Combustion study of rice husk under different heating rates by integrating thermogravimetric analysis and decision tree regression

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Abstract. This study investigates the combustion behavior of rice husk using thermogravimetric analysis coupled with decision tree regression. Results indicated that increasing heating rates caused elevated burnout (T_b) and peak temperatures (T_p) while extending the active combustion stage. The optimized decision tree model effectively predicts mass loss, demonstrated by a perfect coefficient of determination (R^2) of 1 with a low root mean square error (RMSE) of 0.1993 on the validation set. The model's robustness suggested its potential for accurate mass loss prediction in rice husk combustion.

1 Introduction

Biomass combustion has emerged as a promising sustainable technology for converting agricultural residues into valuable heat sources. Among various biomass feedstocks, rice husk stands out due to its abundance and relatively high energy content. As a byproduct of rice milling, rice husk is rich in cellulose (38.56%), hemicellulose (18.38%), and lignin (20.12%) [1], rendering it an attractive candidate for the production of thermal and electric energy through steam boilers by combustion process [2]. The combustion process involves the thermal degradation of rice husk in the presence of oxygen, producing heat, carbon dioxide, and water vapor. This heat can be utilized for power generation and industrial processes. Moreover, the combustion of rice husk contributes to waste management and mitigates the environmental impact associated with rice husk disposal, offering a sustainable solution for energy production and resource utilization. Additionally, the ash content produced from rice husk combustion can be managed by incorporating it into construction materials, ceramics production, energy generation, and water filtration, depending on its properties and local requirements.

Thermogravimetric analysis (TGA) is a well-established technique employed to investigate the thermal degradation of materials, such as combustion. It provides quantitative data on mass loss and decomposition stages during biomass combustion. TGA involves heating a sample under controlled atmospheric conditions while continuously monitoring mass changes as a function of temperature or time. This approach enables the identification

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of crucial thermal events, including dehydration, oxidative pyrolysis, and char combustion [3]. Despite its utility in characterizing thermal behavior, TGA is subject to certain limitations. The sophisticated instrumentation required can lead to high operational costs. Moreover, the analysis process can be time-consuming, particularly for in-depth investigations. The interpretation of TGA data necessitates specialized expertise due to the complex nature of the results and the influence of various experimental parameters [4, 5]. Consequently, while TGA remains an indispensable tool for thermal analysis, its practical application may be hindered by these challenges.

In recent years, machine learning (ML) has emerged as a powerful tool for predicting TGA outcomes. By leveraging extensive datasets and sophisticated algorithms, ML models can uncover intricate patterns and relationships within the data that traditional methods often overlook. For example, Hai [6] demonstrated the capability of a neural network model to accurately predict TGA curves during pyrolysis of groundnut shells, achieving a coefficient of determination (R^2) higher than 0.9999 for both training and validation sets. Similarly, Zhong [7] successfully applied a random forest algorithm to predict the thermal degradation behavior of beech wood with an R^2 at the prediction set exceeding 0.9999. These studies highlight the potential of ML to significantly reduce the time and cost associated with experimental TGA while also enhancing predictive accuracy. Moreover, ML's capacity to handle complex, multidimensional data facilitates a deeper understanding of material thermal behavior. This advancement streamlines thermal analysis presents new opportunities for optimizing combustion processes and developing innovative materials.

Therefore, this study introduces a novel approach that combines TGA with ML, specifically decision tree algorithms, to investigate the combustion behavior of rice husk. By integrating TGA with decision tree models, the research aims to analyze the thermal decomposition of rice husk and leverage the predictive power of these models. The decision tree algorithm is chosen for its effectiveness in handling the complex, non-linear relationships typical of combustion processes. This integrated methodology enhances the understanding of combustion behavior and improves the accuracy of predictions under various conditions. By advancing the fusion of ML with traditional thermal analysis techniques, this research paves the way for innovative methods in biomass conversion.

2 Materials and methods

2.1 Material preparation and characterization

Rice grains of RD6 variety, sourced directly from Thai farmers, underwent a parboiling process in the laboratory. The parboiled rice was then milled, and the rice husk byproduct was used. The rice husk obtained from the milling process had a moisture content of 6.98±0.11% (wet basis), thus negating the need for drying. However, prior to the combustion process, the size of the rice husk was reduced. The milled rice husk was then sieved using a mesh size of 0.5 mm. The rice husk powder that passed through the sieve was used as the raw material for the combustion process. The high heating value (HHV) was measured with a bomb calorimeter (C200, IKA, Germany), while proximate analysis (moisture content, volatile matter, fixed carbon, and ash content) was performed using a TGA (TG209F3 Tarsus, Netzsch, Germany), according to the method described by El-Sayed and Mostafa [8].

2.2 Combustion process

TGA (TG209F3 Tarsus, Netzsch, Germany) was employed to investigate the combustion behavior of RD6 rice husk. For each experiment, 12 mg of rice husk was placed in an alumina crucible and subjected to combustion under a mixture of nitrogen and oxygen of 80:20 atmosphere at a 20 ml·min^{-1} flow rate. A constant initial temperature of 30 °C was maintained for two minutes before ramping to 800 °C at heating rates of 10, 20, 30, and 40 °C·min^{-1} to assess the impact of the heating rate on the combustion process. To enhance the reliability and reproducibility of the results, each sample underwent a minimum of two replications.

2.3 Combustion performance determination

Determining the combustion performance index (C_{CI}, %^{2}·min^{-2}·°C^{-2}) using TGA is a critical step in assessing the thermal decomposition characteristics of biomass (Eq. 1). This index integrates multiple parameters derived from TGA data, such as T_i (ignition temperature, °C), T_b (burnout temperature, °C), DTG_{max} (maximum weight loss rate, %·min^{-1}), and DTG_{mean} (average weight loss rate during T_i to T_b, %·min^{-1}).

$$C_{CI} = \frac{\mathrm{DTG_{max}} \times \mathrm{DTG_{mean}}}{T_i^2 \times \mathrm{T_b}} \quad (1)$$

2.4 Mass change prediction during combustion by decision tree regression

Data extraction from TGA results was smoothed and performed within 1 °C intervals, resulting in 741 data points for each heating rate. The data from the four heating rates is then combined and split into training and testing sets in an 80:20 ratio. The analysis starts with loading these datasets, including predictors and response, from Excel files format using pandas, which structures the data for further processing. A decision tree regressor model is employed to predict mass loss using two input variables: temperature and heating rate. The model's hyperparameters are optimized using GridSearchCV, which systematically searches through a specified parameter grid to identify the optimal combination. This grid includes variations in tree depth (None, 5, 10, 15), minimum samples required to split a node (2, 5, 10), and minimum samples required per leaf (1, 2, 4). The best parameters are determined by minimizing the negative mean squared error (MSE) over a 5-fold cross-validation process.

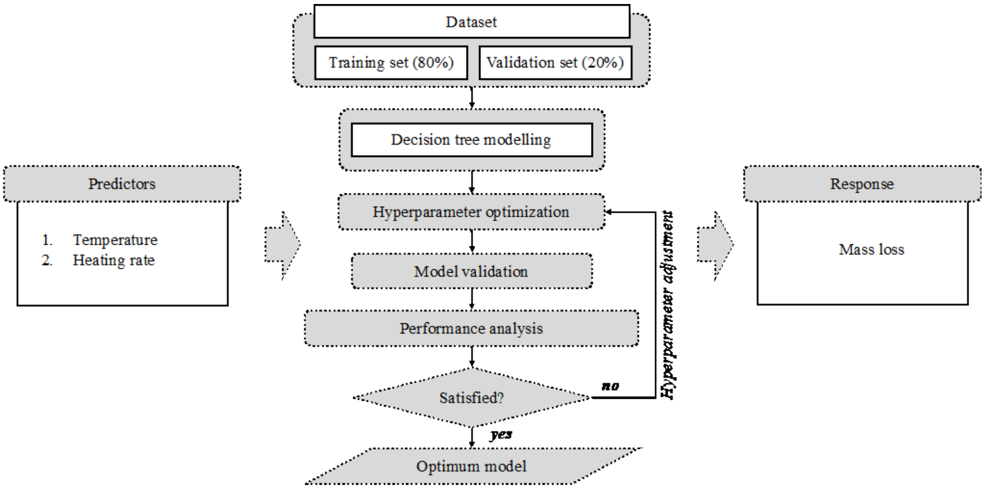

Fig. 1. Training and validation process to predict conversion degree during combustion.

2.5 Model evaluation

Once the optimal model parameters are identified, a decision tree regressor is retrained with these parameters on the full training dataset. Predictions are made for both the training and test datasets. Performance metrics, including coefficient of determination (R^2) and root mean squared error (RMSE), are computed to assess the model's accuracy. R^2 measures the proportion of variance explained by the model, while RMSE quantifies the average magnitude of the prediction errors. The formulas for calculating R^2 and RMSE can be found in Eq. 2 and Eq. 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y - y_p)^2}{\sum_{i=1}^{n}(y - y_v)^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y - y_p)^2}{n}} \quad (3)$$

3 Results and discussion

3.1 Rice husk characteristics

The proximate analysis, including moisture content (MC), volatile matter (VM), fixed carbon (FC), ash content (A), and the high heating value (HHV) of RD6 rice husk, are presented in Table 1. It shows that RD6 rice husk has an MC of 6.98%, VM of 69%, FC of 3.36%, A of 20.66%, and an HHV of 13.52 $MJ \cdot kg^{-1}$. Compared to other studies on rice husk from India [9], Taiwan [10], and Bangladesh [1], which report varying levels of MC, VM, FC, and A, the RD6 rice husk has a lower HHV. This variation highlights differences in fuel properties that are influenced by factors like rice variety, geographical location, climate, soil type, and processing methods, emphasizing the need for specific evaluations when assessing rice husk as a fuel source.

Table 1. Proximate and HHV of rice husk.

Material	Proximate analysis (%)				HHV ($MJ \cdot kg^{-1}$)
	MC	VM	FC	A	
RD6 rice husk	6.98±0.11	69.00±2.78	3.36±2.47	20.66±0.42	13.52±0.12
Rice husk [9]	5.30	62.47	14.85	17.38	15.69
Rice husk [10]	8.54	65.45	15.60	10.41	16.29
Rice husk [1]	7.36	69.75	2.82	20.07	18.50

3.2 Combustion behavior and performance

Fig. 2 displays the TG and derivative thermogravimetric (DTG) curves for rice husk combustion at various heating rates. The TG curves illustrate how weight loss varies with increasing temperature, while the DTG curves, derived from the TG data, highlight the rate of weight loss changes. Similar to other biomass types, rice husk combustion progresses through several stages. Initially, mass loss occurs between the starting temperature and the ignition temperature (T_i), primarily due to the evaporation of moisture and the release of low-molecular-weight volatiles [11]. This is followed by devolatilization and char combustion, which are characterized by two peaks in the active combustion stage (from T_i to T_b) [12], leaving behind residual ash (final mass). During this stage, hemicellulose, cellulose, and lignin are decomposed [13]. Notably, the final mass in the TG curves at the end of combustion (21.35 – 22.66%) remains unaffected by varying heating rates.

Increasing the heating rate during combustion results in several notable shifts in thermal decomposition parameters. The T_p is observed to increase concomitantly with an elevation in the DTG_{peak}. Furthermore, the T_i decreases while the T_b increases with higher heating rates. This phenomenon can be attributed to the accelerated decomposition induced by rapid temperature increases, leading to enhanced volatile and char release [14]. The interplay of thermal lag, characterized by increased thermal buoyancy and impeded heat transfer [15], further contributes to these temperature shifts. Consequently, the decomposition process is expedited, culminating in a higher peak temperature and a delayed termination point. The earlier initiation of decomposition, reflected in the decreased T_i, is a direct consequence of the accelerated temperature ramp. These findings align with previous observations reported by Mayol [16].

Fig. 3 presents the combustion performance index (C_{CI}) at different heating rates. A positive correlation between heating rate and C_{CI} is observed across all samples, suggesting that higher heating rates enhance combustion. The lower C_{CI} at 10 °C·min^{-1} is attributed to its reduced DTG_{peak} and DTG_{mean} as well as T_{peak}. Notably, the 10 °C·min^{-1} heating rate exhibits the lowest DTG_{peak} and DTG_{mean} values of – 9.44 and – 2.57 %·min^{-1}, respectively, compared to higher heating rates.

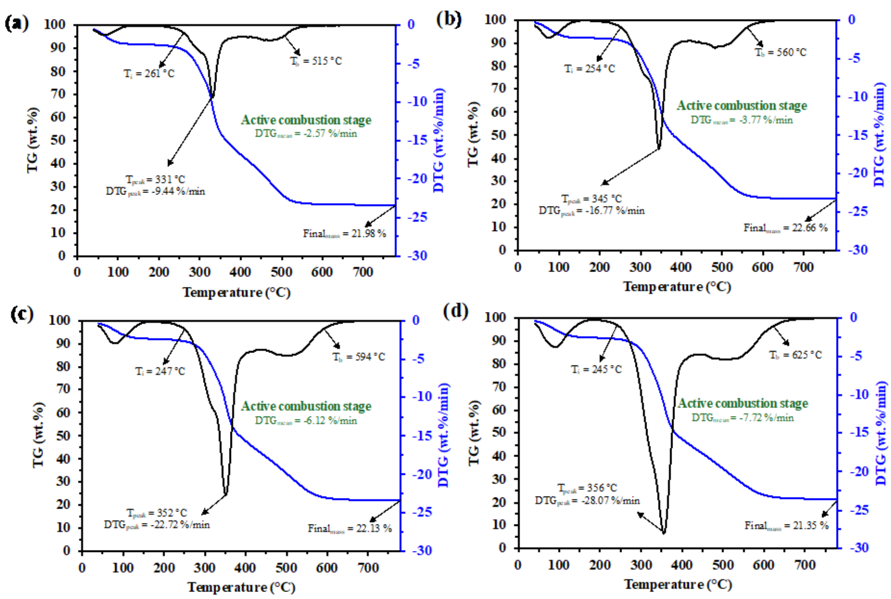

Fig. 2. TG and DTG curves at the heating rate of (a) 10 °C·min^{-1}, (b) 20 °C·min^{-1}, c) 30 °C·min^{-1}, and (d) 40 °C·min^{-1}.

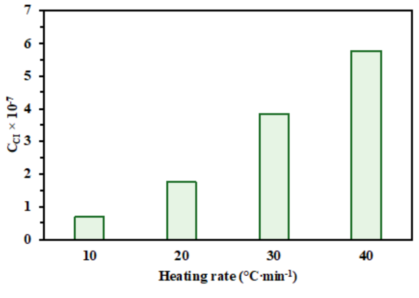

Fig. 3. Combustion performance index at different heating rates.

3.3 Performance of decision tree model

The decision tree regressor model developed to predict mass loss during rice husk combustion at varying heating rates demonstrated exceptional performance. The model exhibited an R^2 value of 1 and an RMSE of 0 on the training set, indicating that it perfectly fit the training data. Similarly, the validation set achieved an R^2 value of 1 and an RMSE of 0.1933, which is very close to zero (Fig. 4). This suggests that the model's predictions were highly accurate even on new, unseen data, and there was no noticeable overfitting. Optimization of the model was conducted using GridSearchCV, which identified the optimal hyperparameters as max_depth set to None, min_samples_leaf equal to 1, and min_samples_split equal to 2. These parameters were instrumental in achieving the model's performance. During 5-fold cross-validation, the model recorded a best negative mean squared error of – 0.0612, indicating high accuracy and minimal error in its predictions. The results affirm the model's effectiveness in forecasting mass loss during rice husk combustion at different heating rates. The excellent performance across training and validation sets and the robust cross-validation results highlight the model's reliability and capacity to generalize well across varying conditions.

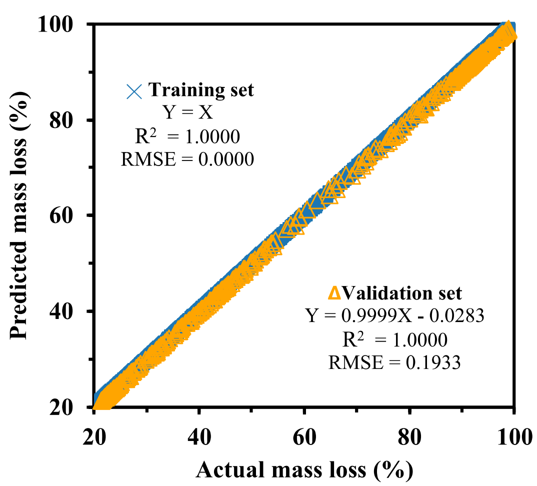

Fig. 4. Regression of actual vs predicted value of mass loss at the training and validation sets.

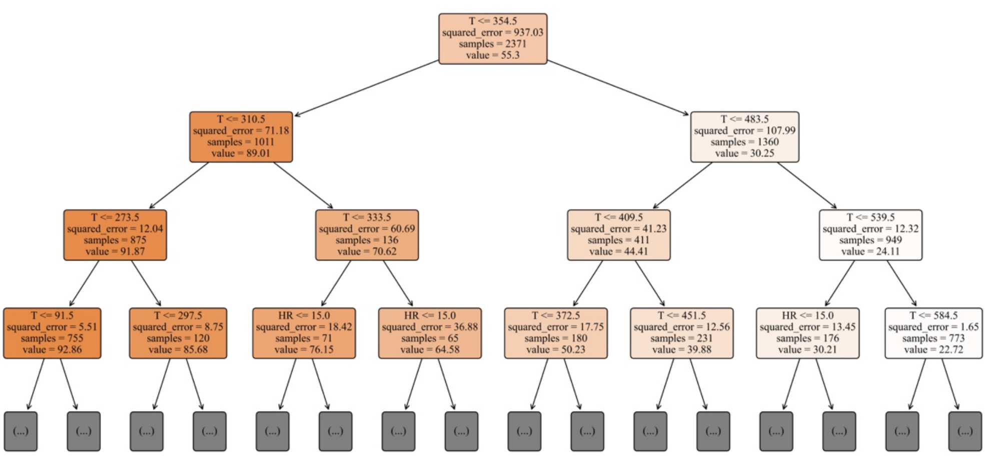

Fig. 5. Simplified decision tree visualization.

Furthermore, the findings of this study are closely comparable to those from studies using artificial neural networks (ANN). For instance, research on mass loss during cattle dung pyrolysis and groundnut shell pyrolysis with ANN models reported R^2 values > 0.99 for both training and validation sets [6, 17]. Despite these similarities, the decision tree model presents several advantages over ANN models. One of the key strengths of the decision tree approach is its simplicity. The simplified decision tree visualization used in this study can be seen in Fig 5. Decision trees are inherently more interpretable than ANN models, providing clear, understandable insights into how predictions are made [18]. This transparency is valuable for understanding the model's decision-making process and communicating results effectively. Additionally, the decision tree regressor requires less computational power compared to ANN models, which often involve extensive hyperparameter tuning and significant computational resources. While ANN models are known for their robust predictive performance, the simplicity and interpretability of the decision tree model, combined with its strong performance metrics, make it a competitive and practical choice in this study.

4 Conclusions

The TG and DTG curves for rice husk combustion at various heating rates reveal key insights into the combustion process. The process progresses through stages of moisture evaporation, devolatilization, and char combustion, ending with residual ash, which remains consistent (21.35 – 22.66%) regardless of heating rates. Higher heating rates lead to increased T_p and DTG_{peak} values, decreased T_i, and increased T_b, due to faster decomposition kinetics and thermal lag. The C_{CI} correlates positively with heating rates, with lower C_{CI} at 10 °C·min^{-1} due to reduced DTG_{peak}, DTG_{mean}, and T_{peak}. A decision tree regressor model accurately predicts mass loss, showing exceptional performance with R^2 values of 1 and minimal RMSE on both training and validation sets. Its optimization using GridSearchCV and strong metrics, combined with the simplicity and interpretability of decision trees, underscore its reliability and practicality over artificial neural networks.

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References

1. Singh, P., Singh, R.K., Gokul, P.V., Hasan, S.-U., and Sawarkar, A.N., Thermal degradation and pyrolysis kinetics of two Indian rice husk varieties using thermogravimetric analysis. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects: p. 1-12.
2. Abaide, E.R., Tres, M.V., Zabot, G.L., and Mazutti, M.A., Reasons for processing of rice coproducts: Reality and expectations. Biomass and Bioenergy, 2019. **120**: p. 240-256.
3. Pambudi, S., Saechua, W., and Jongyingcharoen, J.S., A thermogravimetric assessment of eco-friendly biochar from oxidative torrefaction of spent coffee grounds: Combustion behavior, kinetic parameters, and potential emissions. Environmental Technology & Innovation, 2024. **33**: p. 103472.
4. Yadav, D., Saha, S., Sahu, G., Chavan, P.D., Datta, S., Chauhan, V., and Kumari, N., A comparative review on thermal behavior of feedstocks during gasification via thermogravimetric analyzer. Journal of Thermal Analysis and Calorimetry, 2023. **148**(2): p. 329-354.
5. Ge, H., Zheng, J., and Xu, H., Advances in machine learning for high value-added applications of lignocellulosic biomass. Bioresource Technology, 2023. **369**: p. 128481.

6. Hai, A., Bharath, G., Daud, M., Rambabu, K., Ali, I., Hasan, S.W., Show, P., and Banat, F., Valorization of groundnut shell via pyrolysis: Product distribution, thermodynamic analysis, kinetic estimation, and artificial neural network modeling. Chemosphere, 2021. **283**: p. 131162.
7. Zhong, Y., Liu, F., Huang, G., Zhang, J., Li, C., and Ding, Y., Thermogravimetric experiments based prediction of biomass pyrolysis behavior: A comparison of typical machine learning regression models in Scikit-learn. Marine Pollution Bulletin, 2024. **202**: p. 116361.
8. El-Sayed, S.A. and Mostafa, M.E., Pyrolysis characteristics and kinetic parameters determination of biomass fuel powders by differential thermal gravimetric analysis (TGA/DTG). Energy Conversion and Management, 2014. **85**: p. 165-172.
9. Wu, H.-C., Ku, Y., Tsai, H.-H., Kuo, Y.-L., and Tseng, Y.-H., Rice husk as solid fuel for chemical looping combustion in an annular dual-tube moving bed reactor. Chemical Engineering Journal, 2015. **280**: p. 82-89.
10. Hossain, M.S., Islam, M.R., Rahman, M.S., Kader, M.A., and Haniu, H., Biofuel from Co-pyrolysis of Solid Tire Waste and Rice Husk. Energy Procedia, 2017. **110**: p. 453-458.
11. Pambudi, S., Jongyingcharoen, J.S., and Saechua, W., Thermochemical treatment of spent coffee grounds via torrefaction: A statistical evidence of biochar properties similarity between inert and oxidative conditions. Results in Engineering, 2024: p. 102012.
12. Mian, I., Li, X., Dacres, O.D., Wang, J., Wei, B., Jian, Y., Zhong, M., Liu, J., Ma, F., and Rahman, N., Combustion kinetics and mechanism of biomass pellet. Energy, 2020. **205**: p. 117909.
13. Riaz, S., Oluwoye, I., and Al-Abdeli, Y.M., Oxidative torrefaction of densified woody biomass: Performance, combustion kinetics and thermodynamics. Renewable Energy, 2022. **199**: p. 908-918.
14. El-Sayed, S.A., Khass, T.M., and Mostafa, M.E., Thermal degradation behaviour and chemical kinetic characteristics of biomass pyrolysis using TG/DTG/DTA techniques. Biomass Conversion and Biorefinery, 2023.
15. Gajera, B., Tyagi, U., Sarma, A.K., and Jha, M.K., Impact of torrefaction on thermal behavior of wheat straw and groundnut stalk biomass: Kinetic and thermodynamic study. Fuel Communications, 2022. **12**: p. 100073.
16. Mayol, A.P., Maningo, J.M.Z., Chua-Unsu, A.G.A.Y., Felix, C.B., Rico, P.I., Chua, G.S., Manalili, E.V., Fernandez, D.D., Cuello, J.L., Bandala, A.A., Ubando, A.T., Madrazo, C.F., Dadios, E., and Culaba, A.B. *Application of Artificial Neural Networks in prediction of pyrolysis behavior for algal mat (LABLAB) biomass*. in *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM)*. 2018.
17. Ashraf, M., Aslam, Z., Ramzan, N., Aslam, U., Durrani, A.K., Khan, R.U., and Ayaz, S., Pyrolysis of cattle dung: model fitting and artificial neural network validation approach. Biomass Conversion and Biorefinery, 2023. **13**(12): p. 10451-10462.
18. Costa, V.G. and Pedreira, C.E., Recent advances in decision trees: an updated survey. Artificial Intelligence Review, 2023. **56**(5): p. 4765-4800.