potato peels. This was confirmed using inferential statistics, but not by a descriptive comparison.

Notably, the experiment identified fermentable sugar content as the strongest predictor of ethanol yield, with fermentation pH as the second, but important, predictor, thereby quantitatively supporting long-standing theoretical assumptions in bioethanol fermentation science. The regression modelling experiments also indicated that a significant proportion of the yield change could be attributed to quantifiable physicochemical variables, underscoring the utility of data-driven methods in biofuel research. In addition to technical results, the paper highlights the potential of using agro-waste as an alternative source of sustainable energy to mitigate environmental degradation and optimize resource use, particularly in areas where the bulk of yam, plantain, and potato production occurs.

This work addresses a critical research methodology gap in the field of agro-waste-to-bioethanol research, beyond yield reporting, by statistically testing non-randomised process detection processes. The results indicate that laboratory-level bioethanol experiments and procedures can be converted into optimization procedures and decision-quality research when supported by rigorous statistical analysis. In general, the article advances second-generation bioethanol research by presenting clear data indicating that feedstock choice, pretreatment processes, and control of fermentation conditions are paramount for optimizing ethanol production. These lessons provide a strong foundation for future scale-up, modelling, and policy-driven bioenvironment solutions in initiatives that incorporate waste-to-energy into sustainable development plans.

Recommendations

Recommendations in terms of policy, technical, and research are presented based on the findings of this study. Policymakers and practitioners in the energy sector can view agro-waste-based bioethanol production as a valuable component of a renewable energy portfolio and make it a priority in national waste management and bioenergy policies. Research grants, pilot-plant grants, and waste-to-energy policies may be implemented to stimulate the use of the best fermentation processes, i.e., those using yam and plantain peels, which have demonstrated better performance and minimize environmental waste whilst increasing local food security. In the technical approach, future bioethanol production initiatives must focus on feedstocks that are rich in fermentable sugars and have desirable pH profiles, with yam peels as a key target. It is suggested that pretreatment processes, including technological advances in enzymatic hydrolysis and detoxification techniques, be optimized to reduce the effects of inhibitors, particularly in potato peel substrates.

There is an opportunity to increase ethanol yield and process stability by adopting co-fermentation or feedstock blending strategies. Additionally, the transition from primitive distillation to advanced purification technologies would improve ethanol quality and enhance measurement accuracy. In future research, larger sample sizes and more rigorous experimental designs should be incorporated to enhance statistical power and enable more complex modelling approaches, such as response surface methodology and multivariate optimisation. Alternatives, such as genetically improved microbial strains that ferment hexose and pentose sugars, should be further explored to maximise substrate utilisation. Lastly, it would be advisable to incorporate the techno-economic investigation of Erlkonig and life-cycle analysis in future studies to provide a detailed account of the economic and environmental sustainability of agro-waste-based bioethanol processing. Together, the recommendations are intended to advance agro-waste bioethanol production from laboratory experimentation to a policy-relevant, scalable energy production.

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