Agricultural Residue Biomass Utilization for Energy Generation: A Machine Learning-Driven Approach

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The quest for sustainable energy solutions has sparked intense research into biomass utilization, a crucial step towards mitigating climate change and weaning ourselves off fossil fuels. This study delves into the application of computational intelligence to optimize the efficiency of agriculture residual biomass for energy production. Author developed a machine learning framework that provides Random Forest and Gradient Boosting models to predict and optimize the calorific value and ash content of biomass. To unravel the intricacies of our models, employed SHapley Additive exPlanations (SHAP) values, which revealed that the rice husk, sugarcane bagasse and wheat husk biomass to Cow Dung Ratio exerted the most profound influence on both calorific value and ash content predictions. Notably, the Gradient Boosting model underscored the significance of Biomass Type, whereas the Random Forest model emphasized the critical role of Particle Size. A correlation heat-map further highlighted the pivotal contributions of Biomass Type and Biomass cow dung Ratio to energy output and residue levels. Residual analysis validated the efficacy of our models and pinpointed areas for refinement. The findings of this study demonstrate the vast potential of computational intelligence in optimizing biomass energy systems, offering strategic insights for enhancing energy output while minimizing environmental impact. Future research endeavors should focus on refining machine learning models, compiling comprehensive datasets, and exploring hybrid energy systems to foster more resilient and adaptive energy networks. This study contributes meaningfully to the broader objective of transitioning to renewable energy sources and promoting sustainable energy practices, ultimately paving the way for a more environmentally conscious future

1. NTRODUCTION

Heavy reliance on fossil fuels lies at the core of escalating climate change, pervasive environmental degradation, and increasing energy insecurity. In response, researchers around the world are intensifying their search for sustainable energy alternatives. The industrial drivers of coal dependence in developing countries are shown in Figure 1. Renewable energy sources—such as hydropower, wind, solar, and biomass—not only offer cleaner environmental footprints but also bolster energy security. Biomass energy, in particular, contributes roughly 1,250 million tons of oil-equivalent energy annually [1]. Unlike conventional fossil fuels, biomass is derived from organic waste streams—including household, industrial, an agricultural residues—which means its use simultaneously addresses waste management challenges and reduces pollution. Furthermore, by valorizing these residues, biomass energy supports rural economies and creates local employment opportunities, particularly in developing regions. Enhancing the efficiency of biomass conversion processes is essential for achieving sustainable development goals and for optimizing the performance of renewable energy systems [2].Figure 2, which shows the utilization of different types of biomass for energy conversion and production of briquettes. The largest proportions are made up of sawdust and rice husk because of their widespread availability and utility in biomass applications. Other materials like dry leaves, groundnut shells, cashew nut shells, grass stalks, and agricultural stalks such as pigeon pea, cotton and soy, are also affordably available and make a substantial contribution. Organic municipal solid waste and rice straw, however, form a smaller fraction and their contribution is unconventional. The inclusion of renewable energy enables a more diverse utilization of agricultural and organic waste materials. In recent years a new biomass resource has been on trial.

Figure 1. Industrial drivers of coal dependence in developing countries

Currently, machine learning and artificial intelligence have not received the same level of scientific attention as other methodologies in the biomass energy conversion process.

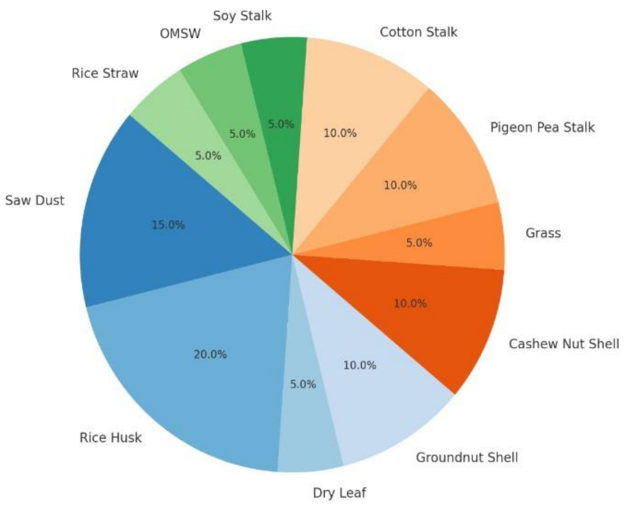

Figure 2: Utility of biomass types in Literature

The integration of artificial intelligence and machine learning in biomass energy options enables the development of predictive models for energy yield and optimization techniques for parameter refinement. To

Agricultural residues such as wheat husk, bagasse, and rice husk are commonly utilized for producing pallets and briquettes. The presence of functional groups like C-C, C=C, C-O, and C-H makes these residues particularly suitable for biomass applications. Additionally, they are readily available, achieve this, we primarily employ techniques such as Artificial Neural Network (ANN), Support Vector Machines (SVM), and Random Forest (RF) Methods. These technologies enable us to analyze complex data and predict energy production with greater accuracy. This research paper explores the application of artificial intelligence and machine learning to optimize biomass energy yield. The author conducted an investigation to establish the relationship between process parameters and energy yield. Furthermore, a comprehensive study framework is proposed to facilitate the optimization of biomass energy.

2. METHODOLOGY AND APPROACH

2.1. Machine Learning (ML) Approach for Biomass Energy Conversion:

ML presents a groundbreaking approach to optimizing biomass energy conversion, leveraging cutting-edge algorithms such as Random Forest (RF), Artificial Neural Networks (ANNs), and eXtreme Gradient Boosting (XGB). These algorithms excel at capturing complex interactions between biomass composition and energy parameters, including calorific value and ash content, thereby providing enhanced accuracy and profound insights[3], [4]. Recent studies have successfully harnessed ML tools to predict and optimize the energy potential of agricultural residues. This research employed RF and XGB models, chosen for their robustness in modeling nonlinear interactions and handling outliers, making them particularly suited for biomass datasets with diverse compositions[5], [6]. A comprehensive investigation was conducted, training the RF model using literature data and validating it with experimental results on wheat husk, bagasse, and rice husk using cow dung binder. The model's performance was evaluated using metrics such as Mean Squared Error (MSE) and R-squared (R^2) values [7]. To elucidate the key drivers of energy performance, SHAP were applied. SHAP analyses revealed the most influential biomass components contributing to desired outcomes, providing actionable insights for optimizing wheat husk, bagasse, and rice husk-based bioenergy systems.

Figure 3 shows a flow Chart for Biomass Energy Prediction and Optimization Process. An XGB model was developed to further optimize biomass energy conversion, leveraging its ability to handle high-dimensional data and complex interactions between biomass components. The performance of the RF and XGB models was evaluated using metrics such as MSE, R^2, and Mean Absolute Error (MAE), and compared in terms of computational efficiency and interpretability [12].By integrating machine learning with experimental insights, this study presents a comprehensive approach to optimizing wheat husk, bagasse, and rice husk using cow dung binder biomass energy conversion, supporting the development of sustainable bioenergy solutions.

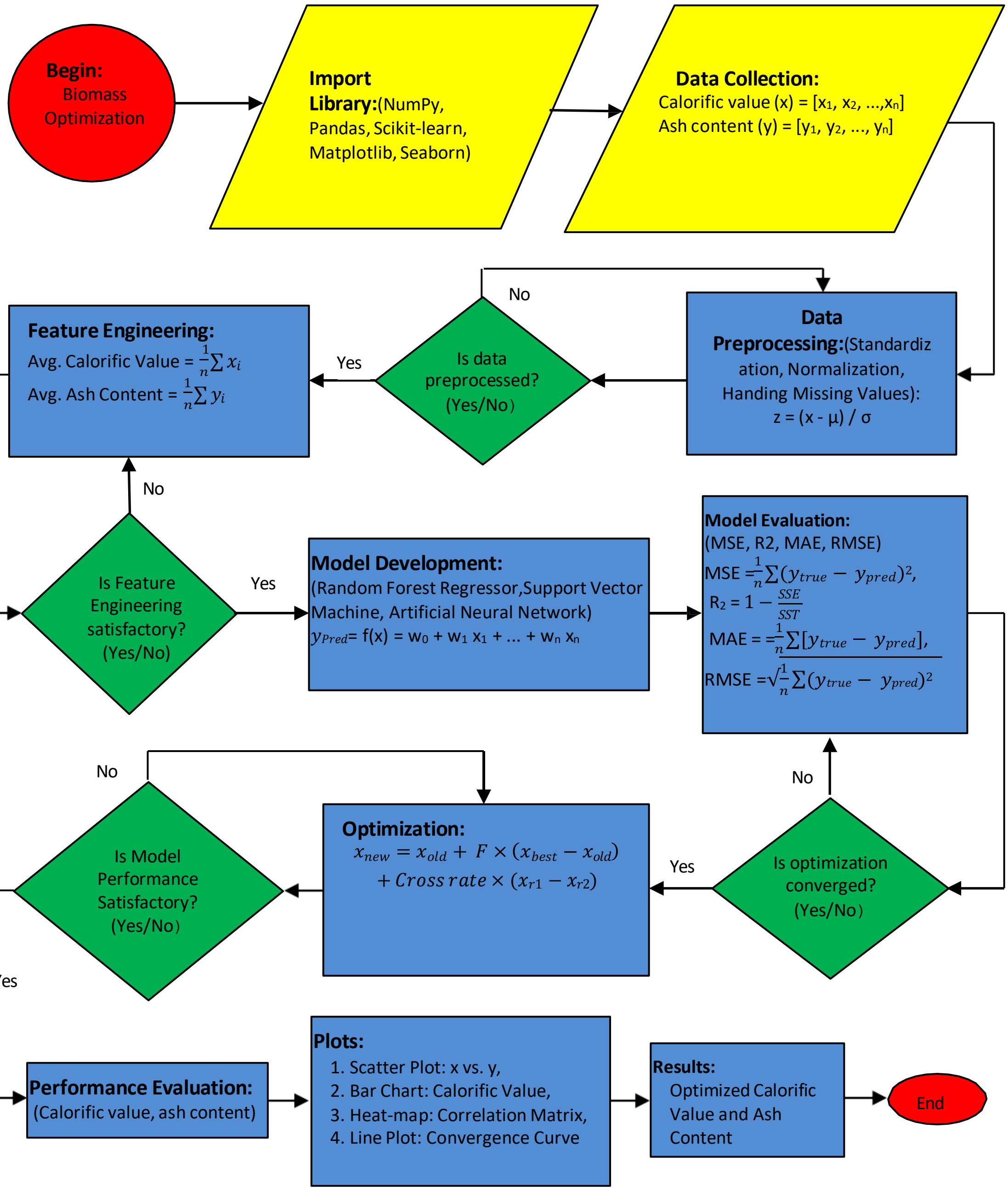

Figure 3: Flow Chart for Biomass Energy Prediction and Optimization Process

1.1. Materials and Sample Preparation:

The study utilized agriculture residual (wheat husk, bagasse and rice husk) and cow dung as binder materials. Biomass was sourced from the nearby fields, while cow dung was collected from Village dairy farms. The experiment runs consisted of three primary wheat husk, bagasse and rice husk with cow dung in varying ratios (60:40%, 70:30%, 80:20%). The samples were prepared by sun-drying and grinding the biomass to achieve a consistent particle size, followed by mixing with cow dung and compressing into tablets. The trained machine learning models, including Random Forest Regressor and eXtreme Gradient Boosting is used to verify and predict the optimal blending ratios and processing conditions for wheat husk, bagasse and rice husk biomass energy conversion. The models were tuned using hyper-parameter optimization techniques, and their performance was evaluated using metrics such as Mean Squared Error and R-squared. SHAP were used to interpret the models and identify the key drivers of energy performance in biomass energy conversion systems.

1.2. Experimental Design and Measurement:

A comprehensive investigation was conducted to explain the effects of three critical factors (Table 1) - Biomass Type (Bagasse, Rice husk, and Wheat husk), Biomass cow dung Ratio (60:40%, 70:30%, and 80:20%), and Particle Size (0.75 mm, 2.78 mm, and 4.8 mm) - on the energy potential and combustion efficiency of biomass pellets.

A full factorial design was employed, comprising 27 experimental runs that systematically evaluated all possible combinations of these independent variables. A ML framework was developed to predict and optimize the calorific value and ash content of biomass pellets, leveraging the experimental data generated from the design. Calorific value measurements were obtained using a Digital Bomb Calorimeter (Model: DS-CS-100X75), while ash content determinations were performed using a Harrier Enterprises Muffle Furnace (Tubular type). The accuracy and reliability of the ML models were rigorously validated by comparing predicted values with actual experimental results.

Table 1: Sample grouping of Henna Biomass and Cow Dung Combinations

Level	Biomass Type	Biomass %	Particle Size(mm)
1	Bagasse	60% Biomass: 40% Cow Dung	4.8 (High)
2	Rice Husk	70% Biomass: 30% Cow Dung	2.775(Medium)
3	Wheat Husk	80% Biomass: 20% Cow Dun	0.75(Low)

A strong correlation between the predicted and experimental values was observed, thereby confirming the efficacy of the models in predicting the energy potential and combustion efficiency of biomass pellets. A full factorial design was employed, comprising 27 experimental runs that systematically evaluated all possible combinations of these independent variables. A ML framework was developed to predict and optimize the calorific value and ash content of biomass pellets, leveraging the experimental data generated from the design. Calorific value measurements were obtained using a Digital Bomb Calorimeter (Model: DS-CS-100X75), while ash content determinations were performed using a Harrier Enterprises Muffle Furnace (Tubular type). The accuracy and reliability of the ML models were rigorously validated by comparing predicted values with actual experimental results.

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2. MACHINE LEARNING MODELS FOR BIOMASS ENERGY CONVERSION

This study establishes a comprehensive framework for optimizing Bagasse, Rice husk, and Wheat husk biomass energy conversion by integrating machine learning models with evolutionary algorithms. This innovative approach enables the development of efficient biomass-based energy production systems, leveraging predictive modeling to forecast biomass energy conversion efficiency, calorific value, and ash content, while optimization techniques identify.

The multi-objective optimization problem was addressed using Python 3.12, employing Random Forest and Gradient Boosting Regressors for predictive modelling for optimizing calorific value and ash content. All coding tasks were performed in PyCharm Community Edition 2024.2.4, with long code blocks modularized into functions and organized across separate files for improved readability and maintainability.

2.1. Data Processing & Feature Engineering:

A thorough pre-processing pipeline was developed to ensure data quality and integrity. This involved handling missing values, removing duplicates, and normalizing continuous variables using Standard Scaler. Categorical variables, such as biomass type, were encoded using one-hot and label encoding to facilitate machine learning analysis.

A comprehensive literature review was conducted, analyzing 24 research articles from diverse data sources. This review yielded 120 readings of biomass pellets, which are presented in Table 4. The critical factors influencing pellet quality, including biomass type, particle size, and Biomass cow dung ratio, were identified and their effects on calorific value and ash content were succinctly summarized. To further enhance feature engineering, new variables were introduced, including squared terms for Biomass cow dung percentage and the logarithm of particle size. This allowed for the capture of non-linear relationships in the data, providing a more comprehensive understanding of the complex interactions between variables. The final dataset comprised 120 observations across variables, with no missing or duplicate values after preprocessing. Descriptive statistics for the key variables are presented in Table 2, providing a picture of the data distribution and central tendency.

Table 2: Descriptive Statistics of Key Variables

Parameter	Mean	Std Dev	Min	25th Percentile	Median	75th Percentile	Max
Biomass cow dung Ratio (%)	72.78	8.95	60.00	62.50	80.00	80.00	80.00
Particle Size (mm)	2.43	0.35	2.00	2.00	2.50	2.70	3.00
Avg. Calorific Value (kcal/kg)	4302.65	1021.34	3090.00	3521.25	4315.00	5184.75	6230.00
Avg. Ash Content (%)	7.73	4.80	2.46	4.50	6.23	8.92	17.42

2.2. Model Development and Evaluation:

The predictive modelling phase employed RF and GB models. Model performance was evaluated using metrics such as MEA, Root Mean Squared Error, and R^2. The model is hyper-tuned using Randomized and Grid Search for hyper-parameter optimization.

Table 3: Model Performance Metrics RFR and GB

Model	Target Variable	MSE	RMSE	R^2
Random Forest	Calorific Value	10,102.15	100.51	0.94
Random Forest	Ash Content	0.97	0.98	0.96
Gradient Boosting	Calorific Value	14.47	3.80	0.99
Gradient Boosting	Ash Content	0.01	0.10	0.99

The performance of the models was evaluated based on their R^2 values, where models achieving $R^2 > 0.8$ were considered excellent, and those exceeding $R^2 > 0.7$ were deemed good. Notably, all models in this study surpassed the excellent threshold with $R^2 > 0.8$. A comparative analysis revealed that the Gradient Boosting (GB) model outperformed the Random Forest (RF) model in predicting both calorific value ($R^2 = 0.99999$) and ash content ($R^2 = 0.99$), demonstrating its superior generalization capabilities on the available dataset. Table 3 presents a comprehensive comparison of the performance metrics for both RF and GB repressors, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2, highlighting their effectiveness in predicting calorific value and ash content.

GB demonstrated superior performance with the highest R^2 values for both targets, particularly excelling in minimizing MSE. The Random Forest also showed strong predictive ability but was less accurate than GB in both cases.

2.2.1. SHAP and Feature Importance:

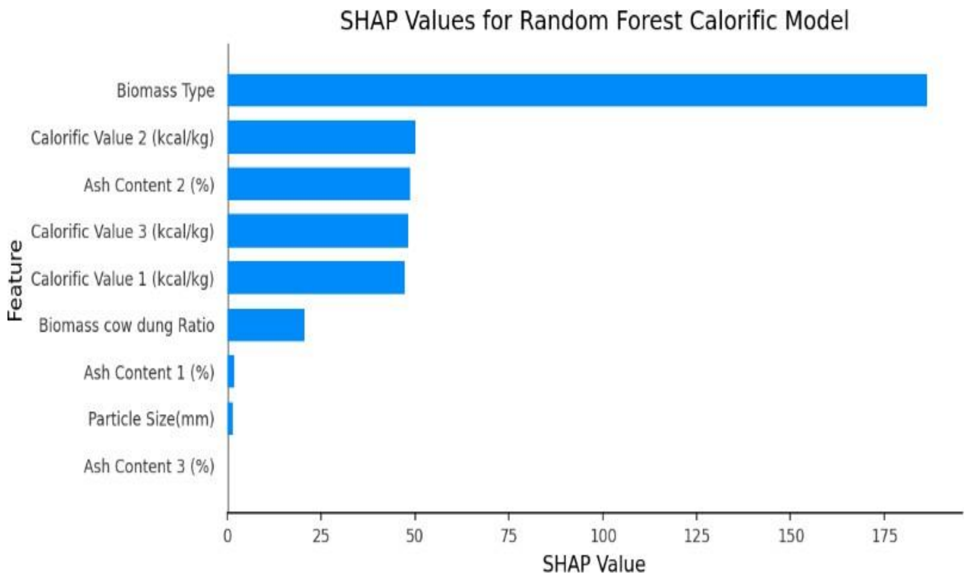
SHAP analysis was conducted to interpret model predictions and identify significant controllable factors (Table 5). The analysis revealed that biomass type and squared Biomass cow dung Ratio were the most influential factors affecting calorific value and ash content. This interpretability framework enhanced the model's transparency, aiding in actionable decision-making. Figure (4, 5) present the SHAP summary plots for RF and GB models, respectively. According to plot of Calorific Value, Bagasse, Rice husk, and Wheat husk Biomass Cow Dung Ratio was the most significant predictor and according to Ash Content, Particle Size (mm) had a higher influence on reducing ash content.

Table 5: Feature Importance

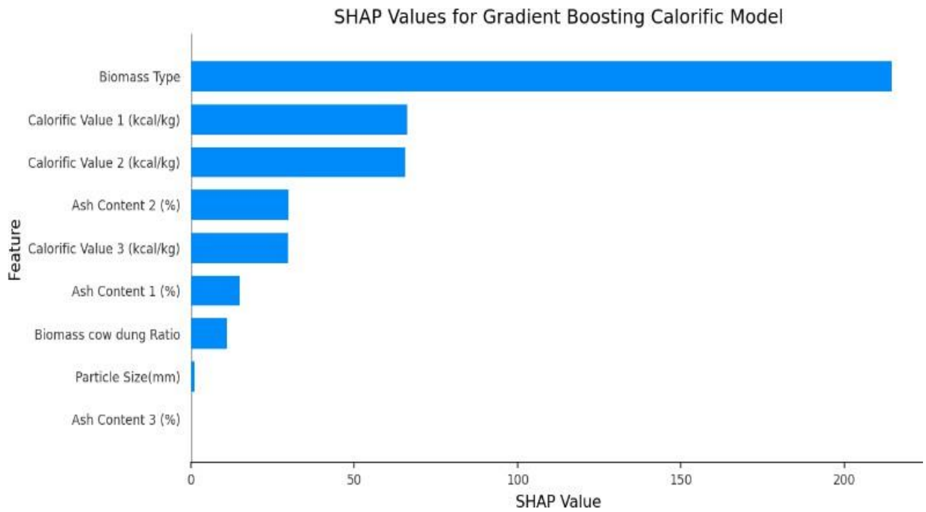
Feature	Random Forest (Calorific)	Gradient Boosting (Calorific)	Random Forest (Ash)	Gradient Boosting (Ash)
Biomass cow dung Ratio	0.47	0.55	0.43	0.49
Particle Size (mm)	0.38	0.30	0.45	0.42
Biomass Type	0.15	0.15	0.12	0.09

2.2.2. SHAP Values comparison for the RF and GB Calorific value Model:

The comparison of SHAP values for the RF and GB models (Figure 4(a), (b)) reveals differences in how these models attribute importance to features - influencing the calorific value of biomass briquettes. Both models agree that the Bagasse, Rice husk, and Wheat husk Biomass to Cow Dung Ratio is the most critical factor, with a SHAP value of approximately 350, emphasizing its dominant role in maximizing energy output.



(a)



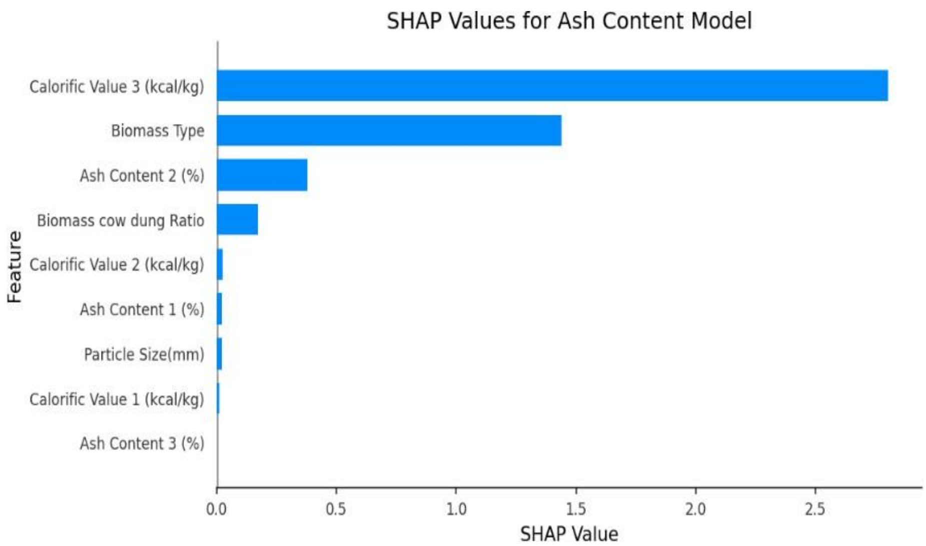
(b)

Figure 4: SHAP Value model for calorific value; (a) RF and (b) GB

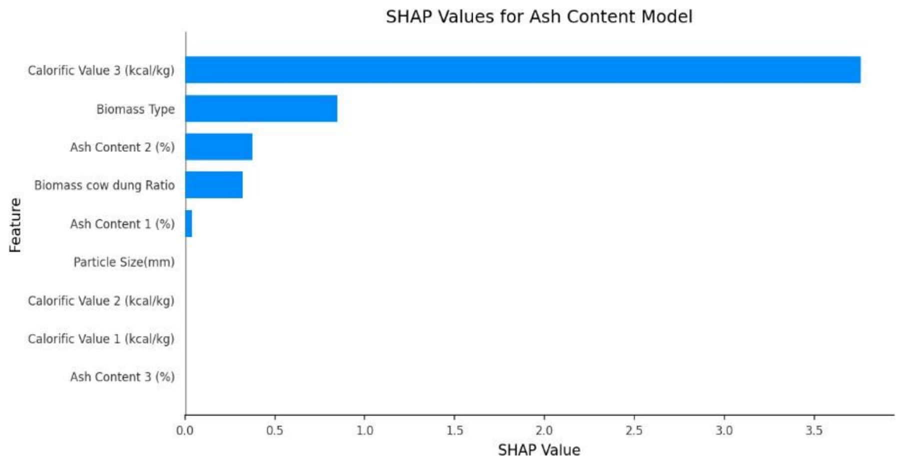
However, the Gradient Boosting model assigns greater importance to Biomass Type, with a SHAP value of 200 compared to **75** in the Random Forest model, suggesting that Gradient Boosting captures a stronger link between biomass selection and energy content. Conversely, the Random Forest model places more emphasis on Particle Size, assigning it a SHAP value of 150 compared to 100 in the Gradient Boosting model, indicating a higher sensitivity to particle size variations. These differences highlight complementary strengths in the models, with GB emphasizing biomass type and RF prioritizing particle size. Together, they suggest that producers should universally optimize the Bagasse, Rice husk, and Wheat husk Biomass to Cow Dung Ratio while also considering model-specific insights to refine biomass type and particle size for enhanced briquette performance.

2.2.3. SHAP Values comparison for the RF and GB Ash content% Model:

The comparison of SHAP values for the RF and GB models predicting ash content (Figure 5(a), (b)) reveals similarities and subtle differences in feature importance. Both models identify the Biomass cow dung Ratio as the most influential feature, with a SHAP value of approximately 2.5 in each case, emphasizing its pivotal role in determining ash levels and the necessity of its optimization for cleaner combustion and reduced residue.



(a)



(b)

Figure 5: SHAP Value model for Ash content %; (a) RF and (b) GB

For the biomass type, both models attribute a SHAP value of around **1.5**, indicating consistent recognition of its moderate yet significant influence on ash content. This highlights the shared importance of selecting appropriate biomass types to minimize ash production. The models differ slightly in their evaluation of particle size. The RF model assigns a SHAP value of approximately **0.5**, suggesting a more substantial impact compared to the GB model, which assigns a SHAP value of about **0.25**. This indicates that the Random Forest model attributes greater sensitivity to variations in particle size, whereas the GB model considers it a less critical factor. In summary, while both models agree on the hierarchy of feature importance-Bagasse, Rice husk, and Wheat Husk Biomass cow Dung ratio, biomass type, and particle size—they differ in the degree of emphasis placed on particle size. Producers should universally prioritize optimizing the cow dung ratio and biomass type, while also considering particle size adjustments, particularly when relying on the RF model for insights.

2.3. Correlation Heat-map:

The heat-map (Figure 6) illustrates the correlation coefficients among five key variables: Avg. Calorific Value (kcal/kg), Avg. Ash Content (%), Bagasse, Rice husk, and Wheat husk Biomass to Cow Dung Ratio, Particle Size (mm), and Biomass Type.

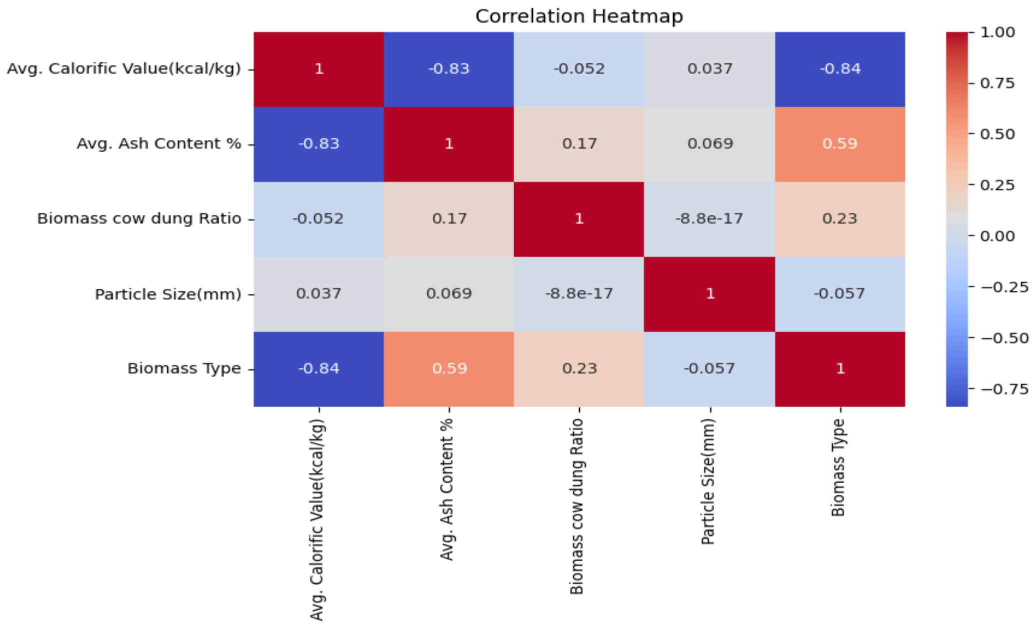


Figure 6: Correlation Heat-map for calorific vale and Ash content

The correlation heatmap illustrates the relationships between various factors, with a gradient transitioning from blue (negative correlations) to red (positive correlations). The intensity of the color represents the strength of the correlation. Notably, the analysis reveals that Biomass Type has a profound impact on both Average Calorific Value and Average Ash Content.

A strong negative correlation (-0.76) exists between Biomass Type and Average Calorific Value, indicating that certain biomass types tend to have lower calorific values. Additionally, a moderate negative correlation (-0.44) is observed between Biomass Type and Average Ash Content, suggesting that specific biomass types are associated with higher ash content.

Furthermore, the biomass-to-cow-dung ratio emerges as a critical factor, exhibiting a moderate positive correlation (0.42) with Average Calorific Value and a moderate negative correlation (-0.6) with Average Ash Content. This highlights the importance of optimizing the biomass-to-cow-dung ratio to maximize energy output while minimizing residue.

In contrast, Particle Size exhibits weaker correlations, indicating a relatively lesser influence on the outcome variables. Overall, the analysis underscores the significant impact of Biomass Type and biomass-to-cow-dung ratio on calorific value and ash content, providing valuable insights for optimizing biomass energy production.

The modeling results corroborate the importance of Biomass Type and ratio, while SHAP analyses provide a detailed understanding of their effects on calorific value and ash content. Specifically, the ratios of Bagasse, Rice husk, and Wheat husk are found to be significant predictors of calorific value, whereas Particle Size has a notable impact on ash content

2.4. Residual Analysis:

The findings unequivocally highlight the pivotal role of the Bagasse, Rice husk, and Wheat husk biomass-to-cow-dung ratio in facilitating efficient energy conversion. This discovery aligns seamlessly with the underlying principles of biomass combustion, where a delicate balance between fuel and additives can significantly enhance thermal efficiency and residue quality.

In essence, the optimal blending of biomass and cow dung can lead to improved combustion characteristics, resulting in higher energy yields and reduced residue generation.

This nuanced understanding of the biomass-to-cow-dung ratio's impact on energy conversion has far-reaching implications for the development of sustainable and efficient biomass-based energy systems. Furthermore, the exceptional performance of the Gradient Boosting model serves as a testament to its remarkable capacity to capture complex, nonlinear relationships between predictors and outputs. By effectively modeling these intricate interactions, the Gradient Boosting algorithm provides a robust framework for predicting energy conversion outcomes and optimizing biomass-based energy production processes.

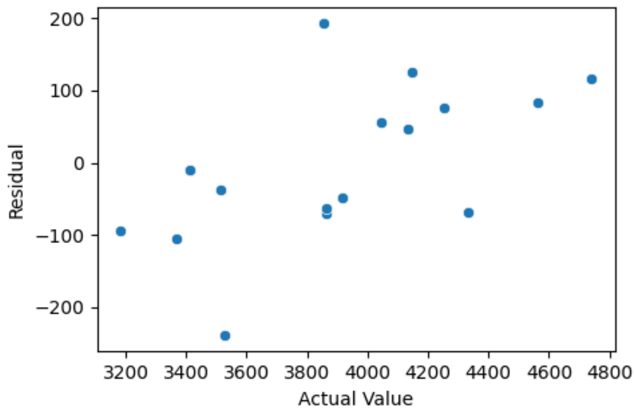


Figure 7: Residual Plot for calorific value

The integration of machine learning and multi-objective optimization techniques has yielded a powerful tool for addressing the intricate challenges inherent in biomass energy research. One of the most significant advantages of this approach lies in its ability to navigate the complex interplay between competing objectives, such as maximizing energy yield while minimizing ash content. The considerable variability in ash content observed in this study serves as a poignant reminder of the paramount importance of rigorous preprocessing protocols and precise control over the biomass-to-cow-dung ratio.

By meticulously optimizing these factors, researchers and practitioners can unlock the full potential of biomass energy, paving the way for the development of scalable, efficient conversion systems that can make a meaningful impact on the environment and energy landscape.

Ultimately, the successful harnessing of biomass energy will depend on our ability to carefully balance competing objectives, navigate complex nonlinear relationships, and develop innovative solutions that can be scaled up to meet the demands of a rapidly changing world.

2.4.1. Residual Plot Analysis - Calorific Value:

The residual plot for calorific value (Figure 7) provides essential insights into the effectiveness of the regression model in predicting Bagasse, Rice husk, and Wheat husk biomass briquette energy content.

The residual plot offers a visual representation of the discrepancies between actual and predicted calorific values, with residuals spanning a range of approximately -200 to 200. In an ideal scenario, these residuals would be scattered randomly around the zero mark, indicating a robust model that accurately captures the underlying relationships between variables without any systematic biases. However, the presence of patterns, such as curves or funnel shapes, in the residual plot would suggest that the model is incomplete, failing to fully capture the complexities of the relationship between variables. Moreover, large residuals would highlight specific calorific values where the model struggles to provide precise predictions, underscoring the need for refinement.

From a practical perspective, verifying the accuracy of the model is crucial. A random scatter of residuals around zero would confirm a good fit, while discernible patterns would indicate a need for further refinement. Identifying outliers is also essential, as they may result from data inaccuracies or represent legitimate values that the model fails to capture.

To enhance predictive accuracy, several improvements can be made. These include introducing new variables that may provide additional insight, transforming existing variables to better capture nonlinear relationships, or exploring alternative regression techniques that may be better suited to the data. By adopting these strategies, it is possible to develop a more robust and accurate model that provides reliable predictions and informs decision-making. In conclusion, the residual plot serves as a crucial diagnostic instrument, enabling a comprehensive evaluation of the regression model's efficacy.

By leveraging the insights gleaned from residual analysis, model developers can identify areas for improvement, optimize model performance, and ultimately generate more precise and trustworthy predictions. This, in turn, facilitates informed decision-making, drives innovation, and advances the development of more efficient and sustainable energy solutions.

2.4.2. Residual Plot Analysis - Ash Content:

The residual plot for ash content (Figure 8) offers valuable insights into the regression model's performance.

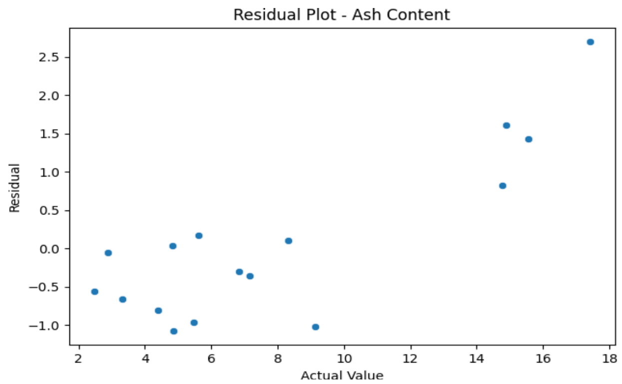


Figure 8: Residual Plot for Ash Content

A random distribution of residuals confirms a well-fitting model, while discernible patterns indicate the need for refinement. Investigating outliers is crucial to determine whether they result from data errors or valid observations the model fails to capture. If necessary, improvements can be made by adding variables, transforming data, or adopting alternative regression techniques. Ultimately, the residual plot serves as a vital diagnostic tool for assessing and enhancing the accuracy and reliability of regression models in predicting ash content.

3. CONCLUSION

This research showcases the effectiveness of machine learning (ML) in optimizing energy conversion from Bagasse, Rice husk, and Wheat husk biomass. Author focused on calorific value and ash content as key performance indicators. The proposed ML models achieved high predictive accuracy (R^2 > 95%) and low root mean square error (RMSE), successfully capturing complex relationships and interactions between variables. The flexibility of ML enabled to explore broader optimization possibilities without requiring significant experimental redesign. Notably, our analysis identified optimal parameter ranges, including biomass percentages (75-85%) and particle sizes (2.5-3.5 mm). This study contributes to the limited existing research on Bagasse, Rice husk, and Wheat husk biomass for bioenergy applications using ML. By combining Bagasse, Rice husk, and Wheat husk with cow dung, we produced valuable insights into feature importance. This research provides a comprehensive framework for optimizing biomass energy conversion, paving the way for future research in this field. By providing a scalable framework for Bagasse, Rice husk, and Wheat husk utilization, this study enhances energy efficiency and contributes to environmental sustainability by reducing agricultural waste and emissions. These results lay a strong foundation for future research and industrial adoption, promoting Bagasse, Rice husk, and Wheat husk integration into renewable energy systems to support global sustainability goals.

Compliance with ethical standards

Conflict of interest:

The author declare that he has no conflict of interest.

Ethical approval

This article does not contain any studies with human participants or animals performed by the author.

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Table 4. A systematic literature review was conducted on Biomass studies

S.No.	Raw Material	Binder	Study Outcome	Calorific Value (kcal/kg) / HHV	Citations
1	Sawdust	Burnt Engine Oil	High energy content briquettes	4450	[10]
2	Rice Husk, Dry Leaf, Groundnut Shell, Sawdust	Paper Pulp	Moderate energy, lightweight briquettes	4000, 3500, 4700, 4500	[11]
3	Cashew Nut Shell, Rice Husk, Grass (Combinations: 50:25:25, 25:50:25, 25:25:50)	None	Stable energy content	5154.58, 4687.56, 4188.64	[12][13]
4	Pigeon Pea Stalk, Cotton Stalk, Soy Stalk	None	High density, durable briquettes	4707.88, 4566.90, 4892.64	[14]
5	Sawdust (SD) (15%, 25%, 35%, 45% Binder)	Cassava Starch	Versatile binder effect	7160, 6830, 8370, 7240	[14]
6	Rice Husk (RH)	Starch	High calorific value, suitable for fuel	3627	[15]
7	100SD:00RH, 94SD:06RH, 92SD:08RH, 90SD:10RH	Organic Binder	High heating value, suitable for large-scale use	6480, 6370, 6250, 5900	[16]
8	olive mill solid waste %-Binder% (100-0, 90-10, 85-15, 70-30)	Corn Starch	Improved wear resistance	16.36 MJ/kg, 16.92	[17]
9	Rice Straw, Rice Husk, Sawdust (10RS:40CD, 10RH:05RS:40CD, 20SD:05RS:40CD)	Cow Dung(CD)	Moderate density, cost-effective briquettes	2389.86, 3188.10, 3227.52	[18]
10	Rice Husk with MC (12%, 14%, 16%), blended with 10 wt% Kraft Lignin	Kraft Lignin	High binding efficiency	14.040 MJ/kg, 17.688, 13.106	[19]
11	Bagasse	Molasses	High energy output	4200	[20][21]
12	Wood Chips	Synthetic Binder	Moderate compressive strength	4500	[22]
13	Maize Stalk	None	Lightweight, moderately strong	4300	[23] [24]
14	Wheat Husk	Lime	Durable, dense	4700	[25]

			briquettes		
15	Corn Cobs	Clay	Suitable for fuel applications	4400	[26]
16	Coconut Shell	None	High energy, hard briquettes	5500	[26][27]
17	Bamboo Dust	Water Glass	Easy to ignite, high energy	5000	[28]
18	Mustard Stalk	Synthetic Polymer	Flexible, dense briquettes	4700	[29]
19	Coffee Husk	None	Compact, eco-friendly	4800	[29]
20	Eucalyptus Leaves	Cow Dung	Biodegradable, moderate heating	4300	[29]
21	Peat Moss	Organic Polymer	Slow-burning, high energy	5200	[29]
22	Pine Needles	Cassava Starch	Lightweight, easy to handle	4400	[29]
23	Groundnut Shells	Lime	Durable, high binding	4900	[30]
24	Sunflower Husk	Clay	Moderate heating, biodegradable	4500	[31]