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Research Article

Application of Machine Learning Algorithms for Prediction and Influential Parameter Analysis of Mechanical Property of Tea Residual-Filled Recycled Polypropylene Composite Materials

Anuchit Khongrit *, Cheevin Limsiri and Sureeporn Meehom

Department of Engineering Management, Faculty of Engineering, Vongchavalitkul University, Mueang Nakhon Ratchasima, Nakhon Ratchasima 30000, Thailand.

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A B S T R A C T

This research aims to study the application of artificial intelligence algorithms or machine learning in analyzing the influence of factors affecting the mechanical properties of recycled polypropylene composite materials mixed with tea residual. The factors examined include the type of tea waste (Thai tea and green tea), the coupling agent (PP-g-MA), and the thermoplastic elastomer.The study uses 5 algorithms: Generalized Linear Model, Decision Tree, Random Forest, Support Vector Machine, and Artificial Neural Network. The results show that thermoplastic elastomer has a negative effect on strength and hardness, but a positive effect on flexibility and impact resistance. PP-g-MA has a positive effect on strength and interfacial adhesion. The type of tea residue affects mechanical property differently depending on structure and chemical composition.

Comparing the prediction performance of algorithms, Decision Tree and Random Forest provide the most accurate predictions for most mechanical properties, with high R^2 values and low error rates. The average R^2 values across all mechanical properties for Decision Tree and Random Forest are 0.856 and 0.858, respectively. The Artificial Neural Network shows excellence in predicting percentage elongation with RSME only 6.73%. Support Vector Machine shows limitations in predicting mechanical property, especially in predicting elongation percentage and impact resistance. The results of this research demonstrate that Decision Tree and Random Forest show the potential of using machine learning techniques to efficiently design and develop composite materials with desired properties.

1. Introduction

Research and development of wood-plastic composites (WPCs) have advanced rapidly in recent years, with increasing applications of artificial intelligence (AI) and machine learning (ML). These methods have shown potential in solving traditional production problems that rely on trial and error, which are time-consuming and costly. Popular ML algorithms used in WPC research include Artificial Neural Networks, Linear and Logistic Regression, Convolutional Neural Networks, and Gaussian Processes. Notable research includes developing Artificial Neural Networks (ANN) models to predict the mechanical property of high-density polyethylene composites mixed with Scots pine wood, achieving high accuracy with an R^2 value over 0.90. Additionally, Graph Neural Networks (GNNs) have been applied to predict the tensile strength of PLA composites mixed with wood powder and formed by 3 D printing, comparing performance with other

*** Corresponding author.**

E-mail address: *anuchit_kho@vu.ac.th*

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models like Support Vector Machine and Extreme Gradient Boosting.

These techniques can accurately predict various mechanical property such as tensile strength, flexural strength, elastic modulus, and impact resistance. Developing reliable and accurate engineering models remains a significant challenge, requiring the selection of suitable ML algorithms and integration with other analysis techniques like finite element methods.

Despite some limitations, ML techniques offer significant benefits in reducing time and cost in research and production processes, especially for manufacturers with limited equipment or specialized expertise. They also aid in designing and optimizing material compositions, such as WPCs, to meet specific requirements and cater to diverse customer needs more effectively. This includes adjusting the mixing ratio, developing materials to withstand tensile or flexural forces according to set standards, and reducing errors from traditional experimental methods. Integrating ML with traditional techniques helps balance model accuracy with practical feasibility, enabling industries to develop innovative materials more efficiently. (Ramesh *et al*., 2022; Rahaman *et al*., 2023; Feng *et al*., 2023; Ma *et al*., 2023; Eroğlu *et al*., 2024; Nakayama and Sakakibara, 2024; Qin and Bing, 2024; Sorour *et al*., 2024)

Previous studies by researchers have identified opportunities to develop wood-plastic composites from recycled polypropylene from beverage containers and tea residual collected from beverage shops. This research aligns with the circular economy approach of creating value from post-consumer materials. The study examined the effects of key variables on the mechanical property of composites made from recycled polypropylene and tea residual. (Ramesh *et al*., 2022; Feng *et al*., 2023; Ma *et al*., 2023; Rahaman *et al*., 2023; Eroğlu *et al*., 2024; Nakayama and Sakakibara, 2024; Qin and Bing, 2024; Sorour *et al*., 2024)

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The reason for the low predictive ability of linear regression analysis is due to the low purity of the recycled material, which contains impurities, and the high dispersion of tea waste particles, leading to high standard deviations in the data. Additionally, the regression analysis showed that linear equations have limited ability to predict the research data because the factors do not have a linear relationship. Therefore, researchers have considered using machine learning (ML) to analyze the research results due to its advantages over traditional statistical methods. ML is better at learning complex and non-linear relationships, especially with large datasets. Unlike traditional statistical models that often rely on linear assumptions and a limited number of predictors, ML algorithms such as Artificial Neural Networks (ANN) and Random Forest can capture complex patterns and interactions within the data more deeply, resulting in higher predictive accuracy, which is significantly better than linear regression models. (Rahaman *et al*., 2023)

From the above, the researchers used a dataset of the modulus of elasticity of composite materials to analyze using five machine learning algorithms: Generalized Linear Regression, Decision Tree, Random Forest, Support Vector Machine, and Artificial Neural Network. These algorithms were used to learn and predict the modulus of elasticity of recycled polypropylene composite materials mixed with tea waste. The research results showed that machine learning algorithms could predict more accurately when comparing actual test results with predicted values, as shown in Figure 1. a) This figure compares the General Linear Regression algorithm, where the P-value indicates that the actual and predicted values differ significantly statistically. For Figure 1 b), it shows the comparison results from the Artificial Neural Network algorithm, which has a higher R^2 value and a P-value greater than 0.05, indicating that the predicted and actual values do not differ significantly and are correlated by 88.28%. (Khongrit *et al*, 2024b)

The conclusion of this study shows that artificial intelligence algorithms using machine learning techniques can learn complex, non-linear data with high variability and predict more accurately than traditional linear regression analysis conducted in previous research. This method can effectively be used to analyze other properties of recycled polypropylene composite materials mixed with tea residual. The expected outcome of this research aims to enhance understanding in using artificial intelligence technology to develop environmentally friendly composite materials. Additionally, it opens opportunities for applying this technique to develop other types of composite materials in the future. This study also plays a crucial role in promoting the utilization of recycled materials and agricultural residual, aligning with the concepts of a circular economy and sustainable development.

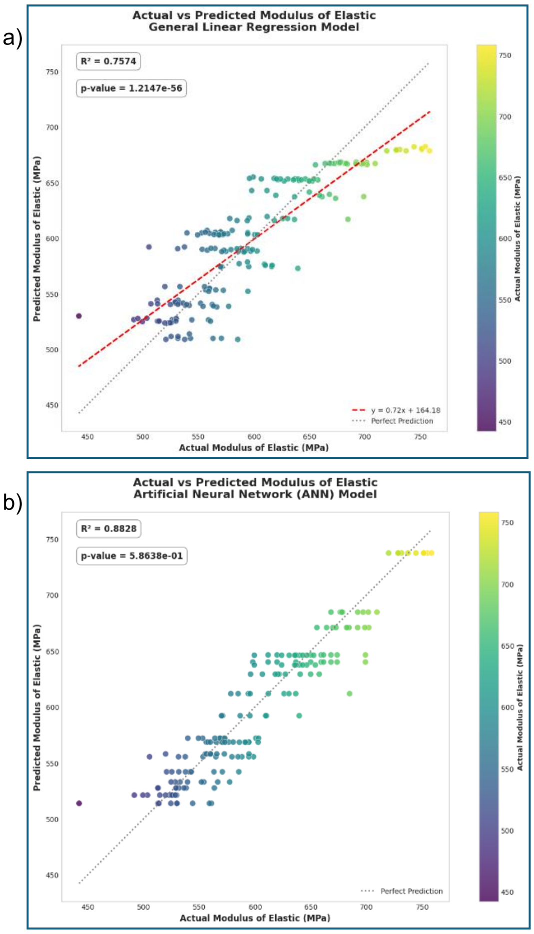

Figure 1 Comparison of Actual vs. Predicted Elastic Modulus Testing for Recycled PP-Tea Residual Composites: a) Generalized Linear Regressgion Model and b) Artificial Neural Network Model (Khongrit *et al*., 2024b)

The above findings lead to the two main objectives of this research:

1.To apply artificial intelligence or machine learning algorithms to study the influence of factors affecting the mechanical property of recycled polypropylene composite materials filled with tea residual.

2.To compare the predictive efficiency of artificial intelligence algorithms on the mechanical property of these composite materials.

2. Materials and Methods

The research process can be illustrated as shown in Figure 2, with the following details:

2.1 Preparation of Composite Materials and Property Testing

The materials, chemicals, and methods for preparing composite materials, as well as the mechanical property testing, are based on previous research (Khongrit *et al*., 2022). The main raw materials include recycled polypropylene from plastic drink cups and natural fillers such as Thai tea waste and green tea waste, which were sun-dried for three days and then sifted through a 30 Mesh sieve. The compatibilizer used was PP-g-MA grade POLYB® AM-920 from Hannanotech at concentrations of 0, 2.5, and 5 wt%. The polyolefin elastomer (TPE) used was Engage 7447 from Dow Chemical at concentrations of 0, 5, and 10 wt%. The antioxidant used was Sunox 168 from Polychem Premier, applied at 0.1 wt% in all formulations. The factors and levels of factors studied are shown in Table 1. This research includes one qualitative factor (type of tea waste) and two quantitative factors (PP-g-MA and TPE). The experiment consists of 18 basic runs (base runs), with each model tested ten times. The instruments and machines used for research and property testing were kindly provided by the Faculty of Engineering and Technology, Rajamangala University of Technology Isan, Nakhon Ratchasima Campus

The preparation of raw materials began with mixing recycled polypropylene, tea waste powder, and other additives according to the formula (the amount of recycled polypropylene varied inversely with the amount of other factors, ranging from 64.9 to 79.7 wt%). The mixture was blended using a mixing machine and then dried for one hour to remove moisture. It was then compounded using a twin-screw extruder with an L/D ratio of 12, operating at temperatures from 200°C to 230°C from the feeding zone to the Metering zone.

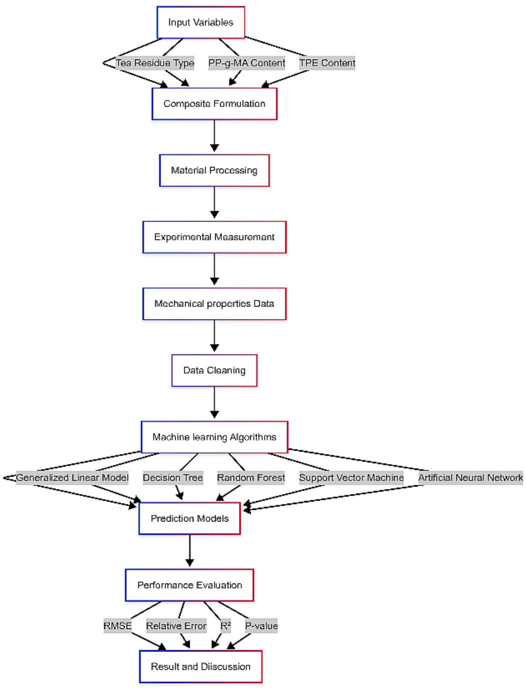

Figure 2 Flow chart of the research methodology

The material was cooled with air and then pelletized. After drying, the material was molded into test specimens according to ASTM standards using injection molding. The molded specimens were stored in a desiccator for 2 days before property testing. The mechanical properties testing was conducted using 10 specimens per experimental model. The mechanical property testing included:

- Tensile testing according to ASTM D638 using a LLOYD LR10K (10 kN) machine at a drawing rate of 50 mm/min. The yield strength, tensile strength (in MPa), and percentage elongation (%Elongation) were measured.

- Impact testing according to ASTM D256 using an Instron CEAST 9050 pendulum impact tester with an energy of 2.7 J. The results were reported in kJ/m².

- Surface hardness testing according to ASTM D2240 using a Teclock GS-612 machine with a 5 kg force applied for 1 second. Each specimen was tested at five different points, and the results were expressed in Shore D units.

Table 1 Factors and levels of factors studied in the research

Composite designation	Type of tea residual(20wt%)	PP-g-MA (wt%)	TPE (wt%)
rPP/T	Thai	0	0
rPP/T/MA2.5	Thai	2.5	0
rPP/T/MA5	Thai	5	0
rPP/T/TPE5	Thai	0	5
rPP/T/TPE10	Thai	0	10
rPP/T/MA2.5/TPE5	Thai	2.5	5
rPP/T/MA5/TPE5	Thai	5	5
rPP/T/MA2.5/TPE10	Thai	2.5	10
rPP/T/MA5/TPE10	Thai	5	10
rPP/G	Green	0	0
rPP/G/MA2.5	Green	2.5	0
rPP/G/MA5	Green	5	0
rPP/G/TPE5	Green	0	5
rPP/G/TPE10	Green	0	10
rPP/G/MA2.5/TPE5	Green	2.5	5
rPP/G/MA5/TPE5	Green	5	5
rPP/G/MA2.5/TPE10	Green	2.5	10
rPP/G/MA5/TPE10	Green	5	10

Table 2 Algorithms and Parameters Used in This Research

Algorithms	Parameters
Generalized Linear Regression	Family : Automatic selection Solver : Automatic selection Reproducible : false maximum number of threads : 4 lambda : 0.0 - 1.79769313486 stopping rounds/tolerance : 3/0.001 alpha : 0.05
Decision Tree	Criterion : gain ratio maximal depth : 10 apply pruning : true confidence : 0.1 minimal gain : 0.01 minimal leaf size/size for split : 2/4 pre-pruning alternatives : 3
Random Forest	number of trees : 100 criterion : gain ratio maximal depth : 10 minimal gain/leaf size/size for split : 0.01/2/4 confidence : 0.1 pre-pruning alternatives : 3 apply pruning : true
Support Vector Machine	kernel type : dot kernel sigma1/2/3 : 1.0/0.0/2.0 kernel gamma : 1.0 kernel cache : 200 complexity constant : 0.0 convergence epsilon : 0.001 max iterations : 100000 L pos/L neg : 1.0/1.0
Artificial Neural Network	operator learns : feed-forward neural network trained : back propagation algorithm activation function : sigmoid function hidden layers : 2 training cycles : 200 learning rate : 0.01 momentum : 0.9 error epsilon : 1.0E-4

2.2 Data Analysis Using Machine Learning

After completing the mechanical property testing, the data was processed through a data cleaning procedure. This involved managing missing values and outliers using Python scripts on Google Collaboration. The cleaned dataset was then saved as a .csv file. The data was imported into AI Studio 2024.1.0, a program used for data preparation, analysis, and prediction, which supports data mining and machine learning. The workflow of the analysis in this research is shown in Figure 2, with the algorithms and parameters detailed in Table 2. This study employed five algorithms: Generalized Linear Regression, Decision Tree, Random Forest, Support Vector Machine, and Artificial Neural Network.

The parameters of each algorithm are shown in Table 2. Cross-validation was used to split the data for training and testing, reducing the risk of random data splits that do not adequately represent the dataset due to its high variability. This approach also helps mitigate overfitting, allowing for a more reliable evaluation of model accuracy across diverse datasets (Faurika *et al*., 2024; Lumumba *et al*., 2024). The influence of each factor will be analyzed using the Model Analysis Description of each algorithm.

Subsequently, the comparison of the predictive performance for mechanical property will utilize the results of Performance Regression obtained from analyzing the efficiency of each algorithm. This is used for statistical evaluation and provides the performance metrics for each algorithm, including:

- Root Mean Square Error (RMSE): This indicates the average magnitude of prediction errors. A lower RMSE value signifies higher predictive accuracy.

- Relative Error: This is the proportion of error relative to the actual value, expressed as a percentage, making it easier to compare.

- Coefficient of Determination (R^2): This value indicates how well the model explains the data variability, ranging from 0 to 1 or 0% to 100%. A higher R^2 value means the algorithm can predict the mechanical property of composite materials more effectively.

- P-Value: This statistical value is used to test hypotheses. In the context of machine learning, it evaluates the significance of the results or the relationship found between actual and predicted values, determining whether they differ significantly (in this study, significance is set at 0.05).

3. Results and Disscussion

3.1 The results of the mechanical property testing

Results of the mechanical property testing include Yield Strength, Tensile Strength, Percentage Elongation, Impact Strength, and Hardness. These properties can be seen in Figures 3 to 7, respectively.

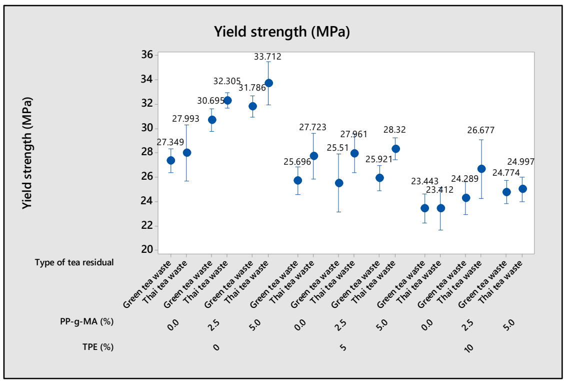

Figure 3 Results of Yield Strength Testing

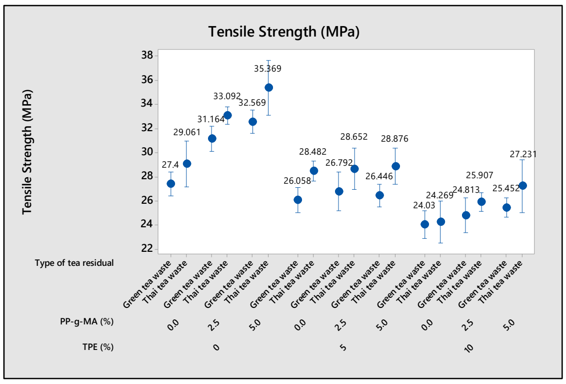

Figure 4 Results of Tensile Strength Testing

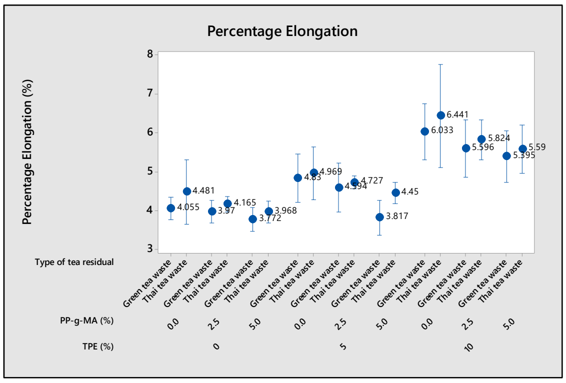

Figure 5 Results of Percentage Elongation Testing

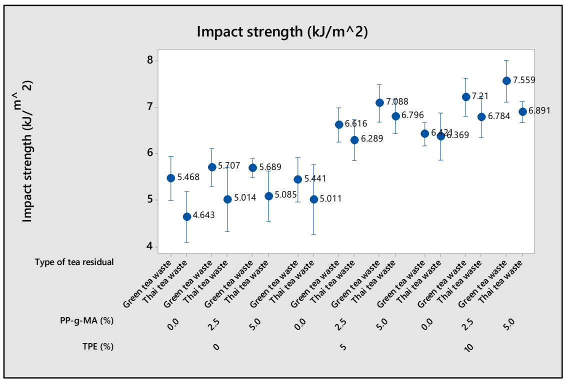

Figure 6 Results of Impact Strength

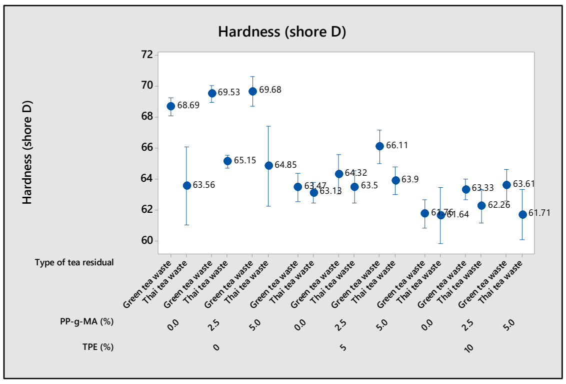

Figure 7 Results of Hardness Testing

The yield strength of rPP composites showed Thai tea waste provided slightly higher values than green tea waste (27.84 ± 2.79 MPa vs 27.05 ± 1.47 MPa). Adding PP-g-MA significantly improved yield strength in both composites, with rPP/T/MA5 reaching the highest at 33.90 ± 2.28 MPa. Conversely, TPE addition reduced yield strength, with rPP/T/TPE10 showing the lowest at 23.97 ± 2.24 MPa. Similar trends were observed for tensile strength, with Thai tea waste composites slightly outperforming green tea waste (29.16 ± 2.28 MPa vs 27.29 ± 1.27 MPa). PP-g-MA enhanced tensile strength proportionally to its content, with rPP/T/MA5 achieving the highest value (35.37 ± 3.01 MPa), while TPE decreased it, with rPP/T/TPE10 showing the lowest (24.27 ± 2.15 MPa). The elastic modulus was comparable for both tea wastes (approximately 625 MPa), indicating tea type minimally affected composite stiffness. PP-g-MA increased the modulus, particularly in Thai tea waste composites (rPP/T/MA5: 742.31 ± 33.88 MPa), while TPE reduced it (rPP/T/TPE10: 513.52 ± 35.82 MPa). Percentage elongation was similar for both composites (3.96 ± 0.39% for green tea waste; 4.28 ± 1.14% for Thai tea waste). PP-g-MA slightly decreased elongation as its content increased, while TPE significantly improved it, with rPP/T/TPE10 showing the highest value at 6.44 ± 1.93%.

Impact Strength of rPP composites with green tea waste showed slightly higher impact strength than those with Thai tea waste (5.49 ± 0.62 vs 4.66 ± 0.87 kJ/m²), suggesting better toughness. Adding PP-g-MA gave a minor improvement in impact resistance, but not clearly proportional to its content. In contrast, TPE significantly increased impact strength, especially at higher levels, with rPP/G/MA5/TPE10 reaching the highest value (7.42 ± 0.69 kJ/m²), indicating TPE is more effective than PP-g-MA for toughness enhancement. Finally, Hardness Property of green tea waste composites had slightly higher hardness than Thai tea waste (68.69 ± 0.90 vs 63.46 ± 3.34 Shore D). PP-g-MA slightly increased hardness in both composites, while TPE addition significantly reduced hardness, especially at 10% content. This reduction in hardness with TPE corresponded with increased elongation and impact strength, showing TPE enhances flexibility and toughness but lowers hardness.

3.2 Studying the Influence of Factors Using Machine Learning Algorithms

After testing the mechanical property of recycled polypropylene composite materials filled with tea residual, the obtained data was used in the machine learning process to analyze and predict the mechanical property of the materials. The results of this analysis not only provided insights into the predictive capabilities of the algorithms but also helped in studying the influence of each factor on the mechanical property of the composite materials. This analysis enabled an understanding of the relationship between various components and the mechanical property of the composite materials in this research. However, due to the large amount of data, we propose to present the analysis results for Yield Strength as an example of how machine learning outcomes can explain the influence of each factor, followed by a summary table of all mechanical property.

Figure 8 shows the results of the analysis using the Generalized Linear Model (GLM). It was found that TPE had the most significant negative effect (Coefficient = -0.616) on the predicted values, with the highest importance at 48.43%. This was followed by PP-g-MA, which had a positive effect (Coefficient = 0.465) and a secondary importance of 18.27%. The factors related to the type of green tea and Thai tea had negative and positive influences, respectively (Coefficients = -0.867 and 0.867), with equal importance weights of 16.65%

for both factors. The intercept value was 29.258, which is a constant used in the algorithm for prediction.

Attribute	Coefficient	Std. Coefficient
Type_of_tea.Green	-0.867	-0.867
Type_of_tea.Thai	0.867	0.867
PP_graft_MA_percentage	0.465	0.951
PTE_Percentage	-0.616	-2.522
Intercept	29.258	27.339

```
Variable Importances:
              Variable Relative Importance Scaled Importance Percentage
        PTE_Percentage            2.522235          1.000000   0.484259
PP_graft_MA_percentage            0.951423          0.377214   0.182669
     Type_of_tea.Green            0.867390          0.343897   0.166536
      Type_of_tea.Thai            0.867390          0.343897   0.166536
```

Figure 8 Model Analysis Description of the Generalized Linear Model Algorithm

Figure 9 shows the results from the analysis using the Decision Tree algorithm. It was observed that TPE played the most crucial role in the decision tree structure. The first splitting criterion at TPE (wt%) > 2.5 and > 7.5 indicated that the percentage of TPE had a negative effect on the predicted values, as the predicted values decreased with increasing TPE content. Meanwhile, PP-g-MA had a positive effect, with predicted values increasing when the percentage of PP-g-MA was higher than 1.250 and 3.750. Additionally, the type of tea residual had both positive and negative effects depending on the type of tea. Green tea was generally associated with lower predicted values, while Thai tea was associated with slightly higher predicted values. The prioritization of factors showed that TPE was the most significant factor, followed by PP-g-MA, and finally the type of tea waste, which had a secondary impact on the predicted values.

Figure 10 shows the results of the analysis using the Random Forest algorithm. It was found that TPE played the most significant role in data partitioning, with values below 2.500 or above 7.500 clearly affecting changes in the predicted values. This indicates a negative effect when TPE values increase. For PP-g-MA, there was a positive effect, particularly when values exceeded 1.250 and 3.750, significantly enhancing the predicted values. The type of tea waste showed different effects depending on the type; green tea was generally associated with lower predicted values, while Thai tea tended to slightly increase the predicted values. The prioritization of factors showed that TPE was the most influential variable, followed by PP-g-MA, and finally the type of tea waste, which had a secondary impact that varied depending on the type of tea.

RegressionTree

```
TPE_percentage > 2.500
|   TPE_percentage > 7.500
|   |   PP_graft_MA_percentage > 1.250
|   |   |   Type_of_tea = Green
|   |   |   |   PP_graft_MA_percentage > 3.750: 24.632 {count=10}
|   |   |   |   PP_graft_MA_percentage ≤ 3.750: 24.063 {count=10}
|   |   |   Type_of_tea = Thai
|   |   |   |   PP_graft_MA_percentage > 3.750: 24.861 {count=10}
|   |   |   |   PP_graft_MA_percentage ≤ 3.750: 26.522 {count=10}
|   |   PP_graft_MA_percentage ≤ 1.250: 23.327 {count=20}
|   TPE_percentage ≤ 7.500
|   |   Type_of_tea = Green
|   |   |   PP_graft_MA_percentage > 3.750: 26.082 {count=10}
|   |   |   PP_graft_MA_percentage ≤ 3.750
|   |   |   |   PP_graft_MA_percentage > 1.250: 24.882 {count=10}
|   |   |   |   PP_graft_MA_percentage ≤ 1.250: 26.030 {count=10}
|   |   Type_of_tea = Thai
|   |   |   PP_graft_MA_percentage > 1.250: 28.415 {count=20}
|   |   |   PP_graft_MA_percentage ≤ 1.250: 27.725 {count=10}
TPE_percentage ≤ 2.500
|   PP_graft_MA_percentage > 1.250
|   |   Type_of_tea = Green
|   |   |   PP_graft_MA_percentage > 3.750: 31.610 {count=10}
|   |   |   PP_graft_MA_percentage ≤ 3.750: 30.179 {count=10}
|   |   Type_of_tea = Thai
|   |   |   PP_graft_MA_percentage > 3.750: 34.241 {count=10}
|   |   |   PP_graft_MA_percentage ≤ 3.750: 32.354 {count=10}
|   PP_graft_MA_percentage ≤ 1.250
|   |   Type_of_tea = Green: 27.291 {count=10}
|   |   Type_of_tea = Thai: 28.154 {count=10}
```

Figure 9 Model Analysis Description of the Decision Tree Algorithm

RegressionTree

```
PTE_Percentage > 2.500
|   PTE_Percentage > 7.500
|   |   Type_of_tea = Green
|   |   |   PP_graft_MA_percentage > 1.250
|   |   |   |   PP_graft_MA_percentage > 3.750: 24.717 {count=9}
|   |   |   |   PP_graft_MA_percentage ≤ 3.750: 24.282 {count=12}
|   |   |   PP_graft_MA_percentage ≤ 1.250: 23.549 {count=7}
|   |   Type_of_tea = Thai
|   |   |   PP_graft_MA_percentage > 1.250
|   |   |   |   PP_graft_MA_percentage > 3.750: 24.904 {count=9}
|   |   |   |   PP_graft_MA_percentage ≤ 3.750: 26.690 {count=8}
|   |   |   PP_graft_MA_percentage ≤ 1.250: 23.526 {count=9}
|   PTE_Percentage ≤ 7.500
|   |   Type_of_tea = Green
|   |   |   PP_graft_MA_percentage > 1.250
|   |   |   |   PP_graft_MA_percentage > 3.750: 25.840 {count=6}
|   |   |   |   PP_graft_MA_percentage ≤ 3.750: 25.088 {count=10}
|   |   |   PP_graft_MA_percentage ≤ 1.250: 25.822 {count=11}
|   |   Type_of_tea = Thai
|   |   |   PP_graft_MA_percentage > 3.750: 28.203 {count=16}
|   |   |   PP_graft_MA_percentage ≤ 3.750
|   |   |   |   PP_graft_MA_percentage > 1.250: 28.063 {count=18}
|   |   |   |   PP_graft_MA_percentage ≤ 1.250: 28.104 {count=8}
PTE_Percentage ≤ 2.500
|   PP_graft_MA_percentage > 1.250
|   |   PP_graft_MA_percentage > 3.750
|   |   |   Type_of_tea = Green: 31.438 {count=8}
|   |   |   Type_of_tea = Thai: 35.440 {count=7}
|   |   PP_graft_MA_percentage ≤ 3.750
|   |   |   Type_of_tea = Green: 30.373 {count=13}
|   |   |   Type_of_tea = Thai: 32.447 {count=12}
|   PP_graft_MA_percentage ≤ 1.250
|   |   Type_of_tea = Green: 27.063 {count=9}
|   |   Type_of_tea = Thai: 28.399 {count=8}
```

Figure 10 Model Analysis Description of the Random Forest Algorithm

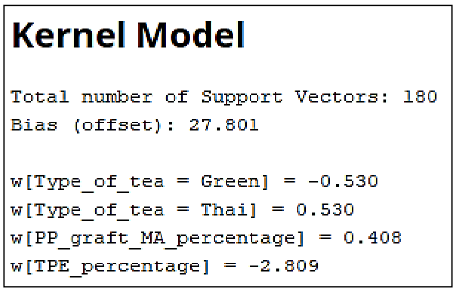

Figure 11 Model Analysis Description of the Support Vector Machine Algorithm

The results of the analysis using the Support Vector Machine (SVM) algorithm are shown in Figure 11. It was found that TPE had a significant negative effect on the predicted values, with a weight of -2.809, indicating a clear reduction in the predicted values. Meanwhile, PP-g-MA had a positive effect with a weight of 0.408, which slightly increased the predicted values. For the type of tea waste, green tea had a slight negative effect (-0.530), while Thai tea had a positive effect of the same magnitude (0.530). The bias (offset) value was 27.801, which is a constant used by the algorithm to calculate the predicted values. In summary, TPE was the factor with the most significant negative impact, followed by PP-g-MA with a positive effect, and the type of tea waste had the least influence compared to other factors.

Finally, the analysis using the Artificial Neural Network (ANN) is shown in Figure 12. It was found that TPE had the most pronounced negative influence, particularly in Node 1 (-4.264) and Node 3 (-2.143) of Hidden Layer 1, indicating that increasing TPE resulted in a decrease in yield strength. Meanwhile, PP-g-MA had a positive influence in Node 3 (1.566) and Node 2 (0.813) of Hidden Layer 1, significantly enhancing the yield strength. For the type of tea, Thai tea waste tended to have a positive effect, such as in Node 1 (0.466) and Node 2 (0.627) of Hidden Layer 1, while green tea had a slight negative influence, such as in Node 1 (-0.436) and Node 2 (-0.600) of Hidden Layer 1. The outputs from all nodes in the hidden layers were processed in the output layer, showing that TPE was the factor that most reduced yield strength, followed by PP-g-MA, which increased yield strength, and Thai tea waste, which tended to slightly increase the value compared to green tea.

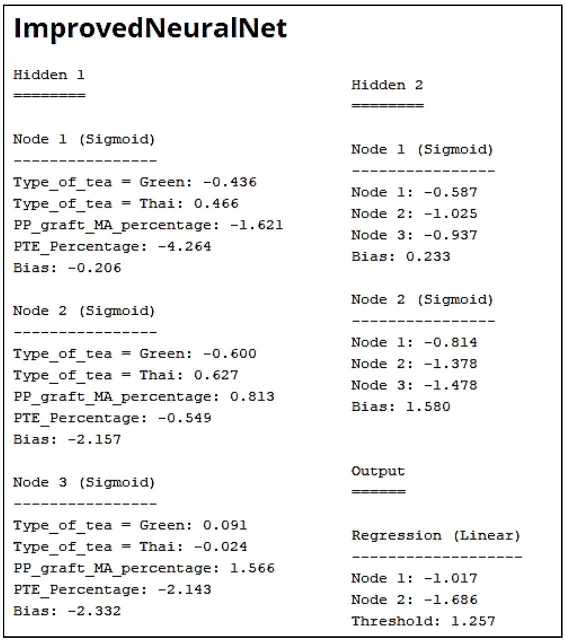

Figure 12 Model Analysis Description of the Artificial Neural Network Algorithm

Table 3 Summary of Factors Influencing Mechanical property Based on Machine Learning Algorithms

Mechanical property	Type of tea		PP-g-MA	TPE
	Thai	Green		
Yield Strength	+	-	+ +	- - -
Tensile Strength	+	-	+ +	- - -
%Elongation	+ +	- -	- -	+ + +
Impact Strength	-	+	+ +	+ + +
Hardness	- -	++	+	- - -

Note: +++ indicates a strong positive influence with the highest weight.

- - - indicates a strong negative influence with the highest weight.

Other mechanical property can be summarized in Table 3, which outlines the influence of various factors on the mechanical property of composite materials. It was found that the type of tea residual, PP-g-MA, and TPE had different effects on each property. Yield Strength and Tensile Strength were positively influenced by Thai tea residual and PP-g-MA but negatively affected by green tea residual and TPE. In contrast, Percentage Elongation was significantly positively influenced by Thai tea waste and TPE but negatively affected by Green tea residual and PP-g-MA. For Impact Strength, PP-g-MA and TPE had a strong positive influence, while the type of tea residual yielded different results; Green tea waste tended to increase impact resistance, whereas Thai tea waste tended to decrease it. Finally, Hardness was positively influenced by Green tea residual but negatively affected by Thai tea residual and TPE, with PP-g-MA having a minor positive effect.

3.3 Comparison of Predictive Capabilities from Machine Learning Algorithms

After testing the mechanical property of recycled polypropylene composite materials filled tea residual, the obtained data was analyzed using supervised machine learning processes. A comparative analysis of the predictive performance for various mechanical property of these composite materials was then conducted. This evaluation considered key metrics such as Root Mean Squared Error (RMSE), Relative Error, R-squared (R^2), and P-Value (α = 0.05) to understand the accuracy, explanatory power, and statistical significance of each algorithm in predicting different mechanical property. The purpose of this analysis was to identify the most suitable algorithm for predicting each type of mechanical property, which would be beneficial for efficiently developing composite materials with desired properties. The results can be seen in Table 4.

From the comparison of the performance of machine learning algorithms in predicting Yield Strength, it was found that Decision Tree and Random Forest algorithms yielded similar results, with the lowest Root Mean Squared Error (RMSE) values of 1.127 ± 0.217 MPa and 1.100 ± 0.224 MPa, respectively. These corresponded to relative errors of approximately 3.21% ± 0.52% and 3.10% ± 0.59%, and both had the highest R^2 values of 0.879. Following these, the Artificial Neural Network had an RMSE of 1.204 ± 0.09 MPa, a relative error of 3.40% ± 0.37%, and an R-squared of 0.859. The Generalized Linear Model had an RMSE of 1.559 ± 0.293 MPa, a relative error of 4.62% ± 1.10%, and an R^2 of 0.758. The Support Vector Machine had the highest RMSE at 1.697 ± 0.064 MPa, a relative error of 4.84% ± 0.15%, and an R^2 of 0.746. Additionally, the P-value of the Support Vector Machine was less than 0.001, indicating a statistically significant difference when compared to actual values. While other algorithms had P-values greater than 0.05, the results for Tensile Strength were similar, with the Decision Tree algorithm still providing outstanding results. It had the lowest RMSE at 0.966 ± 0.184 MPa, a relative error of 2.63% ± 0.57%, and a high R-squared value of 0.913, which was close to the Random Forest algorithm's performance. Random Forest had an RMSE of 0.932 ± 0.159 MPa, a relative error of 2.61% ± 0.49%, and an R^2 of 0.911. The Artificial Neural Network also performed well, with an RMSE of 1.127 ± 0.083 MPa, a relative error of 3.18% ± 0.25%, and an R^2 of 0.88. However, the Generalized Linear Model and Support Vector Machine continued to yield inferior results, particularly the Support Vector Machine, which had the highest RMSE at 1.574 ± 0.050 MPa and a P-value of 0.663, indicating that the results were not statistically significant compared to actual values.

The analysis to determine the capability of algorithms in predicting Percentage Elongation (%Elongation) found that the Artificial Neural Network provided the best results, with the lowest Root Mean Squared Error (RMSE) at 0.454 ± 0.029%, a relative error of 6.73% ± 0.68%, and an R^2 value of 0.761. Following this, the Random Forest algorithm had an RMSE of 0.448 ± 0.140%, a relative error of 6.52% ± 1.57%, and an R^2 of 0.747. The Decision Tree algorithm had an RMSE of 0.468 ± 0.141%, a relative error of 6.94% ± 1.94%, and an R^2 of 0.718. The Generalized Linear Model yielded an RMSE of 0.527 ± 0.123%, a relative error of 8.14% ± 1.82%, and an R^2 of 0.662. Finally, the Support Vector Machine had the highest RMSE at 0.809 ± 0.034%, a P-value less than 0.001, and a relative error of 14.47% ± 0.75%. The results show that the Support Vector Machine's outcomes are statistically significantly different from actual values and have the lowest predictive performance compared to other algorithms.

When considering the ability to predict impact strength, it was found that the Decision Tree and Artificial Neural Network algorithms demonstrated outstanding predictive performance. The Decision Tree had the lowest Root Mean Squared Error (RMSE) at 0.332 ± 0.078 and a Relative Error of 4.44% ± 1.11%, with an R-squared value of 0.877. Meanwhile, the Artificial Neural Network showed similar results with an RMSE of 0.340 ± 0.022, a Relative Error of 4.57% ± 0.35%, and an R-squared value of 0.871. The Random Forest algorithm also performed well, with an RMSE of 0.336 ± 0.083 and a Relative Error of 4.69% ± 1.19%. However, the Support Vector Machine had the highest RMSE at 0.910 ± 0.055 and a P-value < 0.001, indicating a statistically significant difference compared to actual values. The Generalized Linear Model also performed poorly, with an RMSE of 0.462 ± 0.049 and a Relative Error of 6.61% ± 0.90%.

For hardness prediction, the Decision Tree and Artificial Neural Network algorithms again delivered strong results. The Decision Tree had the lowest RMSE at 0.855 ± 0.215 and a Relative Error of 1.00% ± 0.22%, with an R-squared value of 0.893. The Artificial Neural Network showed similar performance with an RMSE of 0.882 ± 0.049, a Relative Error of 1.06% ± 0.06%, and an R-squared value of 0.877. The Random Forest algorithm also performed well, with an RMSE of 0.839 ± 0.240 and a Relative Error of 1.01% ± 0.27%. However, both the Support Vector Machine and Generalized Linear Model had higher RMSE values, particularly the Support Vector Machine, which had an RMSE of 1.409 ± 0.037 Shore D and a P-value of 0.234, indicating no statistical significance compared to actual values. The Generalized Linear Model had an RMSE of 1.308 ± 0.239 Shore D and a Relative Error of 1.66% ± 0.37%.

The analysis of the performance of machine learning algorithms in predicting the mechanical property of recycled polypropylene composite materials mixed with tea residual revealed significant differences among the algorithms. Decision Tree and Random Forest demonstrated the highest performance in predicting several mechanical property, including Yield strength, Tensile Strength, Impact Strength, and Hardness, as reflected by their low RMSE and relative error values, as well as high R^2 values. Additionally, the Artificial Neural Network showed prominence in predicting percentage elongation, although it required appropriate tuning of its structure and hyperparameters. In contrast, the Support Vector Machine showed clear limitations in predicting mechanical property, particularly in predicting percentage elongation and impact strength, with high RMSE and relative error values, along with a P-value indicating statistically significant differences compared to actual values. Meanwhile, the Generalized Linear Model showed performance inferior to that of Decision Tree, Random Forest, and Artificial Neural Network. These analysis results suggest that Decision Tree and Random Forest are the most suitable algorithms for predicting the mechanical property of composite materials in this study.

Table 4 Comparison of the Performance of Machine Learning Algorithms in Predicting Mechanical property

properties	Algorithm	Algorithm Performance		Prediction Performance	
		RMSE	Relative_error	R^2	P-value (α=0.05)
Yield Strength (MPa)	Generalized Linear Model	1.559 ± 0.293	4.62% ± 1.10%	0.758	0.980
	Decision Tree	1.127 ± 0.217	3.21% ± 0.52%	0.879	0.983
	Random Forest	1.100 ± 0.224	3.10% ± 0.59%	0.879	0.967
	Support Vector Machine	1.697 ± 0.064	4.84% ± 0.15%	0.746	<0.001
	Artificial Neural Network	1.204 ± 0.09	3.40% ± 0.37%	0.859	0.873
Tensile Strength (MPa)	Generalized Linear Model	1.493 ± 0.117	4.27% ± 0.43%	0.786	0.984
	Decision Tree	0.966 ± 0.184	2.63% ± 0.57%	0.913	0.982
	Random Forest	0.932 ± 0.159	2.61% ± 0.49%	0.911	0.991
	Support Vector Machine	1.574 ± 0.050	4.52% ± 0.15%	0.760	0.663
	Artificial Neural Network	1.127 ± 0.083	3.18% ± 0.25%	0.880	0.064
Elongation (%)	Generalized Linear Model	0.527 ± 0.123	8.14% ± 1.82%	0.662	0.983
	Decision Tree	0.468 ± 0.141	6.94% ± 1.94%	0.718	0.952
	Random Forest	0.448 ± 0.140	6.52% ± 1.57%	0.747	0.992
	Support Vector Machine	0.809 ± 0.034	14.47% ± 0.75%	0.679	<0.001
	Artificial Neural Network	0.454 ± 0.029	6.73% ± 0.68%	0.761	0.480

Table 4 (Continuous)

properties	Algorithm	Algorithm Performance		Prediction Performance	
		RMSE	Relative_error	R^2	P-value (α=0.05)
Impact Strength (kJ/m^2)	Generalized Linear Model	0.462 ± 0.049	6.61% ± 0.90%	0.760	0.994
	Decision Tree	0.332 ± 0.078	4.44% ± 1.11%	0.877	0.980
	Random Forest	0.336 ± 0.083	4.69% ± 1.19%	0.868	0.983
	Support Vector Machine	0.910 ± 0.055	12.67% ± 0.89%	0.758	<0.001
	Artificial Neural Network	0.340 ± 0.022	4.57% ± 0.35%	0.871	0.830
Hardness (Shore D)	Generalized Linear Model	1.308 ± 0.239	1.66% ± 0.37%	0.740	0.974
	Decision Tree	0.855 ± 0.215	1.00% ± 0.22%	0.893	0.991
	Random Forest	0.839 ± 0.240	1.01% ± 0.27%	0.885	0.983
	Support Vector Machine	1.409 ± 0.037	1.82% ± 0.04%	0.730	0.234
	Artificial Neural Network	0.882 ± 0.049	1.06% ± 0.06%	0.877	0.129

a)

b)

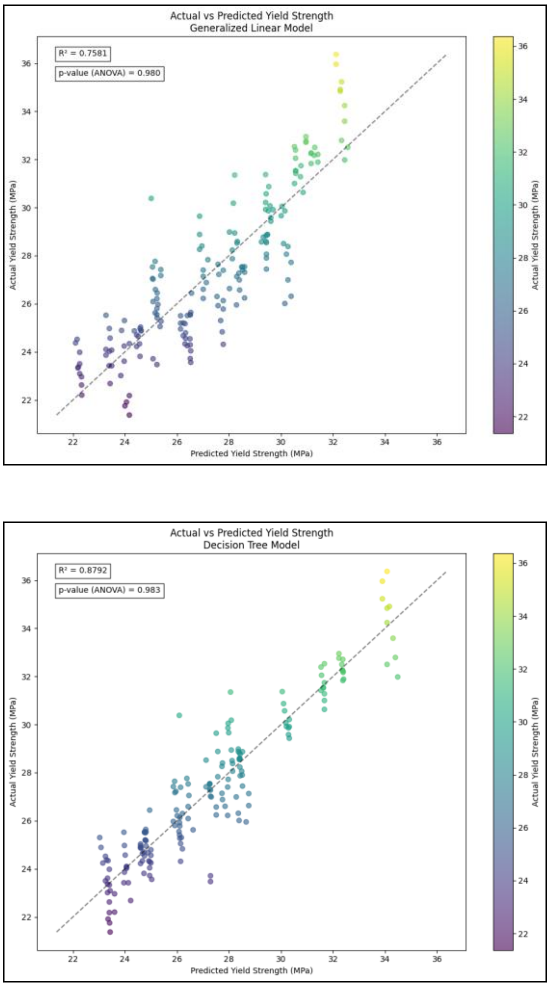

Figure 13 Example of Comparing Actual Yield Strength with Predicted Values for Recycled Polypropylene Composite Materials Mixed with Tea Waste Using Algorithms a) General Linear Regression and b) Decision Tree

3.4 Research Disscussion

From the analysis of the influence of factors on the mechanical property of composite materials, it was found that the TPE factor had the most significant impact, showing a negative effect on Yield Strength, Tensile Strength, and Hardness. However, it had a positive effect on Percentage Elongation and Impact Strength. This phenomenon can be explained by the toughening mechanism of TPE in composite materials, which acts as a high-elasticity phase (elastomeric phase) capable of absorbing a lot of energy. When the composite material is subjected to impact, the energy is distributed and absorbed by TPE particles, increasing impact resistance. Additionally, this leads to an increase in the material's ability to undergo plastic deformation, resulting in higher Percentage Elongation. Therefore, increasing the amount of TPE results in a decrease in the Strength and Hardness of the composite material. (Quaresimin *et al.*, 2015; Jiang *et al.*, 2021; Liu *et al.*, 2024)

The addition of PP-g-MA showed a positive influence on the composite material, enhancing Yield Strength, Tensile Strength, and Impact Strength, as well as having a positive effect on Hardness. However, it had a negative influence on

Percentage Elongation. These experimental results align with the theory of interface improvement in composite materials, as PP-g-MA acts as a coupling agent. The maleic anhydride (MA) groups can form ester or hydrogen bonds with the hydroxyl (-OH) groups on the surface of the tea residual, while the polypropylene (PP) segment can interpenetrate and form physical entanglements with the polypropylene matrix material. This results in more efficient stress transfer between the matrix and reinforcement, leading to increased strength of the composite material. The increase in impact resistance after adding PP-g-MA is due to improved interface properties that reduce stress concentration, which is the starting point for cracking (Gümüş, 2022; Tipboonsri and Memon, 2024). However, the decrease in Percentage Elongation of the composite material in this study is due to the increased stiffness of the composite material following interface improvement.

For the type of tea waste, its influence was less than the first two factors mentioned. The analysis found that Thai tea residual resulted in higher values for Yield Strength and Tensile Strength (+) compared to Green tea residual. However, Thai tea residual led to lower Impact Strength (-) and significantly lower Hardness (-) compared to Green tea residual. In contrast, green tea residual resulted in lower Yield Strength and Tensile Strength (-) than Thai tea residual but provided higher Impact Strength (+) and significantly higher Hardness (++) compared to Thai tea waste. The differences in mechanical property effects between these two types of tea residual can be explained by differences in molecular structure and chemical composition. Thai tea residual may have a cellulose structure that is more suitable for withstanding Tensile forces, leading to efficient stress transfer between tea residual particles and the Polymer Matrix. Green tea waste might have a different lignin composition, affecting its Hardness and ability to absorb energy from impact. The fact that Green tea waste has significantly higher Hardness than Thai tea residual may be related to differences in molecular orientation or crystallinity, which directly affect the composite material's resistance to deformation. Additionally, the microstructural arrangement capable of distributing and absorbing energy in each type of tea residual is related to differences in particle size, shape, or porosity. The uniform distribution of small particles is a key mechanism for enhancing Impact Strength. (Nasri *et al*., 2023; Poopakdee and Thammawichai, 2024; Tamura *et al*., 2024)

The comparative analysis of machine learning algorithms' performance shows that Decision Tree and Random Forest are outstanding in predicting the mechanical property of composite materials. This is due to their key characteristics, including the ability to handle non-linear relationships without requiring predefined relationship forms, especially in datasets with multiple classes and complex interactions between features. Their mechanism for evaluating and selecting important variables helps reduce overfitting and increase predictive accuracy, as well as their robustness to outliers in the dataset. In contrast, the Support Vector Machine (SVM) exhibits significant limitations in its application for predicting mechanical property, particularly its sensitivity to hyperparameter tuning, which requires expertise and high computational resources. The complexity in processing large datasets may necessitate techniques like sampling or decomposition, the difficulty in interpreting physical models from support vectors, and the need to select an appropriate kernel function for the data characteristics. These factors result in SVM having lower performance in predicting mechanical property of composite materials compared to Decision Tree and Random Forest. (Kibrete *et al*., 2023; Wang and Wu., 2023; Sorour *et al*., 2024)

When discussing research related to using artificial intelligence algorithms to predict the mechanical property of Wood Polymer Composites, it is found that each study yields different results depending on the properties of interest, the composition used, and the choice of algorithms. For example, a study by Joo *et al*. (2022) aimed to develop models for predicting the properties of PP composites using Multiple Linear Regression (MLR), Deep Neural Network (DNN), and Random Forest (RF) algorithms. When comparing the performance of these algorithms, it was found that MLR had the highest efficiency in predicting flexural strength (RMSE 8.3122, R^2 0.9291) and melting index (RMSE 2.4072, R^2 0.9406), while DNN was most accurate in predicting tensile strength (RMSE 4.9358, R^2 0.9587). All algorithms had R^2 values above 0.8, exceeding the minimum standard of 0.7. This study confirms that the effectiveness of the same model can vary depending on the desired property, and selecting the appropriate model can lead to highly accurate predictions of the physical properties of composite materials. (Joo *et al*., 2022; Türker *et al*., 2024) conducted research testing the Flexural Properties of Glulam wood with different sizes, reinforced with Carbon Fiber-Reinforced Polymers. They then used Machine Learning techniques to predict these properties using three methods: Artificial Neural Network (ANN), Random Forest, and XGBoost. The study found that as the cross-sectional size of the wood increased, its Flexural Properties also improved. The use of reinforcement materials increased these properties by approximately 22%. Additionally, all three predictive techniques showed high accuracy, but Random Forest provided the best predictive results (R^2 = 0.9892). Therefore, it can be concluded that the Flexural Properties of Reinforced wooden beams of different sizes can be accurately predicted using Machine Learning techniques. (Wang *et al*., 2023; Türker *et al*., 2024) proposed a study on Plant Fiber-Reinforced Composite materials, focusing on predicting Mechanical property for optimal design and application. They conducted Tensile Property tests and simulations using finite element methods combined with Machine Learning. The study found that the type of resin, the interface between fibers and the matrix, the volume fraction of fibers, and the interaction among these factors affected the Tensile Properties of the Composite Materials. In comparing the performance of Machine Learning algorithms, it was found that the Gradient Boosting Decision Tree (GBDT) provided the best predictive results, with an R^2 value of 0.786. Other integrated models, such as Random Forest, XGBoost, and CatBoost, also showed better predictive capabilities than the basic Decision Tree model. Additionally, the analysis indicated that the properties of the resin and the volume fraction of fibers were critical parameters influencing the tensile strength of composite materials. This study provided in-depth insights and an effective approach to analyzing the tensile properties of complex bio-based composite materials. (Wang *et al*., 2023)

From reviewing research related to the application of Artificial Intelligence Algorithms in predicting the Mechanical property of Wood Polymer Composites, it can be concluded that predictive efficiency depends on several factors, including the type of algorithm used, the specific properties being studied, and the composition of the material. It was found that Machine Learning algorithms such as Multiple Linear Regression, Deep Neural Network, Random Forest, Artificial Neural Network, and Gradient Boosting Decision Tree have the ability to accurately predict various mechanical property. Each study found that the algorithm providing the highest performance varied depending on the properties being studied, such as Flexural Strength, Tensile Strength, and Melting Index, with most R^2 values exceeding 0.8, which is considered reliable. Additionally, factors such as the type of resin, the proportion of reinforcing fibers, and the interface between fibers and the matrix were found to significantly affect the mechanical property of composite materials. Therefore, selecting the appropriate algorithm can enhance the accuracy and reliability of predicting the physical and mechanical property of composite materials.

4. Conclusion

Based on the objectives of this research, the findings can be summarized as follows:

1) To apply Artificial Intelligence or Machine Learning Algorithms to study the influence of factors affecting the Mechanical property of Recycled Polypropylene Composite materials filled with tea residual. The study found that Artificial Intelligence Algorithms can effectively demonstrate the influence of various factors, consistent with related research that discovered TPE (Thermoplastic Elastomer) has the most significant impact on mechanical property. TPE negatively affects Strength and Hardness but Positively affects Flexibility and Impact Strength. Meanwhile, PP-g-MA improves Strength and interfacial adhesion between phases. The type of tea residual affects mechanical property differently based on its structure and chemical composition.

2) To compare the predictive efficiency of artificial intelligence algorithms on the mechanical property of recycled polypropylene composite materials mixed with tea waste. In terms of machine learning-based prediction, it was found that Decision Tree and Random Forest algorithms provided the most accurate predictions for most mechanical property, with R^2 values exceeding 0.8 and low error values. This aligns with related research. The study not only provides in-depth insights into the relationship between components and material properties but also demonstrates the potential of using machine learning techniques to efficiently design and develop composite materials with desired properties.

A major challenge in recycled materials research is the variability of data caused by material purity and impurities, making it hard to achieve reliable results. Traditional statistical methods often cannot fully capture the complex, nonlinear influences in such data, highlighting the need for alternative approaches. Machine learning algorithms, now more accessible, can analyze complex datasets more accurately by identifying patterns that traditional methods may miss. As a result, integrating machine learning into materials research enables more precise predictions and deeper insights. This reflects the growing role of artificial intelligence in materials science, driving smarter and more sustainable innovations.

One key limitation of this research is the variability and inconsistency of data quality in recycled materials, which can hinder the accuracy of machine learning predictions. Additionally, the interpretability of complex algorithms remains a challenge, making it difficult for researchers to fully trust and apply these models in practical engineering contexts. The limited availability of large, standardized datasets and the potential lack of generalizability of models trained on specific material types further restrict the broader application of these AI-driven approaches in real-world recycling scenarios. To advance the use of machine learning in recycled materials research, it is important to build high-quality, standardized datasets, develop robust methods for integrating diverse data, and focus on interpretable models to foster trust and adoption. Additionally, applying techniques like transfer learning can help models generalize across different domains, while expanding real-world validation and encouraging interdisciplinary collaboration will ensure practical impact and continued progress in the field.

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