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Original Article

A Comparative Study of Machine Learning Techniques for Predicting Mechanical Properties of 3D-Printed Hybrid TPU/PLA Hybrid Composites

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Abstract - *Thermoplastic Polyurethane (TPU) and Polylactic Acid (PLA) are mostly used thermoplastics due to the special mechanical properties in Fused Deposition Modelling (FDM). PLA is brittle and hard, unlike TPU, which is extremely flexible, tough, and impact-resistant. Although additive manufacturing, materials development, optimization of processes, and the application of machine learning have made great progress, the majority of the current literature deals with single-material systems or homogeneous composites. Even though mixed composites and multi-material methods were explored, no study was done on structured layered hybrid composites with particular reference to the use of TPU alternating with PLA as a layer. Furthermore, ML models have been widely used in prediction, but a large-scale comparative study of layered hybrid TPU/PLA composites has not been conducted. This research focuses on the PLA/TPU alternate layered hybrid composite in an equal (1:1) ratio to acquire a balanced strength and ductile factor to be used in advanced applications in additive manufacturing. The mechanical properties of FDM-fabricated specimens, like Young's Modulus (E or EM) and Tensile Strength (TS or TES), are found at various process parameters. The parameters considered for the Taguchi L27 experimental design are the Thickness of the Layer (LT), the Printing Speed (PS), the Temperature of the Nozzle (TPU/PLA NT), the number of Shell/Wall Layers (SL), and the Bed Temperature (BT) as parameters. The experiment was repeated three times, which gave evidence of the accuracy and repeatability of the experiment and obtained 27 experimental results. The experimental results indicate that the layer thickness and nozzle temperature are the most significant parameters that influence the mechanical performance. This is due to the fact that the thinnest layer has the most interlayer bonding and the highest tensile strength of 40.795 MPa and Young's modulus of 1.188 GPa. With faster printing speed, the mechanical properties are reduced due to a reduction in interlayer adhesion. The tensile strength is most sensitive to the layer thickness. The nonlinear correlations between the process parameters and the mechanical properties are very complicated and are modelled using Machine Learning (ML) techniques such as Linear Regression (LR), Random Forest (RF), Support Vector Machine (SVM), Adaptive Boosting (AdaBoost) and eXtreme Gradient Boosting (XGBoost). XGBoost has the highest predictive capacity with an R^2 of above 0.99 for tensile strength and Young's modulus, among others.*

Keywords - *PLA, TPU, Hybrid composite, Machine Learning.*

1. Introduction

Additive Manufacturing has turned out to be a state-of-the-art manufacturing technology, allowing the creation of complex geometries by a layer-by-layer deposition method using direct input of digital models. Particular benefits of this technology compared to traditional manufacturing technology include minimization of the wastage of material and a high level of design flexibility, as well as a quick prototyping cycle [1, 2]. Shahrubudin et al. [3] illustrated Additive Manufacturing versatility and efficiency by the fact that it is widely applied in such fields as aerospace, automotive, biomedical, and consumer products. Bandyopadhyay et al. [4] found that Additive Manufacturing has found extensive use in biomedical engineering, especially in personalized implants and scaffolding of tissues.

2. Literature Review

Fused Deposition Modelling is one of the most common Additive Manufacturing methods because it is easy to use, cheap, and can be used with polymeric materials. The FDM involves a series of layers and forcing thermoplastics into a nozzle after meltdown. This method is also popular because it is easy to work and can make operational parts with little help [5, 6]. Wankhede et al. [7] found that layer thickness has a great influence on the mechanical properties of FDM- printed parts, which leads to anisotropy and a lack of interlayer bonding. Pawel Madejski et al. [8] showed that infill pattern and internal structure are characteristics of thermomechanical behavior and failure mechanisms.

The other important feature of FDM is that thermoplastic materials can be melted and solidified repeatedly. Traditionally, the materials with non-uniform mechanical and thermal characteristics are used, such as PLA, ABS, PETG, and TPU [9]. The polymer composites have also helped strengthen thermoplastics by adding fibers, particles, and fillers that make the material stronger, stiffer, and more useful [10, 11]. The concentration of fillers significantly influences the mechanical performance of PCL-based composites [12], while reinforcement improves durability and structural integrity [13].

PLA is a thermoplastic material used in FDM as it is easy to print, strong, and biodegradable compared to other thermoplastics. Farah et al. [9] found that PLA has a fundamental weakness of brittle nature and low impact resistance, which restricts its usage in flexible structures. Thermal studies by Zainuddin et al. [14] also indicated that temperature has a major influence on improving the PLA properties. Comparative studies by Youvalari et al. [15] showed that PLA has better fatigue performance and lower impact strength than other materials. Some studies have already shown how wood filler works in PLA composite with wood-filled samples [16, 17]. In theory, natural fillers should make the material stiffer, but this comes at the cost of printability and interface bonding. The degradation study by Shi et al. [18] has also found that the environment affects the performance of PLA.

Thermoplastic Polyurethane (TPU) has received popularity because of its high flexibility, elasticity, and wear resistance. Yijin Xu et al. [19] found that TPU properties are significantly influenced by its molecular structure and phase morphology. Gallu et al. [20] studies focused on TPU blends and demonstrated that the viscoelasticity and compatibility properties of TPU are critical for predicting overall mechanical behavior. Tao Xu et al. [21] research on TPU blends had shown better systems of compatibility in composites and viscoelasticity. Beloshenko et al. [22] TPU lattice structures have demonstrated themselves to be energy-absorbing. Mechanical performance and friction experiments of Wang et al. [23] have given an insight into the behavior of interfaces at the micro-level. TPU has also been shown to work in advanced applications like wearable sensors, as was mentioned, and biomedical scaffolds [24, 25]. It was found that the mechanical properties of TPU were extremely sensitive to the conditions of processing in the parameter study [26, 27].

Researchers have studied TPU/PLA composite systems for rigidity and flexibility. Khorooty et al. [28] reported the TPU/PLA blend study, i.e., TPU is a trade-off between stiffness and flexibility, with an increase in ductility and impact resistance and a decrease in tensile strength. Di Zhang et al. [29] research on PETG-TPU composites revealed superior shape memory and flexibility characteristics, while multi-material techniques such as blended FDM (b-FDM) improved interfacial bonding and energy absorption.

Optimization of the FDM process parameters should be made so that the desired mechanical properties are achieved. This has been greatly achieved through the application of conventional statistical methods like Taguchi design and ANOVA. Wankhede et al. [7] suggested these approaches were implemented to determine the most significant parameters and define the most promising combinations that can lead to the enhancement of the performance. Gupta et al. [30] did the experiment by utilizing the DOE and Taguchi methods; the layer thickness and infill density turned out to be the most important issues, which influence TES and the quality of the surface of a substance. However, the approaches are highly experimental and limited in the list of revelations of nonlinear relationships among variables.

To address these constraints, ML technologies have been used more often in additive manufacturing. SVM, Artificial Neural Networks (ANN), regression models, and ensemble methods are examples of ML models that have been shown to be very accurate in the prediction of mechanical properties. Aktepe and Ergün [31] found that ML applications are effective at modelling complex process-output relationships. The compression strength prediction and tensile strength prediction studies have shown that they were much more accurate than the usual methods [32, 33]. Anerao et al. [34] found that ML methods like XGBoost and AdaBoost have performed better because they are able to learn nonlinear interactions. Ulkir et al. [35] successfully applied ANNs, along with fuzzy logic models, to predict mechanical properties of composite materials. Varma et al. [36] did the optimization of mechanical performance using the BPNN-based models. The same things were also demonstrated by other ML-based works [32, 33], and they showed that ML smoothens the number of experiments that will be needed and enhances the usefulness of prediction. Eslaminia et al. [37] used AI-based methods such as FDM-Bench so that they could focus on smart systems of monitoring and optimization of processes as well.

Although additive manufacturing, materials development, optimization of processes, and the application of machine learning have made great progress, the majority of the current literature deals with single-material systems or homogeneous composites. Even though mixed composites and multi-material methods were explored, no study was done on structured layered hybrid composites with particular reference to the use of PLA alternating with TPU as a layer. Furthermore, ML models have been widely used in prediction, but a large-scale comparative study of layered hybrid TPU/PLA composites has not been conducted.

3. Materials and Methods

TPU and PLA filaments became the key materials to be utilized in the production of composite parts using the FDM process. PLA is one of the biodegradable thermoplastic polymers derived from corn starch and sugarcane and, due to its low melting point, high level of printability, and dimensional stability, is popular in additive manufacturing. It has a moderately good tensile strength and stiffness but has a fundamental brittle nature, low impact resistance, and low elongation, which limits its use in flexible and load-bearing components. However, TPU is an elastomeric polymer that is highly flexible, extendable, resistant to abrasion, and tough.

TPU can handle a lot of stress without breaking, so it can be used in situations where it needs to be flexible and absorb force. However, TPU is comparatively more flexible than PLA, which restricts its application in rigid structural use. Therefore, one of the possible successful methods of finding the balance between strength and flexibility is the combination of PLA and TPU. The coupons represent distributions of PLA and TPU in the alternate layers in the printed samples and are used to study the interaction between the rigid and flexible phases, PLA and TPU, respectively.

Table 1. FDM Process parameters

Parameters	1	2	3
LT (mm)	0.3	0.225	0.18
PS (mm/s)	45	50	55
TPU/PLA NT (°C)	230/220	235/225	240/230
SL	2	3	4
BT (°C)	50	55	60

Process parameters have a great impact on the mechanical performance of FDM-printed components. In this study, five key parameters were selected as shown in the Table 1. They are LT, PS, TPU/PLA - NT, SL, and BT.

Table 2. Taguchi L27 experimental design

Experimental Run	LT (mm)	PS (mm/s)	TPU/PLA NT (°C)	SL	BT (°C)
1	0.30	45	230/220	2	50
2	0.30	45	235/225	2	55
3	0.30	45	240/230	2	60
4	0.30	50	230/220	3	50
5	0.30	50	235/225	3	55
6	0.30	50	240/230	3	60
7	0.30	55	230/220	4	50
8	0.30	55	235/225	4	55
9	0.30	55	240/230	4	60
10	0.225	45	230/220	3	55
11	0.225	45	235/225	3	60
12	0.225	45	240/230	3	50
13	0.225	50	230/220	4	55
14	0.225	50	235/225	4	60
15	0.225	50	240/230	4	50
16	0.225	55	230/220	2	55
17	0.225	55	235/225	2	60
18	0.225	55	240/230	2	50
19	0.18	45	230/220	4	60
20	0.18	45	235/225	4	50
21	0.18	45	240/230	4	55
22	0.18	50	230/220	2	60
23	0.18	50	235/225	2	50
24	0.18	50	240/230	2	55
25	0.18	55	230/220	3	60
26	0.18	55	235/225	3	50
27	0.18	55	240/230	3	55

Table 2 represents the Taguchi DOE technique to analyze the process parameters systematically. Taguchi methodology is common in manufacturing studies to maximize process parameters using fewer experiments. In this experiment, all five parameters were given three levels, and experiments were planned with the Taguchi L27 orthogonal array, where 27 experimental runs were to be done.

The tensile test specimens required for mechanical characterization were designed using SolidWorks software as per ASTM D638 [38] standard, as shown in the Figure 1. These models were converted into STL format and then sliced using software Simplify3D. The slicing process generated G-code instructions, which were used by the 3D printer to fabricate the specimens. The fabrication of specimens was done in AKAR 600 PRO FDM 3D printer, which is an advanced additive manufacturing system with a large build volume of 600 × 600 × 620 mm, as shown in the Figure 2. It is an FDM printer with dual extruders, which enables it to print PLA and TPU in multi-materials. The upper limit of the nozzle temperature of the printer is around 305 °C, and the heated bed can be heated to a maximum of 120 °C, allowing printed components to be bonded correctly.

The recommended printing speed is 30-200 mm/s to achieve the best print quality. The printer has innovative functions like automatic bed leveling (BLTouch sensor), filament run-out sensor, and power loss recovery, which contribute to the increased accuracy and reliability of printing. The use of such features ensures consistent fabrication of specimens and minimizes printing defects.

The Figure 3 shows a PLA/ TPU specimen printed on AKAR 600 Pro. Three specimens were made for each experimental condition to ensure repeatability and accuracy. Thus, 81 specimens were manufactured to undergo a mechanical test to evaluate their performance under different loading conditions.

A tensile test was done in a Universal Testing Machine (UTM) as shown in the Figure 4, in reference to ASTM D638 standards. This test is used to determine the final TES and EM of the material. Three specimens were tested for each test run, and the mean values of tensile strength were obtained to be analyzed further.

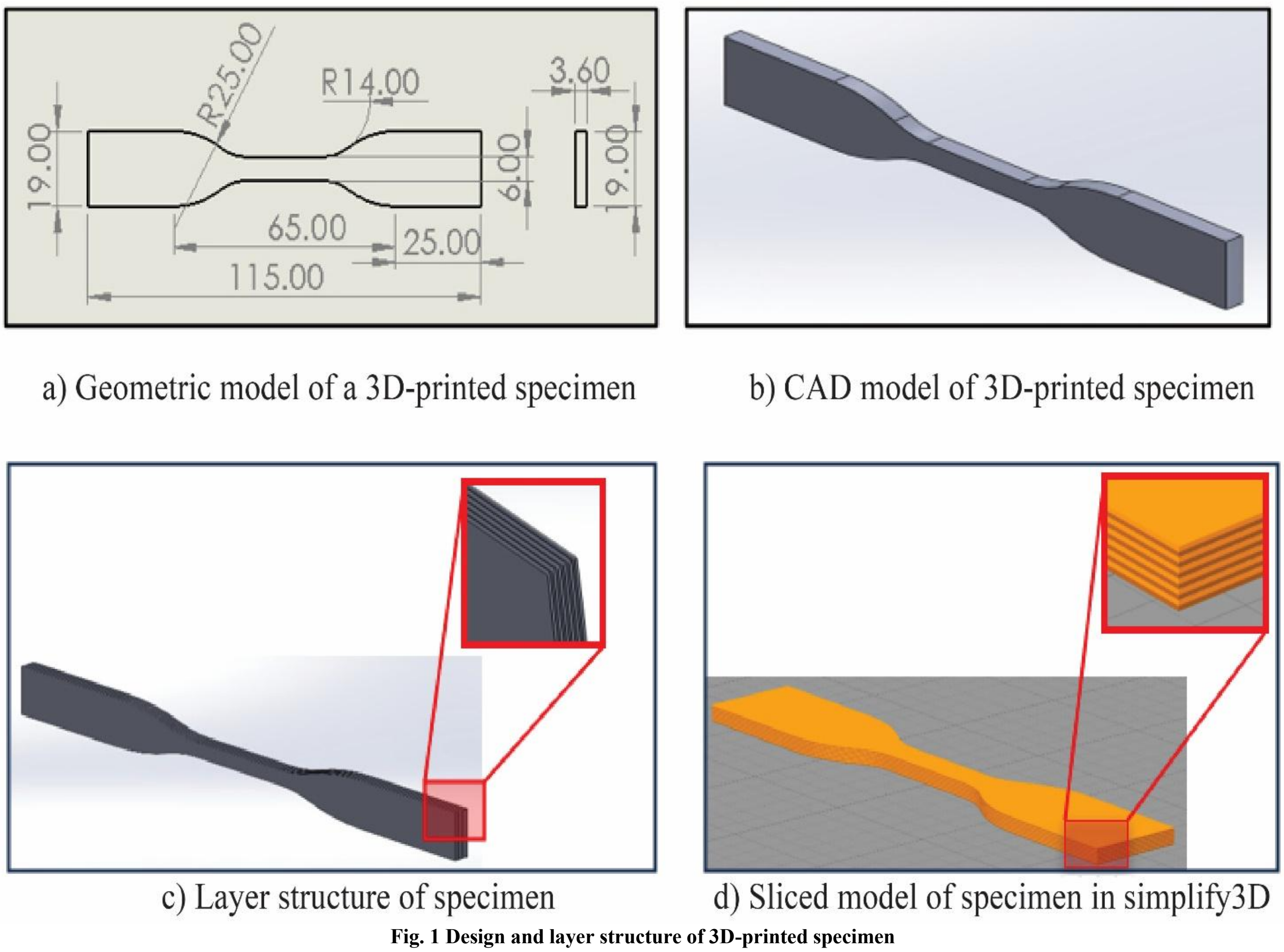

Fig. 1 Design and layer structure of 3D-printed specimen

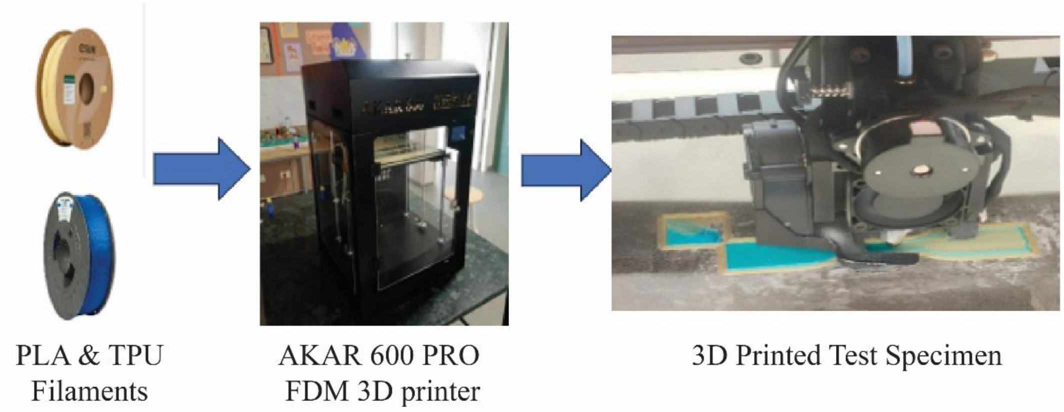

Fig. 2 Fabrication of specimens using the AKAR 600 PRO FDM 3D printer

Fig. 3 3D-printed specimens

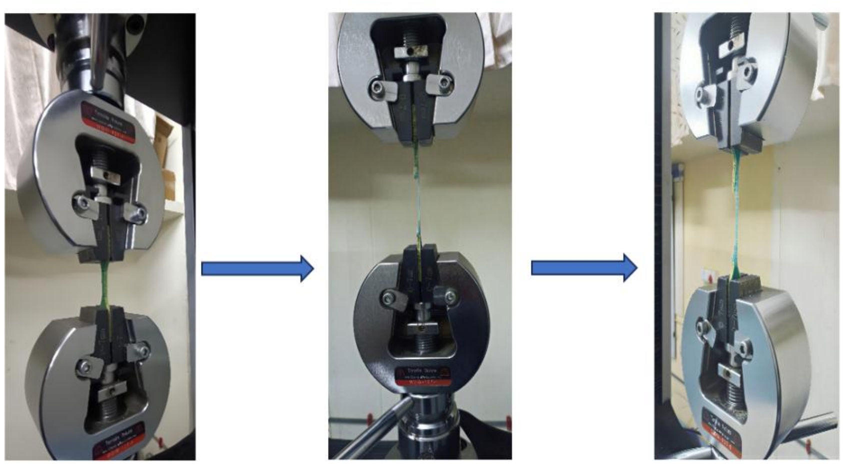

Fig. 4 Tensile testing of 3D-printed specimen using UTM

4. Results and Discussion

4.1. Results from the Tensile test

Table 3 illustrates the TES and EM of tensile tests of each tensile test in the experiment. As the outcome of the experiment is revealed, the mechanical properties do largely depend on the FDM process parameters. The maximum deviation in TES is 0.925 MPa, and in EM is 0.059 GPa, which is within acceptable limits.

Table 3. Tensile test results for each experimental run

Run	Tensile Strength (TES) (MPa)	Young's Modulus (EM) (GPa)
1	31.324 ±0.313	0.918 ±0.015
2	33.517 ±0.447	1.022 ±0.031
3	35.034 ±0.583	1.104 ±0.041
4	31.221 ±0.416	0.954 ±0.015
5	33.415 ±0.557	1.056 ±0.024
6	34.932 ±0.698	1.141 ±0.034
7	31.016 ±0.517	0.978 ±0.009
8	33.212 ±0.664	1.081 ±0.018
9	34.727 ±0.817	1.164 ±0.027
10	35.096 ±0.584	0.984 ±0.029
11	37.228 ±0.744	1.092 ±0.041
12	38.068 ±0.888	1.146 ±0.049
13	35.096 ±0.701	0.996 ±0.023
14	37.228 ±0.868	1.104 ±0.033
15	38.068 ±1.015	1.158 ±0.042
16	33.763 ±0.450	0.888 ±0.014
17	35.895 ±0.598	0.996 ±0.023
18	36.736 ±0.734	1.051 ±0.031
19	37.761 ±0.881	1.032 ±0.037
20	39.216 ±1.045	1.112 ±0.048
21	40.795 ±1.223	1.188 ±0.059
22	36.633 ±0.610	0.912 ±0.027
23	38.089 ±0.761	0.991 ±0.036
24	39.667 ±0.925	1.068 ±0.046
25	36.326 ±0.726	0.961 ±0.021
26	38.253 ±0.892	1.038 ±0.031
27	39.361 ±1.049	1.116 ±0.041

The highest values for tensile strength (40.795 MPa) and Young's modulus (1.188 GPa) were both found in run 21. This could be due to the thinner layer (0.18 mm), slower PS (45 mm/s), higher NT (240/230°C), and more shell layers (4) that were used. These conditions have effects that include making bonding interlayers better and getting rid of internal voids, which makes the printed specimens stronger and better able to hold weight. It is also mentioned that thinning of the layer gives a better mechanical property since it increases the adhesion of the layer as well as decreases the porosity. The same goes for the nozzle: the hotter it is, the better the materials bond between the layers. This makes the tensile strength and inflexibility stronger. The more the shell layers, the more the mechanical strength, as the outer layers take a lot of weight in the load applied, the increase in the printing rate reduces bonding characteristics between the layers and decreases the mechanical properties. Bed temperature has a rather lower influence on TS and E and has a strong influence on the first layer adhesion, but not the total mechanical performance.

5. Dataset Preparation for ML

ML techniques were used to predict the mechanical properties of the TPU/PLA composite against the selected parameters. Five ML algorithms were selected in this paper; they are LR, RF, SVM, XGBoost, and AdaBoost. Google Colaboratory, an online tool for executing machine learning algorithms, was used to run all of the models on Python. The result of the experiment was summarized into a table-based dataset of the input parameters and the output mechanical properties. The data will include 5 input variables (LT, PS, NT, SL, and BT) and output variables, such as TES and EM. Since three samples were used to test 27 experimental runs, the number of data points was 81. The number was formatted in Microsoft Excel, and then the workbook was imported into Python to be analyzed using machine learning. The quality of the dataset was ensured by proper preprocessing, such as data cleaning and normalization. All the ML models were applied to the data on the basis of LT, PS, NT, SL, and BT as a set of independent variables and TES and EM as a set of dependent variables. The dataset was divided into separate training and testing sets, with independent data partitioning adopted to prevent data leakage during model development and evaluation. The preprocessing to separation ratio of the data was 80 and 20 percent, respectively, for training and testing data, with the support of the sklearn library train-test split functions. To obtain the reproducibility of the results, random state 100 was taken. LR was initially used since it is easy and applicable in the modeling of linear relationships between the inputs and responses. A linear model was used to implement the LR model. Further, the SVM was preferred due to its ability to address high-dimensional data as well as eliminate overfitting. It is used with TES and EM Multi Output Regressor, having a regularization parameter (C = 1.0) to forecast both at the same time. Also, the application of the RF was used because the method has the ability to capture nonlinear relationships and eliminate overfitting via the combination of multiple decision trees. The algorithm that was applied in this research to conduct these is from the sklearn. ensemble library, which is the RandomForestRegressor. It was then followed by XGBoost because it is highly capable in nonlinear interaction as well as feature importance. To enhance the accuracy of the prediction, we used an optimization method, the RandomizedSearchCV, in order to optimize the model parameters. Finally, the AdaBoost used the AdaBoostRegressor from sklearn. ensemble. The algorithm improves the accuracy of the prediction by using more than two weak learners to create a strong model.

The training of all ML models was carried out with the help of the training set (X_train and Y_train) through the fit method. After comparing the experimental values with the obtained, the prediction of the test dataset (Xtest and Ytest) was conducted. The effectiveness of both models was measured on the basis of the coefficient of determination (R^2), which is used in the identification of the accuracy of prediction. Figure 5 shows predicted values of TES and EM with the use of the LR model.

LR is implemented in order to compute the coefficients by assuming that the relationship between the input process parameters and the output responses is linear. However, the LR was not in a position to capture the relationship fully since the behavior of the FDM process is nonlinear, and therefore, there would be a lot of deviation, particularly in the Young's modulus.

Table 4 shows that LR comparatively has lower values of R^2 in comparison to developed models. The comparison between the experimental and predicted values obtained by using the RF model is presented in Figure 6. The RF model matches well with experimental results; that is, it may be utilized to capture nonlinear relationships in multiple decision trees. Although there are minor deviations that are observed, the model has a high prediction accuracy relative to LR, as shown by the improved R^2. Figure 7 was generated with the plots of the experimental and predicted values and represents the experiment and prediction with the Support Vector Machine (SVM) model. The experimental values are quite different from the predicted ones, particularly with Young's modulus. This shows that SVM, using the selected linear kernel, can not capture the complex nonlinear interactions in the dataset.

Table 4 shows that SVM gives smaller values of R^2, particularly when the modulus of Young is used, hence it is less applicable in this case. The results of the comparison of experimental and predicted values with the help of ensemble learning models, including AdaBoost and XGBoost, are shown in Figures 8 and 9, respectively. Both models show a very good fit with the experimental data, and the predicted values are very close to the actual values. AdaBoost also enhances the accuracy of the prediction since it is a combination of multiple weak learners, which yield high values of R^2 in both TS and E. XGBoost predicts best, not much different from experimental values. XGBoost has the highest R^2 values (Table 4), and thus it is better to make complex nonlinear associations, efficient gradient boosting, and optimization of feature interactions. Accordingly, it is possible to consider the XGBoost model as the most suitable machine learning model to estimate the mechanical characteristics of the TPU/PLA composite produced under the support of FDM.

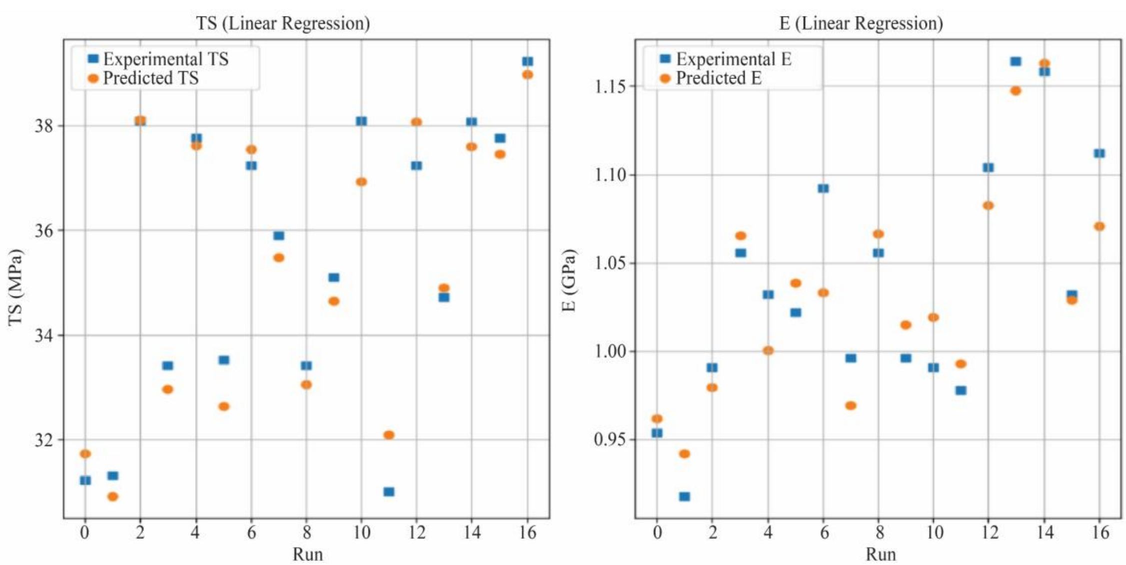

Fig 5. Plot of experimental vs. predicted mechanical properties (TS and E) using Linear Regression.

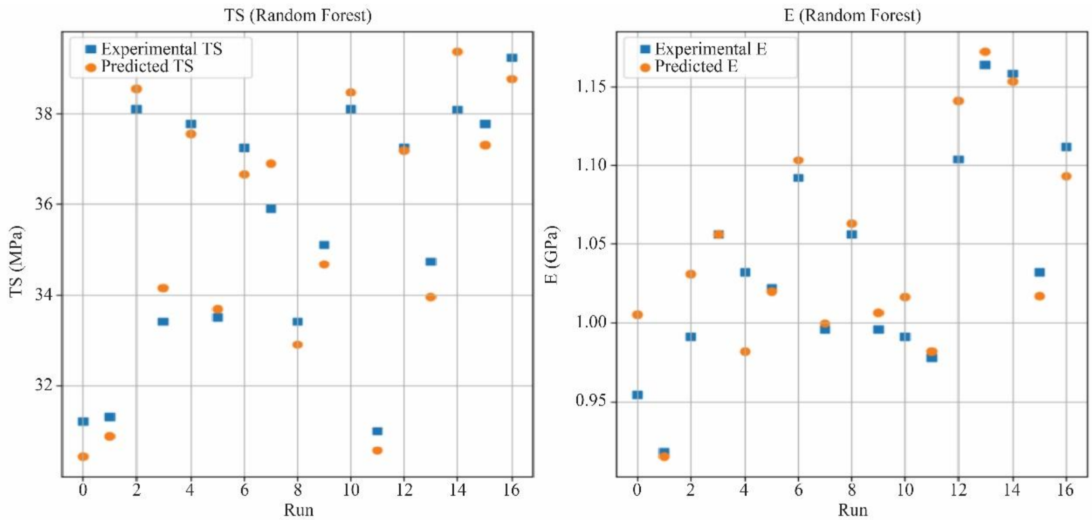

Fig. 6 Plot of experimental vs. predicted mechanical properties (TS and E) using Random Forest.

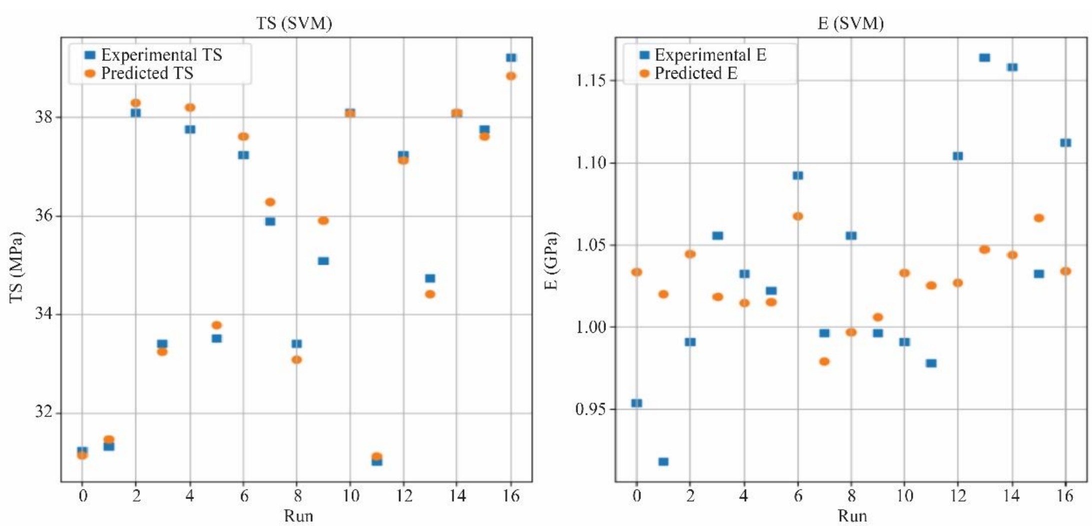

Fig. 7 Plot of experimental vs. predicted mechanical properties (TS and E) using SVM.

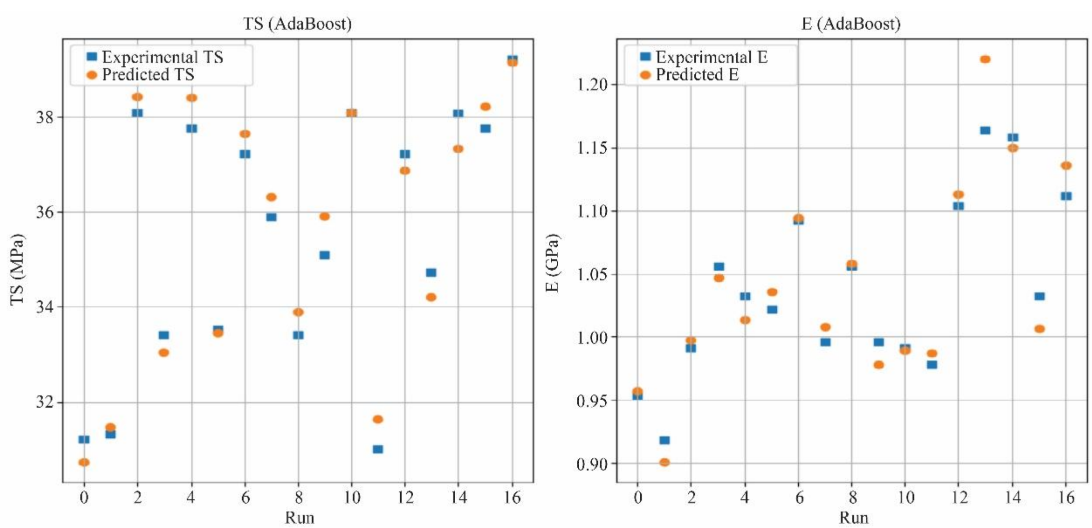

Fig. 8 Plot of experimental vs. predicted mechanical properties (TS and E) using AdaBoost.

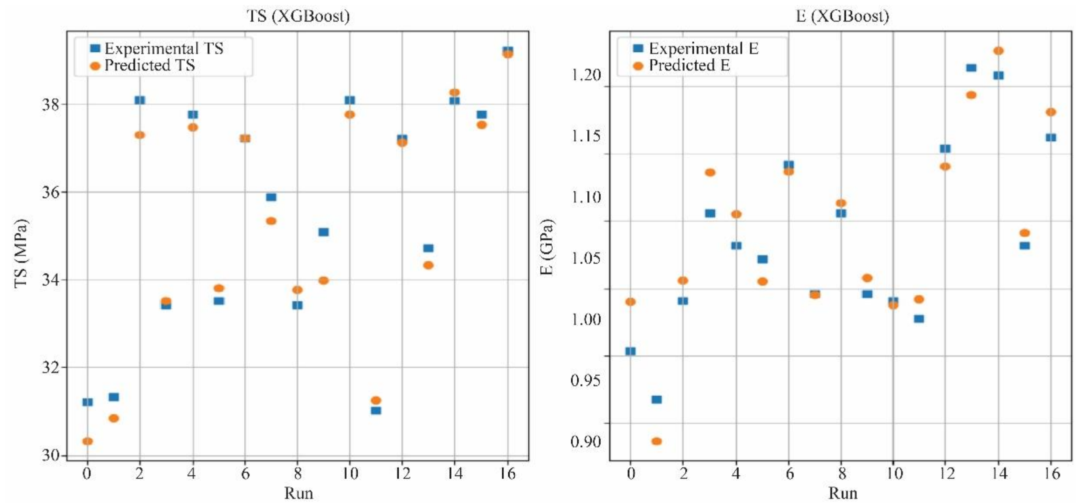

Fig. 9 Plot of experimental vs. predicted mechanical properties (TS and E) using XGBoost.

Table 4. R^2 comparison: Machine Learning models and predicted mechanical properties.

R^2	LR	Random Forest	SVM	AdaBoost	XGBoost
TS	0.9945	0.996	0.9825	0.9973	0.9988
E	0.9826	0.9851	0.5781	0.997	0.9971

6. Conclusion

The TPU/PLA hybrid composite was carefully investigated using the Taguchi L27 experimental design to study the influence of FDM process parameters on mechanical properties, namely tensile strength and Young's modulus. The input parameters considered in this study were layer thickness (0.30 mm, 0.225 mm, 0.18 mm), print speed (45, 50, 55 mm/s), nozzle temperature (TPU/PLA: 230/220 °C, 235/225 °C, 240/230 °C), shell layers (2, 3, 4), and bed temperature (50, 55, 60 °C). The results of the experiment showed that higher nozzle temperatures and optimum bed temperatures affected interlayer bonding strongly, leading to high tensile strength.

The highest tensile strength recorded was 40.795 MPa, and Young's modulus was 1.188 GPa, which showed better mechanical performance of the composite under ideal conditions. The development of ML models such as LR, SVM, RF, AdaBoost, and XGBoost was done to predict TES and EM using the input parameters. The coefficient of determination (R^2) was used in the evaluation of the performance of these models. Linear regression was a good predictor; however, it could not be estimated because of the assumption of linear relationships. SVM demonstrated decent tensile strength prediction ($R^2 = 0.9825$) but did not predict Young's modulus ($R^2 = 0.5781$), which means that it does not have the capability to describe complex nonlinear interactions. Integrated learning models were much better than the standard ones. Random Forest was the most accurate, with R^2 values of 0.9960 (TS) and 0.9851 (E), and AdaBoost added to the performance with R^2 values of 0.9973 (TS) and 0.9970 (E). XGBoost has the highest prediction accuracy model, having its R^2 of 0.9988 in TS and 0.9971 in E, able to determine complex and nonlinear FDM parameters to mechanical properties relationships.

5.1. Future Scope

Although the developed machine learning models demonstrated satisfactory predictive performance, the present study primarily focused on model comparison rather than model interpretability. Future research will incorporate feature importance analysis using Explainable Artificial Intelligence (XAI) techniques, such as SHAP (SHapley Additive exPlanations), permutation feature importance, or sensitivity analysis, to quantify the influence of individual process parameters on the mechanical properties of TPU/PLA hybrid composites. Such analyses will provide deeper physical insight into the relationship between processing conditions and material behavior, thereby improving the engineering applicability and generalizability of the proposed predictive models.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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