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Optimization of Operational Parameters Using Artificial Neural Network and Support Vector Machine for Bio-oil Extracted from Rice Husk

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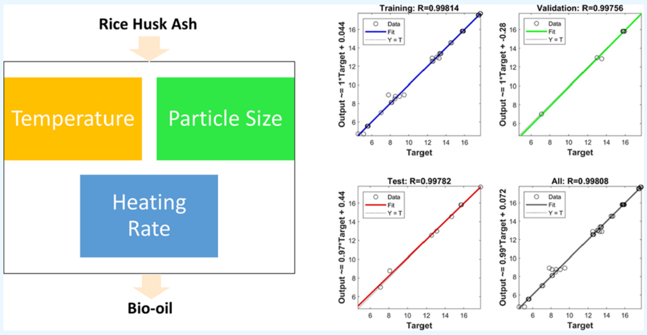

ABSTRACT: Bio-oil production from rice husk, an abundant agricultural residue, has gained significant attention as a sustainable and renewable energy source. The current research aims to employ artificial neural network (ANN) and support vector machine (SVM) modeling techniques for the optimization of operating parameters for bio-oil extracted from rice husk ash (RHA) through pyrolysis. ANN and SVM methods are employed to model and optimize the operational conditions, including temperature, heating rate, and feedstock particle size, to enhance the yield and quality of bio-oil. Additionally, ANN modeling is utilized to create a predictive model for bio-oil properties, allowing for the efficient optimization of pyrolysis conditions. This research provides valuable insights into the production and properties of bio-oil from RHA. By harnessing the capabilities of ANN and SVM, this research not only aids in understanding the intricate relationships between process variables and bio-oil properties but also provides a means to systematically enhance the production process. The predictive results obtained from the ANN were found to be good when compared with the SVM. Several models with different numbers of neurons have been trained with different transfer functions. *R* values for the training, validation, and test phases are around 1.0, i.e., 0.9981, 0.9976, and 0.9978, respectively. The overall *R*-value was 0.9960 for the proposed network. The findings were considered acceptable, as the overall *R*-value was close to 1.0. The optimized operational parameters contribute to the efficient conversion of RHA into bio-oil, thereby promoting the use of this sustainable resource for renewable energy production. This approach aligns with the growing emphasis on reducing the environmental impact of traditional fossil fuels and advancing the utilization of alternative and environmentally friendly energy sources.

1. INTRODUCTION

In pursuing sustainable and renewable energy sources, converting agricultural residues into biofuels has emerged as a promising avenue.[1] Among these residues, rice husk, a byproduct of rice milling, has garnered significant attention due to its abundance and potential as a feedstock for bioenergy production.[2,3] However, it is not only the rice husk that holds promise but also its ash, commonly referred to as rice husk ash (RHA), which presents a valuable resource for bio-oil production.[3,4]

RHA, rich in silica and other organic compounds, is a residue obtained after rice husk combustion.[5] The ash has unique properties that make it an intriguing candidate for producing bio-oil through pyrolysis, a thermochemical process involving decomposing organic materials without oxygen. Pyrolysis, a thermochemical process involving the decomposition of organic materials without oxygen, is a versatile and promising technique for converting RHA into bio-oil.[5] This method harnesses the inherent energy stored in the biomass, transforming it into a valuable and sustainable energy resource.[6] The utilization of RHA for bio-oil production not only addresses the issue of waste management associated with rice husk disposal but also taps into the potential of transforming an agricultural byproduct into a renewable energy resource.[7]

Pyrolysis involves subjecting RHA to controlled temperatures, leading to the thermal degradation of its organic components into bio-oil, biochar, and gases.[5] Bio-oil, the primary product of interest, is a complex mixture of organic compounds that can be utilized as a potential energy source or precursor for various chemicals.[8] Several factors, including

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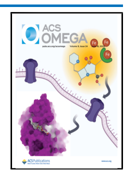

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pyrolysis temperature, heating rate, and the presence of catalysts, influence the characteristics of the bio-oil obtained from RHA.[9] As the demand for sustainable energy intensifies and efficient waste utilization practices grow, exploring RHA's conversion into bio-oil becomes a scientific endeavor and a crucial step toward a more environmentally conscious and sustainable future.[10]

RHA is suitable for pyrolysis because it has a high mesoporous surface area and silica content.[11] The RHA catalytic process can enhance bio-oil physical properties (acid value, caloric value, density, and viscosity).[5] RHA pyrolysis produces high bio-oil quantities at elevated temperatures (450−500 °C). Bakar and Titiloye[6] recommended that RHA could enhance gaseous product yield to 21.6 wt % at a modest temperature of 500 °C. Abbas et al.[7] studied pyrolysis of RHA and found optimal biochar and bio-oil yields of 39 and 19%, respectively, at 500 °C. Acid values and carboxyl groups drastically reduced at higher temperatures (700 °C), while biochar produced at higher temperatures was highly stable.

The resultant product contains 22.5 to 31.7% of liquid compounds, 27.7 to 42.5% of gaseous compounds, and 34.1 to 42.5% of solids. Cao et al.[12] studied the synthesis of biochar to develop an effective catalyst for chemical synthesis. Gui et al.[13] evaluated the fast and slow pyrolyzed bio-oil production processes, focusing on temperature, heating rate, and yield. To create the benchmarks, the study evaluated the coconut shells, RHA, and 50% of each constituent. Islam et al.[14] evaluated the highest yield parameters for bio-oil synthesis utilizing solid waste in a 500 °C fixed bed reactor. The product analysis shows that 30% of liquid products and 33% of solid products are produced from the pyrolysis of RHA. Furthermore, low investment cost, ease of operation, and secondary reaction probation make it an attractive choice.[8]

However, there is limited literature related to the RHA performance for the enhancement of properties.[5] Artificial neural networks (ANNs) and support vector machine (SVM) are powerful machine learning techniques that have been increasingly employed for optimizing operating parameters in converting RHA to bio-oil.[15,16] These techniques offer a data-driven approach to modeling complex relationships between input parameters and desired outcomes, enabling more efficient and effective optimization processes.[17] ANN presents distinct advantages, particularly in tasks requiring the modeling of nonlinear relationships.[18] ANN can automatically learn intricate patterns and features from raw data, eliminating the need for manual feature extraction, which is especially beneficial in domains such as image and speech recognition.[19] SVM excels in high-dimensional spaces, making them suitable for problems with many features like text classification or image recognition.[20] SVM is robust enough to overfit, particularly in situations where the number of features surpasses the number of samples, ensuring the generalization of unseen data. Their versatility in kernel functions allows for adaptation to various data distributions, providing flexibility in capturing complex decision boundaries.[21] Leveraging the capabilities of ANN and SVM to optimize operating parameters in the conversion of RHA to bio-oil provides a data-driven and efficient approach.[22] These models contribute to the ongoing efforts to enhance the efficiency and sustainability of bioenergy production processes.[23] However, identifying the appropriate machine learning method is still challenging in predicting the effect of the operating parameters. This is due to the need for a large volume of accurate data for model development. The current research compares machine learning and statistical approaches to predict the bio-oil production that was not previously modeled ANN and SVM under the combined effect of temperature, heating rate, and particle size.

This study aims to employ advanced techniques, specifically ANN and SVM modeling, to optimize bio-oil production from RHA through pyrolysis. The objective is to enhance bio-oil's yield and quality, focusing on key operational conditions such as temperature, heating rate, and feedstock particle size. The research uses ANN modeling for predictive analysis to optimize pyrolysis conditions efficiently, providing valuable insights into the relationships between process variables and bio-oil properties. Ultimately, the study aims to systematically improve the conversion of RHA to bio-oil, promoting the use of this sustainable resource for renewable energy production in alignment with environmental conservation goals.

2. MATERIALS AND METHODS

2.1. Raw Material Preparation. Rice husk is a commonly available agricultural waste used as a feedstock for bio-oil production through pyrolysis. Preparing rice husk appropriately for pyrolysis is essential before experimentation. The rice husk was collected and cleaned to remove any dirt, stones, or other foreign materials that may interfere with the pyrolysis. The rice husk was dried to reduce its moisture content to less than 10%. Moisture content reduces the biomass's heating value and increases the tar produced during pyrolysis. The rice husk was placed in a thin layer in sunlight and then dried in an oven at 100 C for 2 h. The size of the biomass is reduced to ensure that it can be easily fed into the pyrolysis reactor. The size reduction was made using the milling technique, and a particle size of 2 mm was selected for further processing. The ground rice husk is then burned at a temperature between 500 and 700 °C. The ashing process removes the organic components of the rice husk, leaving behind grayish ash. The RHA is washed to remove impurities and then sieved to remove large particles. A 200-mesh screen was sieved, and particles passing through the sieve were selected for the reactor feed. The RHA is stored in a dry and cool place to prevent moisture absorption and ensure quality.

2.2. Pyrolysis Reactor and Start-Up. The pyrolysis system contains an external heating source and a stainless-steel reactor equipped with a mechanical stirring device, as illustrated in Figure 1. To measure the reactor temperature, we embedded thermocouples. Since pyrolysis is performed without air, an inert atmosphere is ensured by continuously supplying nitrogen gas. The flow rate is initially set at 100 mL/min and gradually reduced. The final nitrogen flow rate is 10 mL/min to maintain an inert environment throughout the process. An inert atmosphere facilitates the pyrolysis process by preventing secondary reactions. A temperature controller sets the desired temperature, allowing the reactor to reach a steady state. RHA is placed inside the reactor, and the lid is tightly sealed to start pyrolysis. To ensure the accuracy of the experiments, triplicates are carried out at five different temperatures ranging from 400 to 480 °C. After pyrolysis, bio-oil and char are collected.

2.3. Bio-oil Characterization. Once the bio-oil is produced, its properties are characterized. This involves an analysis of its chemical and physical properties. The physical properties (viscosity, density, heating value, water, and ash

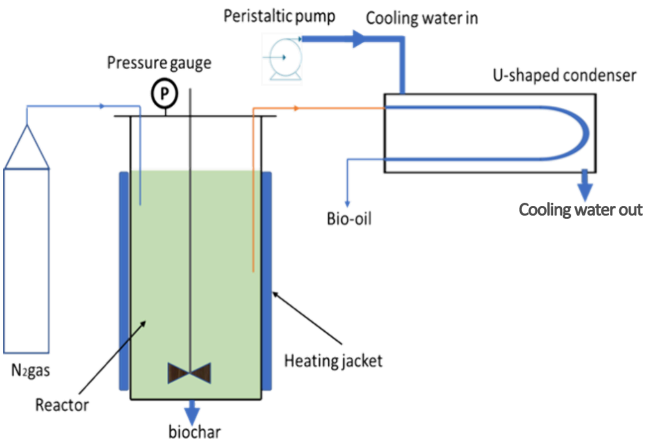

Figure 1. Schematic diagram of the batch stirred reactor.

content) and chemical composition were determined using the standard method.

2.4. Experimental Design Using RSM. The utilization of the RSM software facilitates the examination of various operational factors. To make expensive and challenging analyses more cost-effective, the analysis methods of the Design-Expert software incorporate RSM procedures. RSM relies on two fundamental principles as the foundation of its methodology, namely, establishing the optimal model and evaluating the measured response. Through contour plots or 3D graphics, the RSM allows for the visual interpretation of data. Selecting a rough approximation of the model minimizes unnecessary experimentation, leading to the identification of the most optimal solution. With DOE in mind, select where to measure the response.[24,25] To determine the effect of operating parameters on the bio-oil yield, a 5- 5-level CCD model was employed. The three most influential parameters are the temperature, particle size, and heating rate. Table 1 exhibits the operating parameters selected for the experimentation.

2.5. ANNs and SVM. Data-driven predictive modeling leveraging ANN and SVM represents a formidable strategy for discerning intricate patterns and achieving precise predictions within intricate data sets.[26] By harnessing the computational principles inspired by the human brain in ANN and the mathematical rigor of SVM, this approach excels in handling diverse and multidimensional data.[27] With its layered architecture, the ANN can capture intricate relationships, while the SVM adeptly handles classification and regression tasks by identifying optimal hyperplanes. The strength of this methodology lies in its adaptability to complicated, real-world scenarios, allowing it to navigate complex data structures and distill meaningful insights. As technological advancements continue, the synergy between ANN and SVM modeling is proving indispensable in finance, healthcare, and beyond, facilitating informed decision-making and driving innovation.[16] A brief description of the tuning parameters and the training algorithms used in the models is given in Table 2.

2.6. ANN Modeling. ANN modeling is designed to learn complex patterns and relationships within the data. Comprising interconnected nodes or artificial neurons organized into layers (input, hidden, and output), the ANN processes information through weighted connections, mimicking synapses in the human brain. The training of an ANN involves adjusting these weights based on a labeled data set, allowing the model to generalize and make predictions on new, unseen data. ANN excels in pattern recognition, classification, regression, and function approximation tasks. The ANN, including the layers, neurons, and activation functions, is

Table 1. Parametric Particulars of Trained Models

sr #	(A) temperature (°C)	(B) heating rate (°C/min)	(C) particle size (μm)	bio-oil yield (%)
1	400	80	300	8.1
2	480	40	300	12.5
3	440	60	200	15.8
4	400	40	100	8.1
5	400	80	300	9.0
6	440	60	200	15.7
7	373	60	200	4.5
8	440	60	200	15.9
9	507	60	200	5.5
10	440	60	200	15.8
11	440	60	200	15.9
12	480	80	100	14.5
13	400	40	300	8.5
14	400	80	100	9.5
15	440	60	368	13.0
16	400	40	300	8.5
17	440	60	200	16.0
18	400	80	100	9.5
19	440	26	200	7.1
20	440	60	200	15.8
21	373	60	200	5.1
22	480	80	300	12.6
23	400	40	300	8.5
24	480	40	100	13.3
25	400	80	300	8.6
26	480	40	300	13.3
27	440	60	200	15.8
28	440	94	200	17.8
29	440	94	200	17.8
30	480	80	300	12.6
31	440	60	368	13.1
32	440	26	200	7.0
33	480	40	100	13.4
34	440	60	200	15.8
35	480	40	100	13.5
36	400	80	100	7.8
37	373	60	200	4.5
38	480	80	100	14.7
39	400	40	100	8.1
40	400	40	100	8.2
41	480	40	300	13.5
42	440	26	200	7.1
43	440	60	32	17.6
44	507	60	200	5.6
45	440	60	200	15.8
46	440	94	200	17.7
47	507	60	200	5.6
48	480	80	300	12.5
49	440	60	200	15.9
50	440	60	32	17.6
51	440	60	200	15.8
52	440	60	200	15.8
53	480	80	100	14.6
54	440	60	368	13.0
55	440	60	32	17.5

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Table 2. Parametric Particulars of Trained Models

model particulars	ANN	SVM_1	SVM_2	SVM_3
data distribution	training = 82%, unseen data testing set = 18%	training = 82%, unseen data testing set = 18%	training = 82%, unseen data testing set = 18%	training = 82%, unseen data testing set = 18%
input variables	3	3	3	3
response variable	1	1	1	1
process hypothesis	nonlinear	nonlinear	nonlinear	nonlinear
algorithmic approach	Levenberg–Marquardt	Bayesian optimization	grid search optimization	random search optimization
training method	back-propagation	back-propagation	back-propagation	back-propagation
activation/kernel function	tansigmoid	cubic	cubic	cubic
cost function	MSE	MSE	MSE	MSE
validation checks	*k*-folds = 6	*k*-fold = 5	*k*-fold = 5	*k*-fold = 5

tailored to the specific problem. While ANNs can capture nonlinear relationships, their effectiveness depends on careful design, appropriate hyperparameter tuning, and robust training data sets. Applications of ANN modeling span various domains, including image and speech recognition, financial forecasting, healthcare diagnostics, and natural language processing. As a versatile tool in machine learning, ANN modeling continues to contribute significantly to advancements in artificial intelligence and data analytics.

The ANN serves as a highly efficient classifier for pattern identification.[27] The ANN model is utilized in various applications, with the multilayer BPNN being the most commonly employed network for current analysis.[28] The current research used the ANN to predict bio-oil yield based on operating parameters, eliminating the need for time-consuming and costly experimental procedures. To ensure accuracy, the data for the ANN modeling process was divided into two subsets: 90% for model training and 10% for external validation and testing.[24]

2.7. SVM Modeling. The key steps in SVM modeling involve data preprocessing, feature scaling, and the selection of appropriate hyperparameters, such as the regularization parameter (C) and kernel parameters. During training, SVM aims to find the hyperplane that maximizes the margin while minimizing classification errors. SVM is known for its robustness against overfitting and often performs well in scenarios with limited data. SVM modeling is widely applied due to its versatility and ability to handle complex decision boundaries. It is a valuable tool in machine learning for tasks where an accurate classification or regression is crucial. As with any modeling approach, careful tuning and validation are essential to ensure optimal performance on specific data sets and problem domains.

An optimization system forms the foundation of a contemporary statistical machine learning method that aims to optimize specific parameters. It was adopted to solve classification difficulties, but now it can optimize regression problems. Moreover, it has proven to be an effective technique for optimizing quantitative structure−property relationships (QSPR). With the integration of artificial intelligence, the latest advancements in QSPR analysis enable accurate and reliable predictions. These methods are particularly valued for their easy handling of complex nonlinear scenarios.[29] To achieve a satisfactory fit, SVM focuses on minimizing the summation of errors.

Table 3. Proximate and Ultimate Analyses of Bio-oil

type	property	value (%)
proximate analysis	moisture	11.67
	volatile matter	56.32
	ash	14.56
	fixed carbon	17.45
	calorific value	2.06 MJ/kg
ultimate analysis	carbon	38.4 ± 0.2
	hydrogen	5.5 ± 0.1
	nitrogen	1.2 ± 0.1
	oxygen	54.9 ± 0.2

3. RESULTS AND DISCUSSION

3.1. Proximate and Ultimate Analysis. Proximate and ultimate analysis of the bio-oil was performed on a dry basis. Proximate analysis provides information about the basic composition of a substance and is typically expressed as a percentage of the total material (Table 3). Moisture content in bio-oil is a critical parameter affecting its stability and combustion properties. High moisture content can lead to increased viscosity and a decreased heating value. Efficient drying processes during bio-oil production are essential to minimize moisture content and enhance the overall quality and stability of the bio-oil. Volatile matter represents the combustible components in the bio-oil. A higher volatile matter content generally indicates good flammability and combustion characteristics. Fixed carbon is the residue after volatile matter has been driven off. It contributes to the overall energy content and stability of bio-oil. Balancing fixed carbon content is crucial; too low fixed carbon may lead to instability, while too high fixed carbon may reduce the bio-oil's combustibility. Ash content indicates the inorganic residues in the bio-oil. Excessive ash can lead to combustion issues, equipment fouling, and corrosion. Employing cleaner feedstocks and optimizing pyrolysis conditions can minimize the ash content. The choice of biomass feedstock significantly influences the ash content.

The ultimate analysis provides insights into the elemental composition of bio-oil, which is crucial for understanding its energy content and combustion behavior (Table 3). The desired elemental composition involves selecting the appropriate biomass feedstocks and optimizing the pyrolysis conditions. High carbon and hydrogen contents are generally desirable for energy production.

3.2. ANNs. The ANN model was trained using Matlab 2020b and the available toolbox within the software. Multiple data divisions were utilized in this study to obtain optimized results. Among these divisions, it was found that the most

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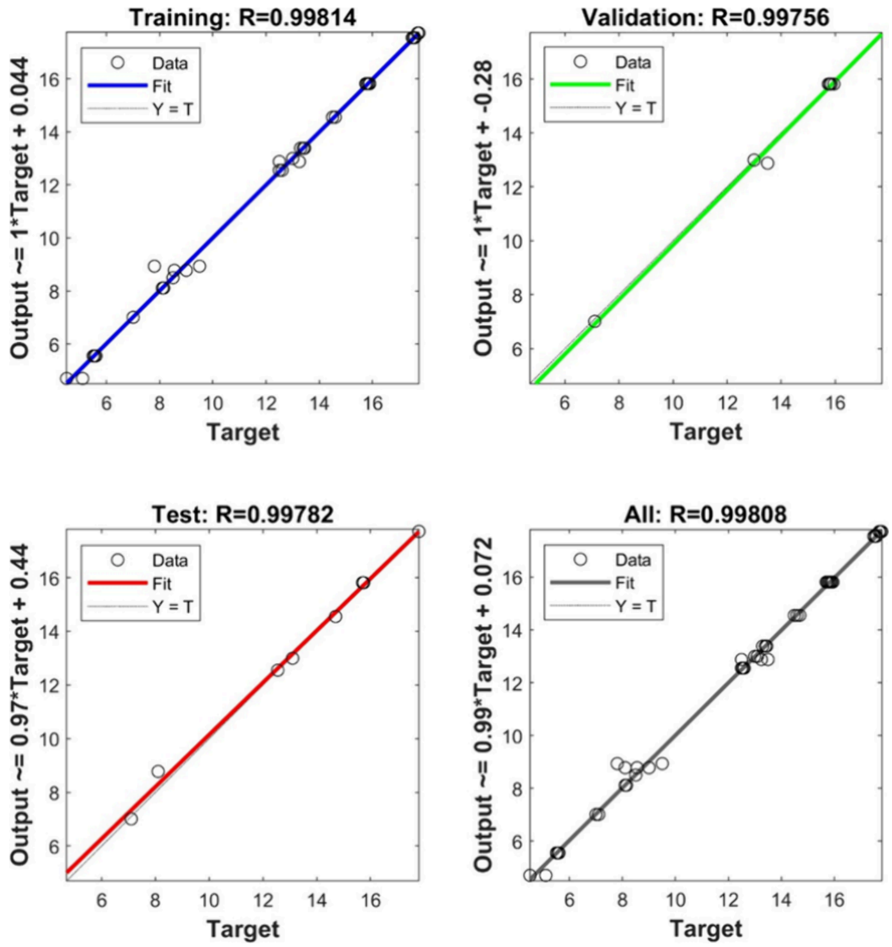

Figure 2. Regression analysis *R*-values for the trained network.

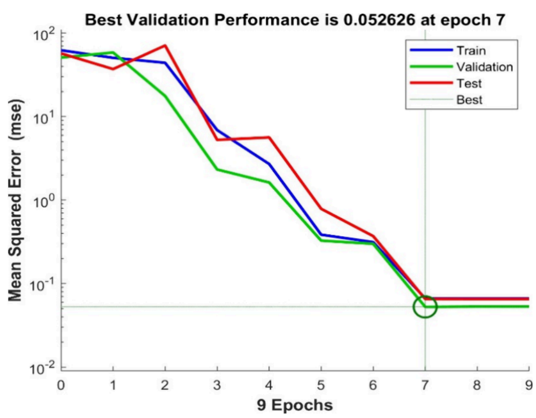

Figure 3. Best Performance Evaluation at Epoch 7.

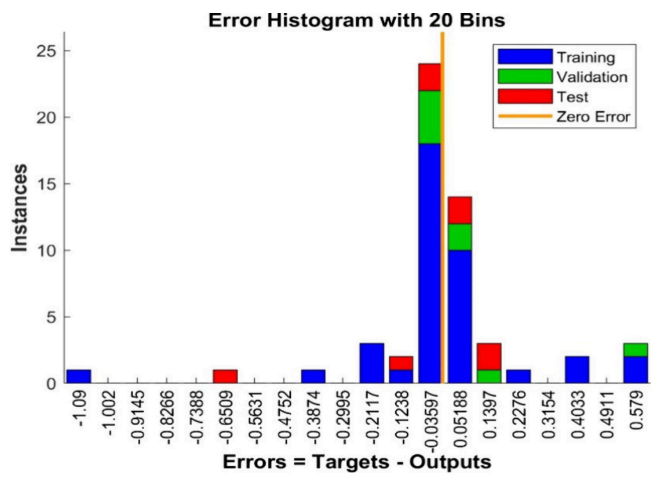

Figure 4. Error histogram of the ANN.

optimized results were achieved when 90% of the data was used for training the ANN model. In comparison, the remaining 10% was set aside as an unseen test data set to evaluate the accuracy of the trained model's predictions. The internal data division used default values during the ANN training process. The optimal model design had 3 neurons in the input layer, 9 in the hidden layer, and 1 in the output layer. Given the nonlinear nature of the data, the sigmoid function tansig was utilized.[30]

R-square values indicate extremely high correlation coefficients for the overall training, validation, and testing sets, ranging from 0.99978 to 0.9999, as shown in Figure 2, suggesting that the model performs exceptionally well and exhibits strong predictive accuracy across different data sets. The values being close to 1 indicate a nearly perfect linear relationship between the predicted and actual values, underscoring the reliability and consistency of the model across various evaluation scenarios.

The mean square error (MSE) values for the training, validation, and testing sets are 0.079, 0.068, and 0.087, respectively. The lower MSE values suggest that the model accurately predicted outcomes. The reference to the root-

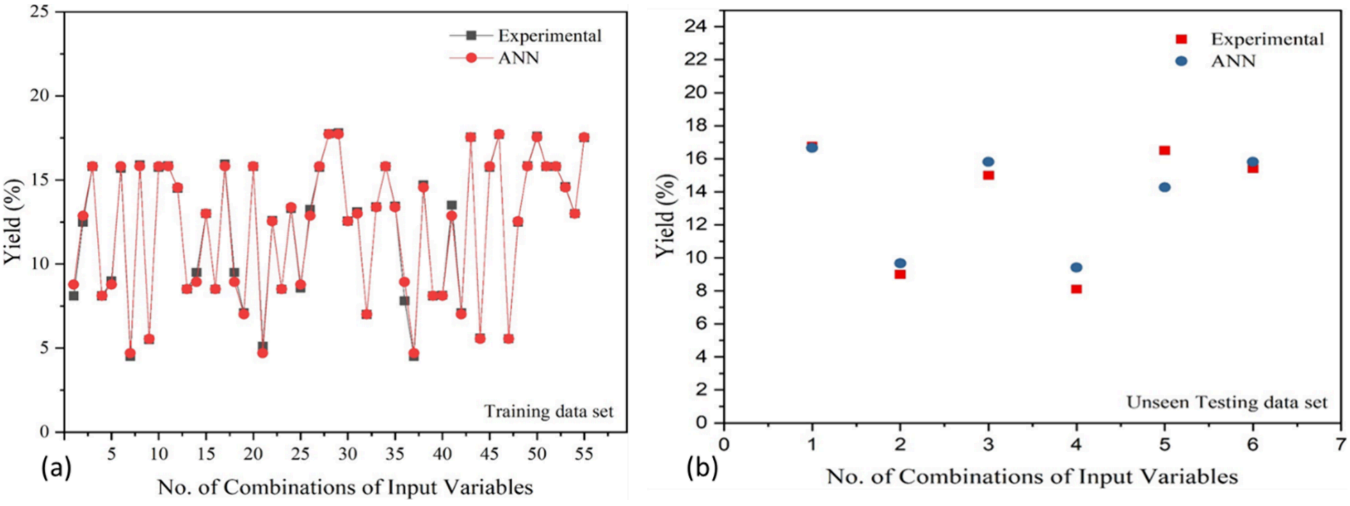

Figure 5. Experiment vs predicted yield using ANN for the (a) training data set and (b) unseen data set.

Table 4. Comparison of Performance Indices for the Trained Models

	ANN		SVM_Bayesian optimizer		SVM_grid search optimizer		SVM_random search optimizer	
performance index	training	testing	training	testing	training	testing	training	testing
MAE	0.135	0.921	0.108	2.89	0.235	1.284	0.169	1.281
RMSE	0.254	1.155	0.282	3.486	0.304	1.547	0.332	1.486
MBE	−0.007	−0.148	0.025	0.652	−0.017	−0.444	−0.072	−0.328
R-squared	0.998	0.908	0.995	0.122	0.994	0.905	0.994	0.894
MAPE	1.50%	7.50%	1.20%	25%	2.50%	10%	1.90%	10%

mean-square error (RMSE) emphasizes the actual error in the data with lower RMSE values indicating better model performance. Additionally, the paragraph mentions that the most optimized network achieved the best validation performance with a minimum achievable MSE at epoch seven, as depicted in Figure 3, and includes an error histogram in Figure 4 for further analysis and visualization of the model's performance. Overall, the combination of low MSE, high *R*-squared values, and optimization efforts demonstrates the accuracy and reliability of the trained model.

Moreover, Figure 5a,b depict plots comparing experimental and predicted yields for the training and testing data sets. The visual representation of the unseen test data set in the plot reveals satisfactory predictive performance, with the predicted and actual values closely aligning.

3.3. SVM. The current study used the Regression Learner Application in MATLAB 2020a to train the models. A total of 61 data points were used for this purpose. The SVM model, which can be optimized, was trained using different kernel functions.[31] The training data set can accurately predict the bio-oil yield at specific input variable combinations.[32] The performance of the generated model was evaluated by minimizing the MSE. The hyperparameters were adjusted iteratively until no further improvements could be achieved.[33] Figure 6 illustrates the process of hyperparameter adjustment to obtain the best possible results. The hyperparameters determined optimal for the trained model through Bayesian optimization (C = 999.18, γ = 1) and grid basis search (C = 2.1) are reported. In contrast, Figure 7 displays the experimental versus predicted yield for the unseen test data sets.

3.4. Predictive Performance Comparison of ANN and SVM. The evaluation of predictive performance involved comparing the training data set with an unseen test data set. This analysis utilized several statistical indices, including RMSE, MBE, MAE, MAPE, and R-squared. RMSE provides a measure of accuracy across the entire data set range. Due to its squared scale, it is highly responsive to even minor variations in model output and particularly sensitive to larger inaccuracies at higher values.[24] Table 4 presents a comprehensive analysis of the statistical performance indicators for each trained model. While all the models yielded similar outcomes, the ANN exhibited more favorable results, as evidenced by the significantly lower values of key error metrics such as RMSE, MBE, MAE, and MAPE in the training and testing data sets.

3.5. Environmental Impact of Replacing Fossil Fuel with Bio-oil. Bio-oil is a promising alternative to conventional fossil fuels, such as coal, oil, and gas, in terms of environmental impact and sustainability.[34] The production and use of bio-oil have several advantages over commercial fuels. Fossil fuel extraction and refining are highly energy-intensive processes that require large amounts of energy from nonrenewable sources, which results in substantial greenhouse gas emissions. Bio-oil combustion releases significantly lower amounts of greenhouse gases than conventional fuels (Table 5). This is because bio-oil is produced from renewable biomass sources, which absorb carbon dioxide from the atmosphere during their growth, offsetting the emissions produced during combustion.[35]

Bio-oil contains fewer pollutants, such as sulfur and nitrogen oxides, than conventional fuels. This reduces harmful particulate matter emissions and improves air quality, particularly in urban areas where pollution is a major health concern.[36] Bio-oil is produced from renewable biomass sources, such as agricultural and forestry residues, and is

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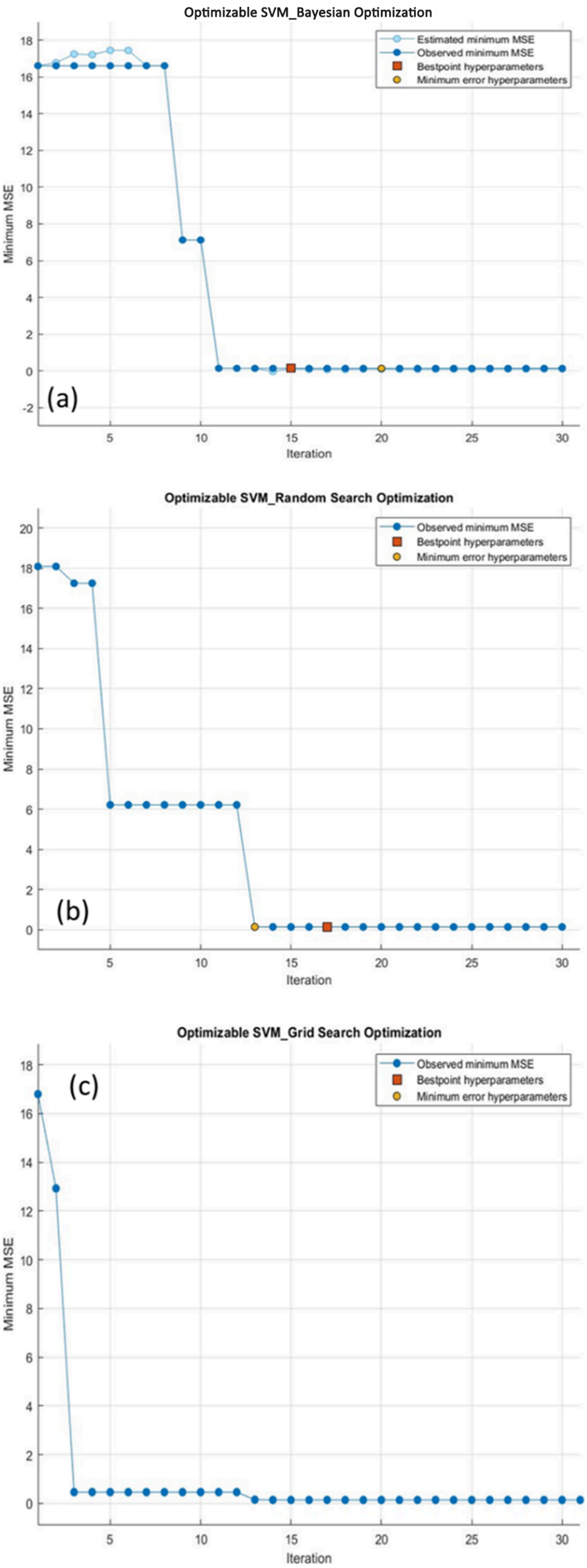

Figure 6. Training of SVM regression models using (a) Bayesian optimization, (b) random search optimization, and (c) grid search optimization.

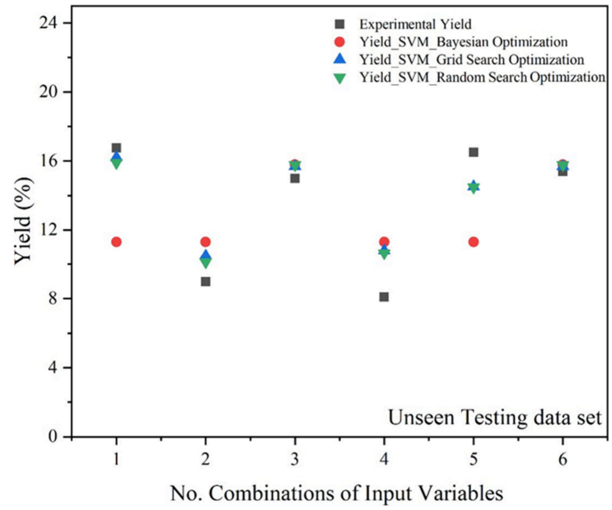

Figure 7. Experimental vs predicted yield using SVM for the unseen data set.

Table 5. Comparison of Bio-oil and Fossil Fuels

sr#	aspect	bio-oil	fossil fuels
1	greenhouse gas emissions	lower than fossil fuels	high
2	air quality	improved compared to fossil fuels	cause air pollution and health issues
3	renewable source	yes	no
4	price	more expensive	varies depending on market conditions
5	energy density	lower than fossil fuels	higher than bio-oil
6	storage	requires specialized storage	stored easily
7	transportation	it may require modification to the infrastructure	well-established infrastructure for transport

grown and harvested sustainably. This makes bio-oil a more sustainable and environmentally friendly alternative to fossil fuels, which are finite resources and require extensive extraction and processing.[37] Bio-oil is produced locally, reducing the need for long-distance transport and associated emissions. This supports local economies and creates jobs in rural areas. Bio-oil substitutes conventional fuels in various applications, such as power generation, heating, and transportation.[38] It is blended with other fuels or upgraded to higher-quality fuels like biofuels. Bio-oil offers significant environmental and sustainability benefits compared with commercial fuels. Therefore, it is essential to holistically consider the environmental impacts of bio-oil production and strive to use sustainable and environmentally friendly practices throughout the production process. However, further research and development are needed to improve its production efficiency, reduce its cost, and enhance its properties to make it a viable and competitive alternative to fossil fuel.

4. CONCLUSIONS

This study signifies a significant stride in bioenergy production by investigating the optimization of bio-oil production from RHA through innovative techniques such as ANN and SVM modeling. Utilizing these advanced methods for modeling and optimizing operational conditions has proven instrumental in enhancing both the yield and quality of bio-oil. The predictive

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capabilities of ANN modeling have provided a streamlined approach to optimize pyrolysis conditions efficiently. The outcomes of this research contribute valuable insights into the intricate relationships between process variables and bio-oil properties and offer a systematic means of enhancing the production process. By optimizing operational parameters, this study advocates for the efficient conversion of RHA into bio-oil, aligning with a broader initiative to reduce the environmental impact of traditional fossil fuels. The emphasis on advancing alternative and environmentally friendly energy sources underscores the importance of this research in fostering sustainable practices in the field of renewable energy production.

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Notes

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