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A Comparative Study of Machine Learning Techniques for Predicting Mechanical Properties of Fused Deposition Modelling (FDM)-Based 3D-Printed Wood/PLA Biocomposite

Prashant Anerao [a] *, Atul Kulkarni [a], Yashwant Munde [b], Namrata Kharate [c]

[a] *Department of Mechanical Engineering, Vishwakarma Institute of Information Technology, Pune 411048, India*

[b] *Department of Mechanical Engineering, Cummins College of Engineering for Women, Pune 411052, India*

[c] *Department of Computer Engineering, Vishwakarma Institute of Information Technology, Pune 411048, India*

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ABSTRACT

Wood/PLA biocomposite filament is a 3D printing material that blends Polylactic Acid (PLA), a biopolymer, with wood powder acting as reinforcement. This combination results in a sustainable 3D printing filament that has grown in popularity in recent years due to its eco-friendliness and the natural appearance of 3D-printed parts. To assess the suitability of wood/PLA biocomposite for various additive manufacturing applications, it is essential to determine its mechanical properties. This study employs fused deposition modeling (FDM) as the additive manufacturing process and focuses on assessing the mechanical properties (tensile, flexural, and impact) of 3D-printed biocomposite. The Taguchi L_{27} design of the experiments is utilized, and the key process parameters under consideration are infill pattern, layer thickness, raster angle, nozzle temperature, and infill density. A layer thickness of 0.3 mm and an infill density of 100% yielded the highest tensile strength of 42.46 MPa, flexural strength of 83.43 MPa, and impact strength of 44.76 J/m. The dataset has been carefully prepared to facilitate machine learning for both training and testing, and it contains the experimental results and associated process parameters. Four distinct machine learning algorithms have been selected for predictive modeling: Linear Regression, Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), and Adaptive Boosting (AdaBoost). Given the intricate nature of the dataset and the presence of nonlinear relationships between parameters, XGBoost and AdaBoost exhibited exceptional performance. Notably, the XGBoost model delivered the most accurate predictions. The results were assessed using the coefficient of determination (R^2), and the achieved values for all observed mechanical properties were found to be greater than 0.99. The results signify the remarkable predictive capabilities of the machine learning model. This study provides valuable insights into using machine learning to predict the mechanical properties of 3D-printed wood/PLA composites, supporting progress in sustainable materials engineering and additive manufacturing.

1. Introduction

Fused Deposition Modeling (FDM) has emerged as a commonly adopted additive manufacturing (AM) technique, gaining popularity due to its ease of use, low cost, compact size, and safety [1]. FDM mostly uses polymeric materials like acrylonitrile butadiene

* **Corresponding author.**
E-mail address: prashant.anerao@viit.ac.in

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styrene (ABS) and polylactide (PLA) to construct 3D objects layer by layer. The industry's commitment to eco-friendly practices and rising awareness of environmental sustainability led to a major shift in material choices in the manufacturing sector [2,3]. In response, an increase in the use of natural fiber or filler-reinforced polymeric materials has been explored by many researchers for the FDM process [4]. Numerous studies have been conducted on the natural fiber reinforcements such as jute [5], abaca [6], animal feathers [7], kenaf [8], cotton [5], and lemongrass [9], and their impact on the mechanical properties of polymer composites; however, the application of these green composites for 3D printing is still limited. The functionality of 3D-printed components largely depends on mechanical characteristics, and mechanical performance depends on the characteristics of reinforcement as well as matrix material and process variables of FDM [10].

Zandi et al. [11] demonstrated the effect of varying printing parameters on timberfill (PLA reinforced with wood fibers) and found infill density had the largest influence on tensile strength. Kechagias et al. [12] achieved maximum strength in tension of 17.42 MPa for PLA reinforced with coconut flour. Also, this study indicated no influence of print speed on mechanical characteristics. Huang et al. [13] reported that the rounder shape and low surface roughness value of the wood particle resulted in a stiffer and stronger 3D-printed wood-plastic composite. Chaidas and Kechagias [14] examined the effect of the thickness of the printing layer on the surface properties of wood/PLA composite. A lower value of the parameter resulted in enhanced surface finish and dimensional accuracy. The study by Anerao et al. [15] demonstrates that the incorporation of biochar significantly enhances the mechanical properties. Suggesting the potential suitability of the additively fabricated biochar/PLA biocomposite for applications demanding higher stiffness and impact resistance. According to Morales et al.'s [16] investigation, an early initiation of degradation was seen in a 3D-printed rice husk-reinforced recycled plastic composite. Sekar et al. studied the acoustic performance of 3D-printed wood/PLA composites, but the mechanical properties were not explored in detail [17]. Maximum strength in tension of 22 MPa was achieved by Vigneshwaran and Venkateshwaran with 0.08 mm layer thickness [18]. Sultana et al. conducted a study on the effect of various FDM process parameters on the properties of 3D-printed wood/PLA composites and found that layer thickness had the largest contribution, accounting for 69% of the tensile strength [19].

It is difficult to model the complex mathematical relationships found in the AM process because of a variety of elements, including working conditions, processing parameters, and material qualities. Machine learning (ML) can detect latent knowledge and understand hidden patterns to enhance decision-making in terms of process optimization and quality control; it presents a promising path for improving AM operations [20, 21]. By analyzing vast amounts of data, ML algorithms can find optimal settings and predict potential problems before they occur, significantly improving the efficiency of the additive manufacturing process. Mishra and Jatti [22] employed a machine learning algorithm (graph neural networks) to forecast the strength of 3D-printed PLA components under tension, which resulted in a prediction with 78% accuracy. Mishra et al. [23] compared the performance of the nine ML models for predicting the roughness value of the surface of 3D-printed PLA items, and the result demonstrates that XGBoost outperformed the rest of the ML models.

Limited literature is available on prediction modeling using machine learning (ML) algorithms for the mechanical characteristics of biocomposites that are additively fabricated. Therefore, this paper offers a novel perspective by conducting a comparative analysis of various ML approaches for predicting the mechanical properties of FDM-based 3D-printed wood/PLA biocomposite, addressing a gap in the existing literature.

2. Materials and Methods

2.1. Material, Fabrication, and Testing of Wood/PLA Biocomposite

Wood-filled PLA composite filament, composed of 30% wood and 70% PLA, was procured from 3D Master, Pune, India. CAD models for each type of testing were created using SolidWorks and then translated into STL format. Key FDM process parameters, i.e., infill pattern (IP), layer thickness (LT), raster angle (RA), nozzle temperature (NT), and infill density (ID), were selected for investigation. Three levels of variations were decided (refer to Table 1), and using MINITAB software, experiments were designed, emphasizing Taguchi L_{27}. Table 2 depicts the details of 27 experiment runs and corresponding process parameters. As per the Taguchi L27, the process parameters were set in Kisslicer Slicer software, and G-codes were generated for each experiment run. The test specimens were fabricated using the Accucraft i250+, which is an FDM-based 3D printer (refer to Fig. 1).

Table 1. Levels of FDM Process parameters in DoE

Parameters	1	2	3
LT (mm)	0.2	0.3	0.4
RA (°)	0	45	90
NT (°)	200	210	220
ID (%)	33.33	50	100
IP	Line	Octagonal	Rounded

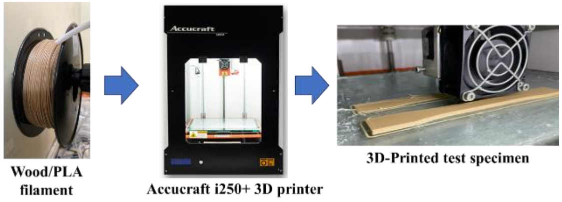

Fig. 1. Fabrication of a test specimen using the Accucraft i250+ 3D printer

Table 2. Experimental design utilizing a Taguchi L_{27} orthogonal array for Wood/PLA biocomposite mechanical testing.

Experimental Run	IP	LT (mm)	RA (°)	NT (°C)	ID (%)
1	Line	0.2	0	200	33.33
2	Line	0.2	45	220	100
3	Line	0.2	90	210	50
4	Line	0.3	0	220	50
5	Line	0.3	45	210	33.33
6	Line	0.3	90	200	100
7	Line	0.4	0	210	100
8	Line	0.4	45	200	50
9	Line	0.4	90	220	33.33
10	Octagonal	0.2	0	200	50
11	Octagonal	0.2	45	220	33.33
12	Octagonal	0.2	90	210	100
13	Octagonal	0.3	0	220	100
14	Octagonal	0.3	45	210	50
15	Octagonal	0.3	90	200	33.33
16	Octagonal	0.4	0	210	33.33
17	Octagonal	0.4	45	200	100
18	Octagonal	0.4	90	220	50
19	Rounded	0.2	0	200	100
20	Rounded	0.2	45	220	50
21	Rounded	0.2	90	210	33.33
22	Rounded	0.3	0	220	33.33
23	Rounded	0.3	45	210	100
24	Rounded	0.3	90	200	50
25	Rounded	0.4	0	210	50
26	Rounded	0.4	45	200	33.33
27	Rounded	0.4	90	220	100

Figure 2 illustrates the 3D-printed test specimens for tensile, flexural, and impact tests, along with the corresponding ASTM standards. To determine the tensile strength (TS) and tensile modulus (TM), tests were done following the ASTM D638 standard. In accordance with the ASTM D790 standard, flexural strength (FS) and flexural modulus (FM) were evaluated. For impact strength (IS), testing was performed as per the ASTM D256 standard. The various testing apparatus used for determining the mechanical properties of the 3-printed wood/PLA test sample is shown in Fig. 3.

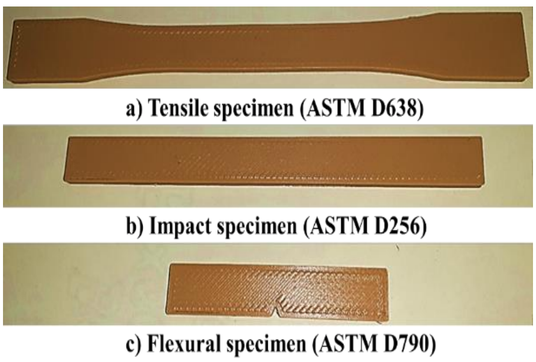

Fig. 2. 3D-printed Wood/PLA biocomposite specimens.

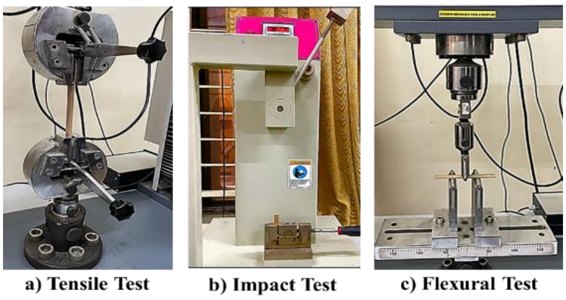

Fig. 3. Apparatus setup for various mechanical testing on Wood/PLA biocomposite.

2.2. Implementation of Various ML Models for Prediction Modeling

The results from the experimentation were carefully recorded, and the dataset was composed of the process parameters as described in Table 2 along with the resulting mechanical properties tabulated in Excel. For each experimental run, three samples were tested to ensure the precision and reproducibility of the experimental results. Hence, a total of 81 data points were present in the dataset for machine learning. Machine learning (ML) was used to create a prediction model for the essential mechanical properties of the wood/PLA 3D-printed biocomposite concerning the process parameters of the FDM method under investigation. Four ML models, namely linear regression (LR), support vector machine (SVM), extreme gradient boosting (XGBoost), and adaptive boosting (AdaBoost), were selected. All ML algorithms were implemented and executed using Google Colaboratory, a cloud-based platform for running Python code. Each ML model was systematically applied to the dataset, considering IP, LT, RA, NT, and ID as feature variables and UTS, TM, FS, FM, and IS as target variables. The dataset was split according to the IP, as it is a categorical variable. Further, the dataset was subdivided into datasets for training and testing of the ML model with a proportion of 80% and 20%, respectively using *'train_test_split'* from the *'sklearn'* library. A random state of 100 was set to ensure reproducibility.

At first, LR was selected as the prediction model for this task due to its simplicity and effectiveness in handling linear relationships. The module of LR was implemented for the '*sklearn.linear_model*' library. The second algorithm selected was SVM, due to its ability to handle high-dimensional spaces and its resistance to overfitting. The SVR's essential hyperparameters comprised a linear kernel and a regularization parameter C of 1.0, which balances the trade-off between obtaining low error on training data and minimizing model complexity. To allow various mechanical properties to be predicted at the same time, a '*MultiOutputRegressor*' was used within the linear kernel of SVM. Next, XGBoost was used because of its capacity to handle non-linear correlations and feature interactions. '*RandomizedSearchCV*' was used to tune the model's parameters and improve its performance. Lastly, AdaBoost was used for training and prediction purposes due to its ability to enhance the performance of weak learners by combining them into a strong predictive model. The '*AdaBoostRegressor*' from the '*sklearn.ensemble*' module was used in this implementation.

All ML models were trained on the training dataset (X train and Y train) using the 'fit' method. Following training, the model was tested on the test dataset (X test and Y test) by predicting the target variables. The predicted values from each ML model were compared with the mean values obtained from experiments. The coefficient of determination (R^2) values were calculated to assess the performance of each ML model.

3. Results and Discussions

3.1. Mechanical Testing

Table 3 presents the mean values obtained for TS, TM, FS, FM, and IS related to each experimental run. According to the results, the highest values for all mechanical properties correspond to 100% infill density. This is because more material is available to sustain the loading. An enhancement in mechanical strengths has been observed for 0.3 mm layer thickness. Using ANOVA, the significance of each process parameter for mechanical properties was calculated and presented in Table 4. IP, NT, and RA had insignificant effects on the mechanical properties. ID appeared as the most important process parameter, followed by LT.

Table 3. Mechanical properties for each experimental run.

Experimental Run	UTS (MPa)	TM (MPa)	FS (MPa)	FM (MPa)	IS (J/m)
1	29.72±1.64	1027.12±98.82	61.84±3.86	2470.09±943.15	33.33±3.61
2	42.36±0.34	948.87±298.20	82.93±1.04	3659.68±330.18	35.42±3.61
3	26.03±0.50	801.27±51.24	58.51±0.79	2973.49±328.62	33.33±3.61

4	25.62±0.51	638.54±9.36	62.67±2.50	2534.82±187.76	31.25±0.00
5	27.33±2.27	927.77±113.27	57.09±1.35	3214.78±200.06	35.42±3.61
6	36.86±4.18	848.93±46.77	69.65±2.89	3237.49±254.24	44.79±4.77
7	37.94±0.52	727.74±11.39	75.62±0.11	2933.24±577.46	41.67±3.61
8	24.43±1.37	802.00±95.35	59.95±0.84	2931.69±337.06	39.58±1.80
9	25.53±1.46	715.16±267.78	47.49±2.41	2729.46±398.41	37.5±6.25
10	29.57±0.18	1049.06±71.95	57.22±0.56	3356.93±771.56	29.17±3.61
11	28.02±0.22	895.07±77.02	50.87±0.98	2409.34±406.32	31.25±0.00
12	38.48±0.69	851.03±63.01	74.62±1.51	3389.32±219.84	34.38±5.41
13	39.46±1.39	888.36±313.74	83.44±0.56	3725.24±354.65	40.63±3.13
14	27.14±0.78	893.10±43.44	53.49±2.55	2742.45±119.20	39.58±3.61
15	29.31±0.41	719.70±95.68	59.85±0.32	2865.40±172.26	27.08±3.61
16	22.95±0.83	690.85±39.10	50.50±1.82	2677.57±258.00	36.46±4.77
17	37.40±0.16	789.06±19.31	78.51±0.72	3007.53±824.49	42.71±1.80
18	26.16±0.75	752.08±46.95	46.08±0.22	1778.21±329.85	38.54±1.80
19	37.74±5.82	1135.22±98.75	70.30±16.0	3429.52±663.90	37.50±5.41
20	27.82±0.05	963.76±13.53	49.81±0.94	2322.84±387.24	35.42±3.61
21	24.64±0.36	738.80±21.88	56.15±0.42	3570.00±609.49	33.33±3.61
22	24.79±0.36	670.70±11.70	61.80±1.51	3176.69±581.68	29.17±7.22
23	42.46±0.47	817.13±89.16	83.10±1.99	3694.52±570.61	40.63±3.13
24	26.64±1.13	698.36±22.61	62.62±0.63	2497.70±441.79	36.46±4.77
25	24.29±2.38	727.33±165.48	55.20±0.42	2719.85±460.24	33.33±3.61
26	24.29±0.30	680.26±69.52	56.11±0.76	2937.69±547.48	33.33±7.22
27	35.52±0.47	621.70±9.30	70.64±2.19	2974.44±784.22	41.67±1.80

Table 4. Summary of the significance of the process parameter based on ANOVA results.

Source of Variation	% Significance on UTS	% Significance of TM	% Significance of FS	% Significance on FM	% Significance of IS
IP	1	4	1	2	2
LT	5	45	6	10	18
RA	1	13	2	2	5
NT	0	6	2	8	1
ID	88	4	75	36	42
Residual Error	6	28	14	41	33

3.2. Prediction of Mechanical Properties Using Various ML Models and their Comparison.

Predicted values of various mechanical properties, i.e., UTS, TM, FS, FM, and IS, using the linear regression (LR) model are presented in Fig. 4. LR calculates the coefficients to minimize the difference between predicted and actual values, assuming a linear relationship exists between feature and target parameters. As the dataset lacks linearity, LR did not fully capture the relationship. As can be seen from Table 5, LR resulted in lower R^2 values for all mechanical properties.

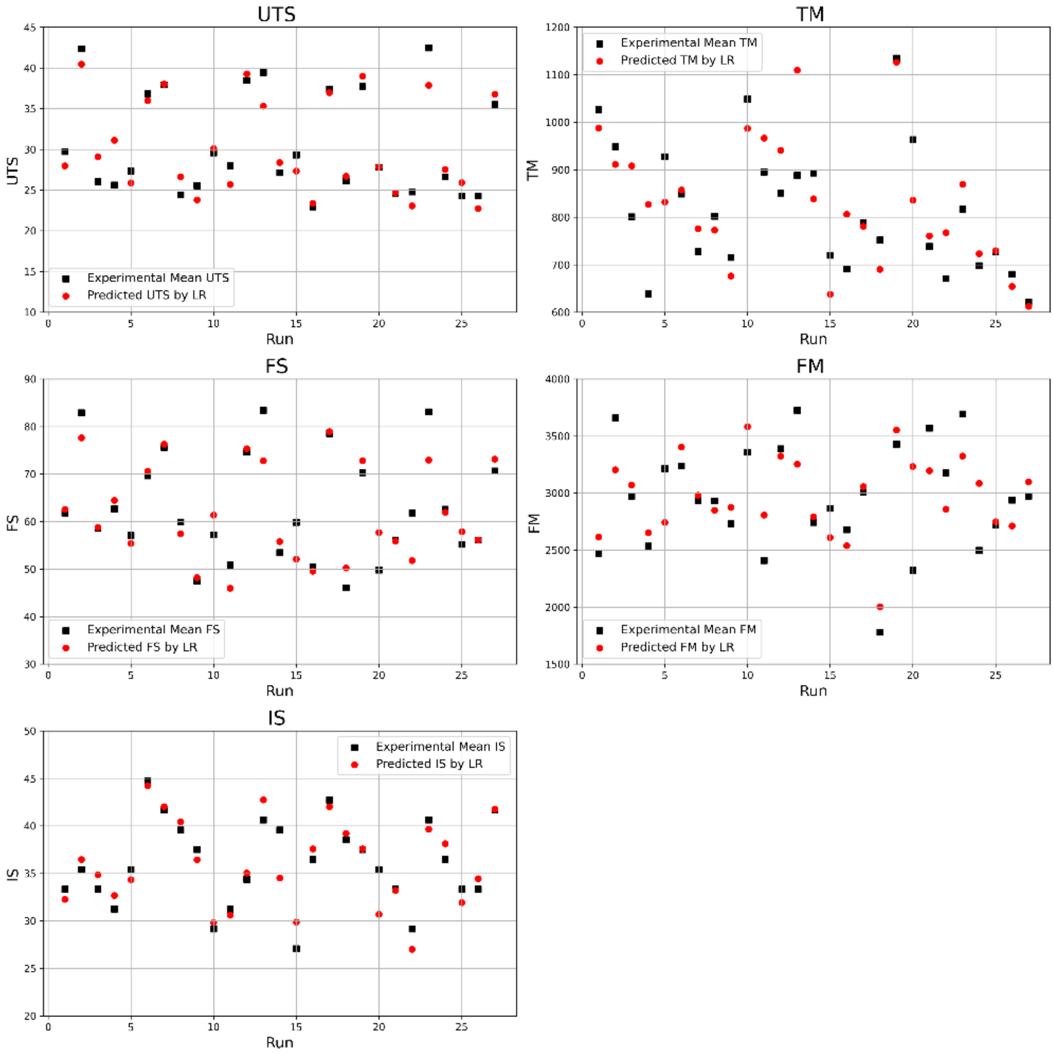

Fig. 4. Plot of experimental mean vs. predicted values of various mechanical properties by linear regression.

Table 5. R^2 comparison: machine learning models and predicted mechanical properties.

R^2	LR	SVM	XGBoost	AdaBoost
UTS	0.8834	0.0639	0.9970	0.9822
TM	0.5904	0.0214	1.0000	0.5495
FS	0.8263	0.0530	0.9990	0.9907
FM	0.5219	0.0392	1.0000	0.6811
IS	0.8367	0.2683	0.9944	0.8650

Figure 5 provides the plots of the experimental mean values vs. predicted values by Support Vector Machine (SVM) for each experimental run. The graph clearly shows that the predicted values significantly deviate from the actual values. Based on Table 5, it can be concluded that SVM with consistently low values of R^2 might not be suitable for capturing complex relationships present in the dataset.

The plot of experimental values vs. predicted values by two ensemble learning models, i.e., XGBoost and AdaBoost, is presented in Fig. 6 and Fig. 7, respectively. With very high R^2 values (refer to Table 5), XGBoost provides accurate prediction for all properties (e.g., UTS, TM, FS, FM, and IS), making it the most suitable ML model for the given dataset. AdaBoost effectively leverages the ensemble approach to improve predictive accuracy, as seen by high R^2 values (refer to Table 5), particularly for UTS and FS.

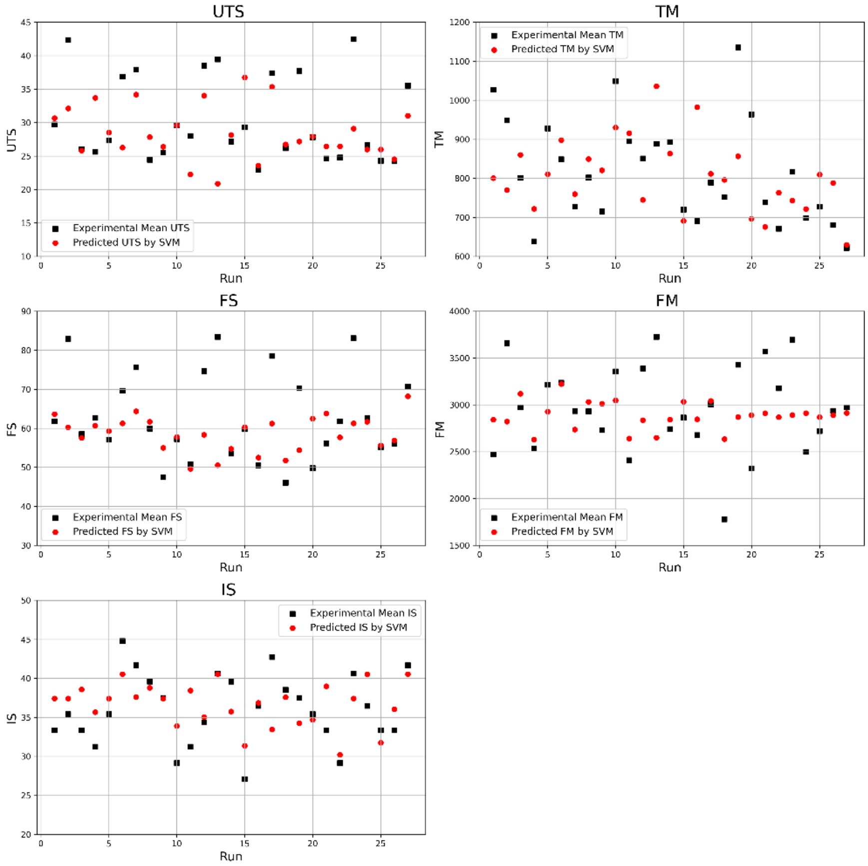

Fig. 5. Plot of experimental mean vs. predicted values of various mechanical properties by SVM.

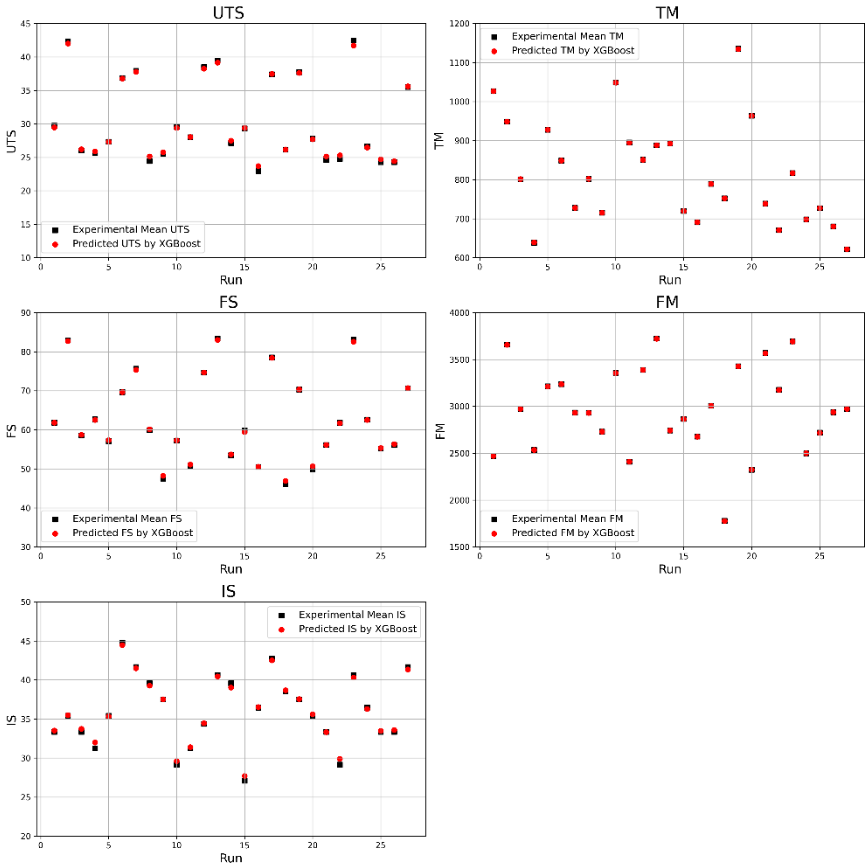

Fig. 6. Plot of experimental mean vs. predicted values of various mechanical properties by XGBoost.

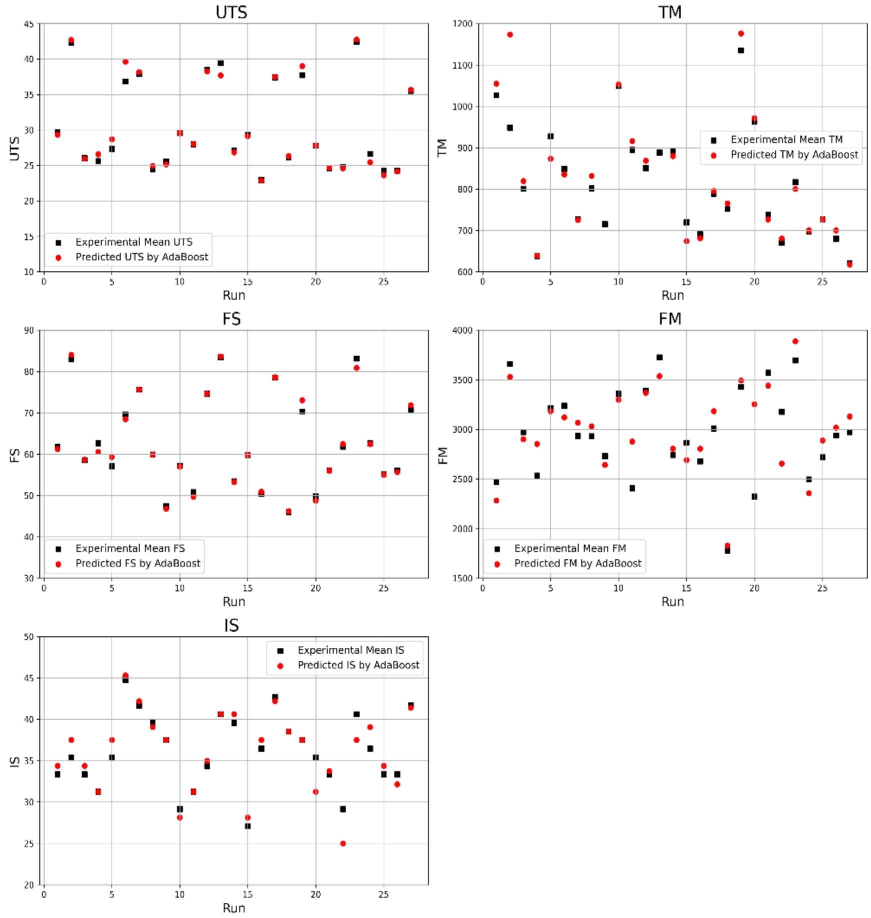

Fig. 7. Plot of experimental mean vs. predicted values of various mechanical properties by AdaBoost.

4. Conclusions

Wood/PLA biocomposite, chosen due to its sustainability, underwent a comprehensive investigation for mechanization utilizing the Taguchi L_{27} experimental design. ANOVA suggested ID as the predominant FDM process parameter, followed by LT. ID accounted for 88% of the variation in ultimate tensile strength (UTS) and 75% in flexural strength (FS) in the study. A 0.3 mm LT and 100% ID resulted in maximum tensile, flexural, and impact strengths of 42.46 MPa, 83.43 MPa, and 44.76 J/m, respectively. With a consistently low R^2 score, the SVM model failed to generalize the complex relationship between FDM process parameters and the resulting mechanical properties. Notably, XGBoost outperformed all other ML models and achieved the highest R^2 values for every mechanical property. XGBoost effectively captured the intricate and non-linear relationships in the dataset. This study contributes by investigating the use of sustainable materials in additive manufacturing for commercial applications such as packaging, transportation, and the automotive industry, and shedding insight into the important FDM process parameters that determine its performance. Further research is required to optimize FDM process parameters to achieve enhanced mechanical properties by employing advanced AI and ML techniques.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

References

[1] Mazzanti, V., Malagutti, L., and Mollica, F., 2019. FDM 3D printing of polymers containing natural fillers: A review of their mechanical properties. Polymers. 11 (7).

[2] Palaniappan, S.K., Singh, M.K., Rangappa, S.M., and Siengchin, S., 2024. Eco-friendly Biocomposites: A Step Towards Achieving Sustainable Development Goals. Applied Science and Engineering Progress.

[3] Suyambulingam, I., Rangappa, S.M., and Siengchin, S., 2023. Advanced Materials and Technologies for Engineering Applications. Applied Science and Engineering Progress.

[4] Prajapati, A.R., Dave, H.K., and Raval, H.K., 2021. Effect of fiber volume fraction on the impact strength of fiber reinforced polymer composites made by FDM process. in: Mater Today Proc, Elsevier Ltd, pp. 2102–2106.

[5] Kurien, R.A., Santhosh, A., Paul, D., Kurup, G.B., Reji, G.S., and Selvaraj, D.P., 2021. A Study on Recent Developments in Jute, Cotton, Coir, Silk and Abaca Fiber-reinforced Composites. in: pp. 375–384.

[6] Kurien, R.A., Selvaraj, D.P., Sekar, M., Koshy, C.P., Paul, C., Palanisamy, S., et al., 2023. A comprehensive review of the mechanical, physical, and thermal properties of abaca fiber for their introduction into structural polymer composites. Cellulose. 30 (14), pp.8643–8664.

[7] Kurien, R.A., Biju, A., Raj, A.K., Chacko, A., Joseph, B., Koshy, C.P., et al., 2023. Comparative Mechanical Properties of Duck Feather–Jute Fiber Reinforced Hybrid Composites. Transactions of the Indian Institute of Metals. 76 (9), pp.2575–2580.

[8] Kurien, R.A., Santhosh, A., Paul, D., Kurup, G.B., and Reji, G.S., 2021. A Review on Recent Developments in Kenaf, Sisal, Pineapple, Bamboo and Banana Fiber-Reinforced Composites. in: pp. 301–310.

[9] Kurien, R.A., Preno Koshy, C., Santhosh, A., Kurup, G.B., Paul, D., and Susan Reji, G., 2022. A study on vetiver fiber and lemongrass fiber reinforced composites. Materials Today: Proceedings. 68 pp.2640–2645.

[10] Anerao, P., Kulkarni, A., and Munde, Y., 2023. A review on exploration of the mechanical characteristics of 3D-printed biocomposites fabricated by fused deposition modelling (FDM). Rapid Prototyping Journal.

[11] Zandi, M.D., Jerez-Mesa, R., Lluma-Fuentes, J., Jorba-Peiro, J., and Travieso-Rodriguez, J.A., 2020. Study of the manufacturing process effects of fused filament fabrication and injection molding on tensile properties of composite PLA-wood parts. International Journal of Advanced Manufacturing Technology. 108 (5–6), pp.1725–1735.

[12] Kechagias, J.D., Zaoutsos, S., and Chaidas, D., 2021. Parameter design of PLA/Wood Fused Filament Fabrication using Taguchi optimization methodology.

[13] Huang, Y., Löschke, S., and Proust, G., 2021. In the mix: The effect of wood composition on the 3D printability and mechanical performance of wood-plastic composites. Composites Part C: Open Access. 5.

[14] Chaidas, D. and Kechagias, J.D., 2022. An investigation of PLA/W parts quality fabricated by FFF. Materials and Manufacturing Processes. 37 (5), pp.582–590.

[15] Anerao, P., Kulkarni, A., Munde, Y., Shinde, A., and Das, O., 2023. Biochar reinforced PLA composite for fused deposition modelling (FDM): A parametric study on mechanical performance. Composites Part C: Open Access. 12.

[16] Morales, M.A., Atencio Martinez, C.L., Maranon, A., Hernandez, C., Michaud, V., and Porras, A., 2021. Development and characterization of rice husk and recycled polypropylene composite filaments for 3d printing. Polymers. 13 (7).

[17] Sekar, V., Eh Noum, S.Y., Sivanesan, S., Putra, A., Chin Vui Sheng, D.D., and Kassim, D.H., 2021. Effect of Thickness and Infill Density on Acoustic Performance of 3D Printed Panels made of Natural Fiber Reinforced Composites. Journal of Natural Fibers. 00 (00), pp.1–9.

[18] Vigneshwaran, K. and Venkateshwaran, N., 2019. Statistical analysis of mechanical properties of wood-PLA composites prepared via additive manufacturing. International Journal of Polymer Analysis and Characterization. 24 (7), pp.584–596.

[19] Sultana, J., Rahman, M.M., Wang, Y., Ahmed, A., and Xiaohu, C., 2023. Influences of 3D printing parameters on the mechanical properties of wood PLA filament: an experimental analysis by Taguchi method. Progress in Additive Manufacturing.

[20] Qin, J., Hu, F., Liu, Y., Witherell, P., Wang, C.C.L., Rosen, D.W., et al., 2022. Research and application of machine learning for additive manufacturing. Additive Manufacturing. 52.

[21] Ladani, L.J., 2021. Applications of artificial intelligence and machine learning in metal additive manufacturing. JPhys Materials. 4 (4).

[22] Mishra, A., Di Milano, P., and Jatti, V., 2023. Graph Neural Networks (GNN) for Tensile Strength Prediction in Additive Manufacturing.

[23] Mishra, A., Jatti, V.S., Sefene, E.M., and Paliwal, S., 2023. Explainable Artificial Intelligence (XAI) and Supervised Machine Learning-based Algorithms for Prediction of Surface Roughness of Additively Manufactured Polylactic Acid (PLA) Specimens. Applied Mechanics. 4 (2), pp.668–698.