

Original Article

Comparative Analysis of Machine Learning Methods for Predicting Tensile Strength of Dual-Extruded FDM 3D-Printed ABS/PC Composite

D S Madhuri^{1*}, Venkata Sushma Chinta¹, Nagini Yarramsetty¹, Katta Sugamya², K Lakshmi Chaitanya³

¹Department of Mechanical Engineering, Chaitanya Bharathi Institute of Technology, Telangana, India.

²Department of Information Technology, Chaitanya Bharathi Institute of Technology, Telangana, India.

³Department of Mechanical Engineering, R V R & J C College of Engineering, Andhra Pradesh, India.

^{1*}Corresponding author: dsmadhuri_mech@cbit.ac.in

Received: 01 July 2026

Revised: 18 September 2026

Accepted: 22 September 2026

Published: 26 October 2026

Abstract - The mechanical behaviour of FDM composite materials is largely influenced by process variables, material composition, & inter-layer bonding. In order to predict the tensile strength of dual-extruded FDM composites fabricated from alternating layers of Acrylonitrile Butadiene Styrene (ABS) and Polycarbonate (PC) using a dual-extrusion printer, this study compares various Machine Learning (ML) algorithms. Such kind of systematic comparison of ML modelling on an alternating-layer ABS/PC composite along with the use of permutation importance analysis has never been performed before. The following process parameters are taken into account: layer height (0.20, 0.25, 0.30 mm), nozzle temperature (250, 255, 260 °C), print speed (50, 55, 60 mm/s), shell/wall layers (2, 3, 4), and bed temperature (90, 95, 100 °C). The experimental design is based on Taguchi L27 orthogonal array and ASTM D638 is used for preparing the tensile specimens. The tensile results range between 22.98 MPa and 49.38 MPa, indicating a strong influence of process parameters. Four ML regression models-Linear Regression (LR), Support Vector Regression (SVR), Gradient Boosting (GB), and AdaBoost are used, with the best model selected based on the highest Coefficient of Determination (R^2) and the lowest RMSE value. LR achieves the highest R^2 value of 0.4595, followed by AdaBoost (0.4478), SVR (0.4211), and GB (0.3947). Learning-curve analysis reveals that ensemble models are overfitting. Permutation importance, which is model-independent, predicts layer thickness as the most important parameter. The results show that data-driven modelling can provide reasonable predictions of the tensile strength of dual-extrusion FDM composites.

Keywords - Dual-extruded FDM composite, Machine learning regression models, Partial dependence, Permutation importance, Taguchi L27.

1. Introduction

The most prevalent additive manufacturing technologies, both in industry and academia, involve Fused Deposition Modelling (FDM) techniques. The FDM process involves the production of geometrically complex parts with minimum tooling costs and short lead times by depositing thermoplastic filament in a molten state on a build platform, layer by layer. Compatibility with various engineering-grade plastics and their composites has made this technology increasingly popular for rapid prototyping and low-volume production of structural elements in aerospace, automotive, and biomedical applications [1, 2].

Dual-extrusion systems are one of the most important developments in FDM techniques, in which two different polymer materials are extruded simultaneously to form a composite with mechanical advantages. Acrylonitrile Butadiene Styrene (ABS) and Polycarbonate (PC) are

engineering thermoplastics that are extensively considered for FDM applications because of their favorable combinations of toughness, strength, thermal resistance, and functional performance. Each material has certain limitations while processing them. ABS has high impact resistance, good processability, and dimensional stability but can exhibit reduced mechanical performance due to interlayer defects and thermal shrinkage. PC has high tensile strength, flexural modulus and superior heat resistance, but generally requires more demanding processing conditions.

Consequently, combining ABS and PC through multi-material or dual-extrusion FDM provides an opportunity to exploit the complementary characteristics of the two polymers and tailor the mechanical response of the printed component. Previous investigations have demonstrated the feasibility of fabricating dual-material ABS/PC structures and have reported improvements in mechanical performance compared



with conventional single-material ABS structures, particularly when the material architecture and post-processing conditions are appropriately controlled. Several experimental investigations have examined the effect of FDM process parameters on the mechanical properties of ABS, PC, and PC-ABS materials. Conventional statistical approaches such as the Taguchi method and Analysis of Variance (ANOVA) have been extensively used to identify influential process parameters and determine favorable parameter combinations. For example, experimental investigations of dual-material PC-ABS specimens have demonstrated that parameters such as layer height, infill percentage, and material ratio can influence tensile strength to a great extent [4].

Problems associated with optimizing these parameters with Design-of-Experiments (DOE) techniques are that they require a lot of time, are expensive and limited in their ability to reveal complex parameter interactions. An interesting alternative is Machine-Learning (ML) regression techniques. If an experimental dataset with a good representation of the entire parameter space is available, then ML can learn the nonlinear relationship between the process parameters and mechanical properties. Thus, the tensile strength can be predicted for any parameter combination without any physical testing. Recent studies have demonstrated the application of algorithms such as artificial neural networks, support vector regression, decision trees, random forests, and ensemble learning methods for predicting mechanical properties of FDM-printed polymers [5, 6].

However, an important research gap remains. Existing studies can broadly be divided into two categories: (i) experimental and statistical investigations of dual-material ABS/PC or PC-ABS FDM, and (ii) machine-learning-based prediction of mechanical properties for predominantly single-material FDM or PC-ABS systems. Although recent work has investigated machine learning prediction of mechanical properties of FDM-produced PC-ABS filament specimens using algorithms including Decision Tree, Random-Forest, K-Nearest-Neighbors, and Multilayer-Perception, the investigated process variables were primarily printing speed, infill density, and raster angle [7]. Similarly, recent studies have demonstrated the capability of Taguchi and ML approaches for predicting tensile characteristics of polymers printed through FDM, but these investigations have mainly focused on single-material systems [8, 9].

Although machine learning has recently been applied to predict mechanical properties of FDM-produced PC-ABS materials, limited attention has been given to comparative ML modelling of tensile strength for specimens fabricated through dual-extrusion of separate ABS and PC materials using a systematic L27 experimental design and a combination of thermal, deposition, and geometric process parameters. The present study addresses this gap by experimentally investigating the tensile strength of specimens made by dual-

extrusion of ABS/PC filaments using an FDM 3D printer and subsequently developing and comparing multiple machine learning models for tensile-strength prediction. Five important process variables, namely layer thickness, nozzle temperature, printing speed, shell/wall layers, and bed temperature, are systematically varied using a Taguchi L27 experimental design. Tensile specimens are fabricated and tested according to ASTM D638, and the resulting experimental dataset is used to develop predictive models based on Extreme Gradient Boosting, AdaBoost, Support Vector Regression (SVR), and Genetic Algorithm-Artificial Neural Network (GA-ANN) approaches.

The novelty in the present work lies not only just in applying machine learning to FDM, but in establishing a comparative data-driven framework for predicting the tensile strength of a dual-extruded ABS/PC laminate using experimentally generated data from a Taguchi L27 design. In contrast to studies that investigate single-material FDM or use a limited set of process parameters, the present work considers the combined influence of thermal, geometric, and deposition-related parameters in a dual-material extrusion environment. The study further compares the predictive capability of fundamentally different ML approaches under the same experimental conditions and identifies the relative importance of the process parameters governing tensile strength. The resulting framework provides both predictive and interpretive information that can assist in selecting suitable FDM processing conditions for achieving the desired tensile performance of dual-extruded ABS/PC components.

Accordingly, the aim of this study are to: (i) experimentally characterize the tensile strength of dual-extruded ABS/PC specimens made with different FDM processing conditions; (ii) develop ML models for predicting tensile strength from the selected process parameters; (iii) comparatively evaluate the prediction performance of LR, SVM, Gradient Boosting, and AdaBoost models using appropriate statistical performance metrics; and (iv) identify the most influential process parameters affecting tensile strength through model-based feature-importance analysis. The findings are expected to be helpful in the development of reliable data-driven techniques for process selection and mechanical-property prediction in multi-material FDM.

2. Literature Review

Researchers have studied about how the mechanical properties are affected by changing the process parameters. Ahmed et al. [10] investigated CF-PLA/ABS hybrid FDM composites and demonstrated that printing at a lower speed and layer height, together with an appropriate clad ratio, resulted in enhanced tensile strength. Their findings highlighted the potential of multi-material laminate architectures for improving the mechanical properties of FDM-printed components. Likewise, Yap et al. [11] studied the mechanical properties of multi-material ABS/PC samples

and studied the effect of printing speed, infill percentage, and nozzle diameter. As a result of the combination, 38.46% increase in tensile strength and a 23.40% increase in Young's modulus was reported in comparison to pure ABS. These findings demonstrate that the combination of ABS and PC can provide a significant mechanical advantage over single-material ABS establishing the potential of dual-material FDM for tailoring mechanical properties.

Moreover, machine learning models have become more and more popular for the evaluation of the complicated and nonlinear dependencies between the process variables and mechanical characteristics of FDM parts. For instance, Shehbaz et al. [12] compared various ML models for predicting the mechanical properties of additively manufactured materials taking into account certain selected process parameters.

It turned out that ML techniques were capable of effectively capturing complex process-property relationships and provide accurate predictions of mechanical performance. Pazarcıkcı et al. [7] worked upon the tensile properties of PC-ABS specimens which were FDM-printed. They included print-speed, infill percentage, and raster angle as process variables within a Taguchi experimental framework.

Four ML algorithms, namely RF, DT, KNN, and MLP, were evaluated for tensile-property prediction. The RF model demonstrated the highest predictive capability, the reported R^2 values ranged as 0.94 to 0.99, thereby demonstrating the potential of ensemble-based learning methods for modelling the nonlinear process-property relationships of PC-ABS materials. However, the study considered a comparatively limited set of process parameters and did not investigate a dual-extrusion system involving separately deposited ABS and PC materials.

Yadav et al. [13] studied PETG, ABS, and multi-material (50% ABS + 50% PETG) FDM specimens, applying a hybrid GA-ANN model to optimize tensile strength through infill

density, extrusion temperature, and material density which is a direct analogy to the present work. Özkül et al. [14] assessed 25 ML algorithms for ABS-based FDM property prediction, identifying MLP as the superior algorithm for capturing the inherent nonlinearity of FDM process-property relationships, motivating the inclusion of nonlinear ensemble methods in the present study. Fetecau et al. [15] examined the mechanical characteristics of 3D-printed Carbon Fiber (CF), Polyamide 12 (PA), and Glass Fiber (GF) reinforced PA composites using Artificial Neural Network (ANN) models. In order to ascertain the mechanical properties, tensile samples were manufactured by FFF while taking into account two input parameters, such as printing orientation and infill density.

The ANN models were later trained and the effect of the input variables: raster angle and layer height was analysed on the ductile-to-brittle transition at the ABS-PC interface, reporting $R^2 = 0.97$ for tensile strength prediction. The ANN models predict tensile strength and Young's modulus effectively and accurately, according to post-training performance analysis. Ramasamy et al. [16] conducted a study on PC-ABS MEX laminates using SVR and concluded $R^2 > 0.93$ for adhesion energy prediction, providing direct precedent for the SVM approach investigated here. The literature review reveals that ML-based FDM tensile strength prediction has been extensively explored for single-material systems (PLA, ABS, PETG) and some multi-material composites (PLA/TPU, wood/PLA). Limited research has focused on dual-extrusion ABS-PC structures, interfacial bonding behaviour, and optimization of process parameters using advanced machine learning techniques. Hence, a systematic comparative ML study targeting the alternating-layer ABS/PC composite - using the full algorithm suite of LR, SVM, Gradient Boosting, and AdaBoost, complemented by learning curve and permutation importance analysis has been presented.

3. Materials and Methods

Figure 1 shows the sequential steps of the work flow. The following sections detail the steps carried out.

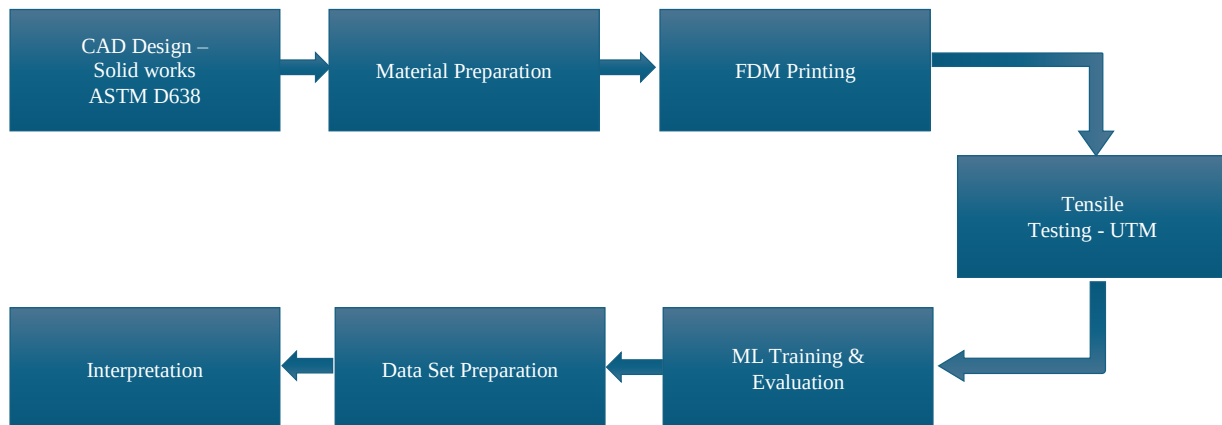


Fig. 1 Series of workflow

3.1. Material System

ABS is extruded at temperatures ranging from 220-260°C at the nozzle with bed temperatures of 80-110°C, whereas Polycarbonate (PC) is handled at 260-300°C and requires elevated bed temperatures ranging between 80°C and 120°C. Both require an enclosed build environment to prevent warping. The ABS and PC filaments are subjected to drying at 80 degrees Celsius for at least 4 hours before printing to avoid moisture-related void formation, surface blistering, and weak layer adhesion. The filaments are kept in airtight containers containing desiccants during intervals between printing sessions to avoid moisture reabsorption.

3.2. Equipment

All specimens have been fabricated using the AKAR 600 PRO dual-extrusion FDM printer, whose build volume is 600 × 600 × 620 mm and has two independent extrusion nozzles. The Nozzle 1 extruded ABS, whereas Nozzle 2: PC. The printer was thermally stabilised for 10-15 minutes before initiating each print job, with actual nozzle and bed temperatures confirmed within ±2 °C of setpoint.

3.3. Specimen Production and Design

Tensile specimens conforming to ASTM D638 Type IV geometry [13] were modelled in SolidWorks and subsequently STL files were obtained for slicing. Slicing was done using Simplify3D. A strict alternating-layer deposition strategy was maintained across all 81 runs: Nozzle 1 deposited layers of ABS: black in colour and Nozzle 2: PC that was white in colour, creating an ABS-PC-ABS-PC... laminate through the specimen thickness. Figure 2 shows the final specimen obtained.



Fig. 2 Alternating-layer deposition in ABS-PC printed specimen

3.4. Design of Experiments

A Taguchi L27 orthogonal array was selected as the DoE framework. Figure 3 exhibits one batch of 27 specimens. Table 1 defines the five parameters and their three levels. Table 2 presents the complete 27-run parameter matrix. For each run, 3 specimens were printed. The values measured for TS, YS and elongation at break were averaged and tabulated.

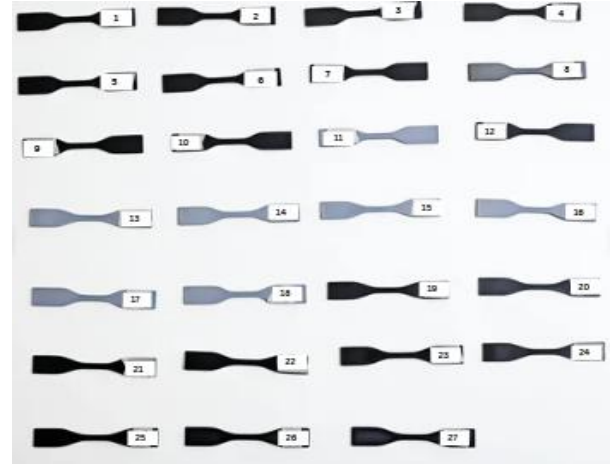


Fig. 3 ABS/PC specimens before testing

All 81 specimens were tested using a calibrated Universal Testing Machine (UTM) per ASTM D638. The test measured ultimate Tensile Strength (TS) and Yield Strength (YS). Figure 4(a) shows the specimen mounted in the UTM grips, prior to axial loading. Figure 4(b) shows a representative fractured specimen post-testing, where the fracture zone within the gauge section confirms valid ASTM D638 test conditions.

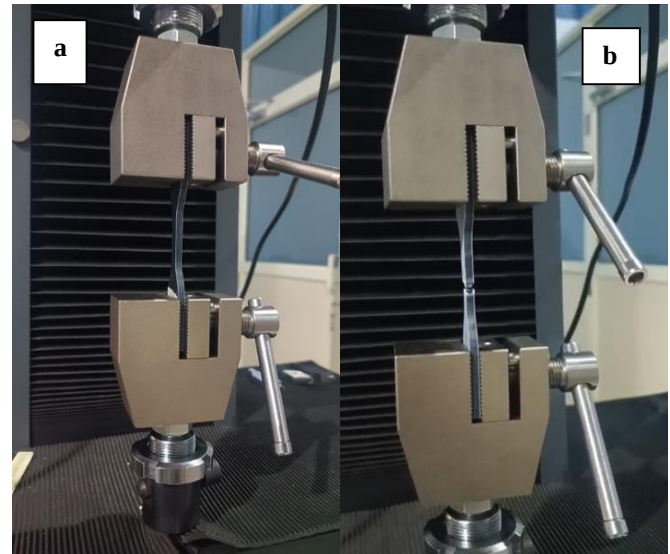


Fig. 4 Specimen Photographs, (a) Mounted on UTM grips, and (b) Specimen showing gauge section failure.

3.5. Machine Learning Methodology

The comparative study focuses on four regression models for machine learning. These four models include Linear Regression (LR), Support Vector Machine (SVM), Gradient Boosting (GB), and AdaBoost, respectively. The selection of models is based on their increasing complexity. They range from the least complex (the simplest to understand) Linear Regression (LR) model to the most complex, powerful sequential ensemble learning algorithms of GB and AdaBoost.

All four models receive the same five input features and predict a single output - Tensile Strength (MPa).

3.5.1. Data Preprocessing

The final dataset consists of 27 samples. The data was split into two sets: a set to train (80%) and a set to test (20%). This was done using the `train_test_split` function with `random_state = 42`, which ensures the results are reproducible.

StandardScaler was used to scale all the input features (LT, NT, PS, SL, BT) to zero mean and unit variance. This

step is important as it may be the case that some models such as Support Vector Machines are sensitive to feature scale. For example, NT (range: 250-260) would otherwise dominate LT (range: 0.20-0.30). A five-fold cross-validation method (KFold, shuffle=True, random_state=42) was used to obtain reliable estimates for the performance of the models. It should be noted that the 80/20 split for $N = 27$ results in only about five test samples, and that the test R^2 and RMSE values are sensitive to which test samples are actually run within the test partition. The cross-validation estimates should then be interpreted in conjunction with the single split test estimates to make inferences about model performance.

Table 1. Process variables and Taguchi L27 levels

Process Variable		L1	L2	L3
Layer Thickness	LT (mm)	0.2	0.25	0.3
Nozzle Temperature	NT ($^{\circ}\text{C}$)	250	255	260
Printing speed	PS (mm/s)	50	55	60
Shell / Wall Layers	SL	2	3	4
Bed Temperature	BT ($^{\circ}\text{C}$)	90	95	100

Table 2. Complete Taguchi L27 experimental matrix with tensile test results

Run	LT (mm)	NT ($^{\circ}\text{C}$)	PS (mm/s)	SL	BT ($^{\circ}\text{C}$)	TS (MPa)	YS (MPa)	Elong. (%)
1	0.2	250	50	2	90	26.51 $\pm$ 0.25	21.08 $\pm$ 0.08	2.17
2	0.2	250	55	3	95	27.36 $\pm$ 0.19	21.92 $\pm$ 0.12	3.05
3	0.2	250	60	4	100	30.75 $\pm$ 0.28	25.5 $\pm$ 0.19	1.75
4	0.2	255	50	3	100	25.34 $\pm$ 0.29	27.81 $\pm$ 0.05	0.88
5	0.2	255	55	4	90	31.04 $\pm$ 0.56	29.73 $\pm$ 0.14	2.08
6	0.2	255	60	2	95	26.73 $\pm$ 0.32	21.25 $\pm$ 0.18	2.1
7	0.2	260	50	4	95	42.85 $\pm$ 0.27	37.8 $\pm$ 0.06	3.85
8	0.2	260	55	2	100	22.98 $\pm$ 0.16	18.07 $\pm$ 0.11	1.2
9	0.2	260	60	3	90	28.21 $\pm$ 0.64	22.91 $\pm$ 0.41	2.17
10	0.25	250	50	3	95	30.73 $\pm$ 0.87	25.46 $\pm$ 0.03	1.13
11	0.25	250	55	4	100	33.04 $\pm$ 0.42	27.34 $\pm$ 0.32	1.1
12	0.25	250	60	2	90	29.23 $\pm$ 0.97	23.5 $\pm$ 0.08	2.01
13	0.25	255	50	4	90	42.38 $\pm$ 1.02	35.37 $\pm$ 0.12	3.17
14	0.25	255	55	2	95	42.99 $\pm$ 0.92	36.23 $\pm$ 0.23	3.07
15	0.25	255	60	3	100	42.51 $\pm$ 0.75	35.03 $\pm$ 0.17	3.17
16	0.25	260	50	2	100	34.12 $\pm$ 0.53	25.29 $\pm$ 0.08	2.13
17	0.25	260	55	3	90	29.79 $\pm$ 0.19	23.77 $\pm$ 0.12	1.78
18	0.25	260	60	4	95	31.21 $\pm$ 0.83	25.84 $\pm$ 0.06	1.88
19	0.3	250	50	4	100	42.95 $\pm$ 1.01	37.54 $\pm$ 0.12	4.23
20	0.3	250	55	2	90	42.24 $\pm$ 0.59	36.36 $\pm$ 0.25	4.15
21	0.3	250	60	3	95	43.25 $\pm$ 0.97	37.93 $\pm$ 0.09	4.02
22	0.3	255	50	2	95	49.38 $\pm$ 1.22	43.92 $\pm$ 0.29	4.38
23	0.3	255	55	3	100	42.51 $\pm$ 0.49	37.78 $\pm$ 0.07	4.04
24	0.3	255	60	4	90	42.15 $\pm$ 0.74	36.82 $\pm$ 0.59	4.05
25	0.3	260	50	3	90	39.39 $\pm$ 0.67	32.3 $\pm$ 0.24	4.17
26	0.3	260	55	4	95	40.07 $\pm$ 0.82	33.65 $\pm$ 0.56	4.95
27	0.3	260	60	2	100	39.21 $\pm$ 0.98	34.28 $\pm$ 0.93	3.15

3.5.2. Linear Regression (LR)

Linear Regression finds a relationship between inputs and output by minimizing squared errors. This model is easy to interpret, but it assumes a linearity between variables. The model estimates coefficients $\beta_0, \beta_1, \dots, \beta_5$ by minimizing the sum of squared residuals (Ordinary Least Squares).

$$TS = \beta_0 + \beta_1 \cdot LT + \beta_2 \cdot NT + \beta_3 \cdot PS + \beta_4 \cdot SL + \beta_5 \cdot BT \quad (1)$$

While LR is unlikely to fully capture the nonlinear interactions in FDM process-property relationships, it serves as an essential interpretability baseline. If the R^2 of LR is close to that of more complex models, the relationship is predominantly linear; a large gap indicates significant nonlinearity that justifies the use of ensemble methods. LR also provides direct coefficient estimates that indicate the direction and magnitude of each parameter's linear influence on tensile strength.

In analogous FDM studies, LR has achieved R^2 values of 0.98-0.99 for tensile strength despite its linearity assumption, suggesting that the dominant effects may be quasi-linear in the constrained parameter ranges of a Taguchi design [5].

3.5.3. Support Vector Regression (SVR)

SVR predicts continuous output values by constructing a regression function that fits the relationship between input and target variables within a predefined error margin (ϵ). Data points falling in this margin do not contribute to the model error, while only the points outside the margin, known as support vectors, influence the regression function. This technique allows the SVR to obtain good generalization while minimizing the impact of noise. For the purpose of identifying complicated relations among the different variables, the SVR makes use of the kernel function to convert the input variables into a high-dimensional space.

3.5.4. Gradient Boosting (GB)

A supervised ensemble machine learning algorithm called Gradient Boosting (GB) can be used for both classification and regression tasks. A series of decision trees are trained by the model, and each new tree gains knowledge from the errors or residuals generated by the preceding trees. GB trains the model incrementally and sequentially rather than growing each tree separately, and the final prediction is the weighted sum of all the trees.

The algorithm can manage intricate and nonlinear relationships between the input variables and the desired output by minimizing a user-defined loss function using a gradient-based optimization technique. The number of estimators, learning rate, maximum tree depth, minimum samples needed for splitting, and subsampling ratio are a few of the hyperparameters that impact a Gradient Boosting model's performance [17].

3.5.5. Adaptive Boosting (AdaBoost)

Adaptive Boosting, or AdaBoost, is a sequential ensemble technique that combines several weak learners, usually shallow decision trees (stumps) with `max_depth` 1 or 2- into a strong learner by iteratively re-weighting training samples. Samples that are misclassified (or poorly predicted in the regression context) by the current ensemble receive higher weights in subsequent iterations, forcing the next learner to focus on difficult cases.

The final prediction is a weighted sum of the weak learners. AdaBoost with the SAMME.R (real-valued) algorithm and DecisionTreeRegressor base learners is implemented using Sklearn's AdaBoost Regressor

3.5.6. Evaluation Metrics

The following metrics are used to assess all four models on the held-out test set:

1. Determination Coefficient R^2
2. RMSE or Root Mean Square Error
3. MAE or Mean Absolute Error

4. Results and Discussion

4.1. Experimental Tensile Strength (TS) Results

Figure 5 presents the TS values obtained from all 27 experimental runs in their experimental sequence, with the results grouped according to Layer Thickness (LT). This plot provides a direct view of the variation in TS across the complete experimental dataset before applying any machine learning model.

A noticeable variation in tensile strength can be observed among the three layer-thickness levels. The specimens produced with $LT = 0.30$ mm show several of the higher tensile-strength values, whereas the results obtained at $LT = 0.20$ mm are generally distributed toward the lower and intermediate strength levels. The $LT = 0.25$ mm specimens show an intermediate and more scattered behaviour. This pattern suggests that LT has a noticeable influence on TS in the dataset taken here.

The higher TS values observed at $LT = 0.30$ mm may be related to the larger amount of material deposited in each layer, which can provide better layer continuity and reduce the number of interfaces within the printed specimen.

A suitable layer thickness can also promote more effective bonding between adjacent deposited layers when combined with appropriate nozzle temperature and print speed. However, the figure also shows some overlap between the different layer-thickness groups, showcasing that tensile strength is not influenced by layer thickness alone. The influence of layer thickness is therefore dependent on its interaction with other parameters, particularly nozzle temperature and print speed.

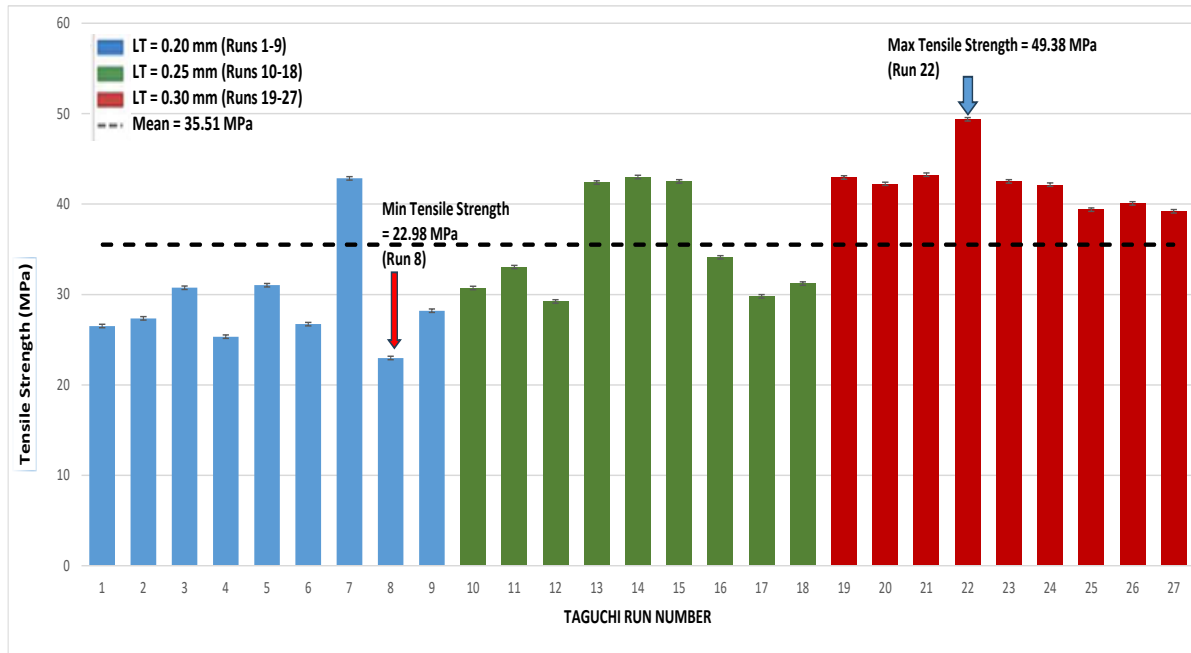


Fig. 5 Tensile strength results across all 27 Taguchi runs, color-coded by layer thickness level

4.2. Effect of Process Parameters - Taguchi Main Effects

The effect of each process parameter on the tensile strength is presented in Figure 6, based on the mean tensile strength for each level of each process parameter.

4.2.1. Layer Thickness

The tensile strength of the specimens obtained from LT of 0.30 mm was consistently higher than the other specimens

at lower LT. This paradoxical finding of improved tensile strength with increasing LT is believed to be caused by increased thermal bonding between ABS and PC interface with thicker layers, as thicker beads retain heat for a longer time, which leads to greater polymer chain inter-diffusion across the interface.

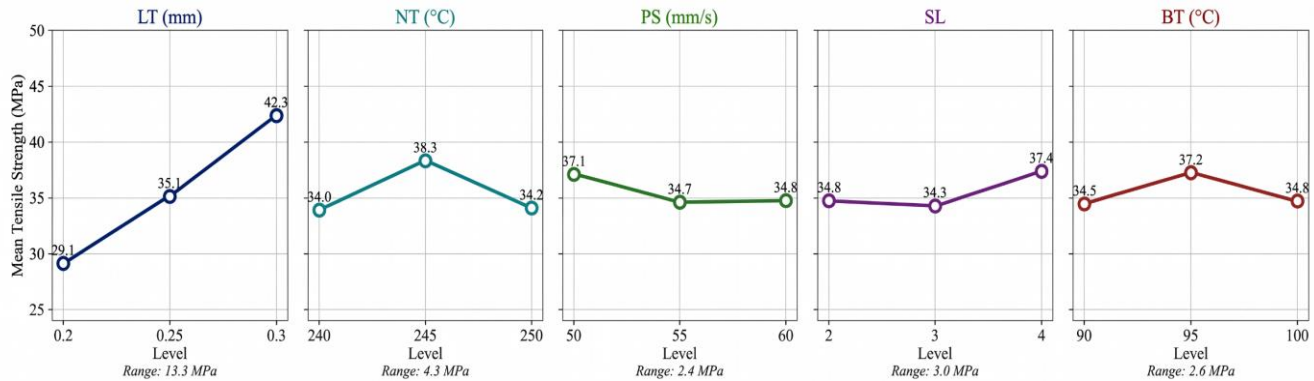


Fig. 6 Taguchi main effects plot: mean tensile strength at each level of all five process parameters

4.2.2. Nozzle Temperature (NT)

The intermediate NT 255 °C specimens had the highest mean tensile strength, with runs 13, 14, 15, and 22 achieving tensile strengths above 42 MPa. Intermediate nozzle temperature of 255 °C led to the highest mean tensile strength with runs 13, 14, 15, and 22 giving tensile strengths more than 42 MPa. The low tensile strengths noted for 250 °C may have been caused by insufficient melt flow and interlayer diffusion which in turn might reduce bonding of the two alternating ABS and PC layers.

Raising the nozzle temperature to 255 °C improves polymer flow and hence increases wetting and interfacial bonding, leading to improvement in the load-transfer capability of the printed laminate. At 260 °C, however, the results show greater variation, possibly due to excessive melt flow and changes in deposited layer geometry, which can affect dimensional accuracy and introduce local defects. Therefore, 255 °C seems to be a suitable balance between adequate polymer fusion and stable deposition, for achieving improved and more consistent tensile strength.

4.2.3. Print Speed (PS), Shell Layers (SL), and Bed Temperature (BT)

It is evident that the print speed had a clear impact on tensile strength. Specimens printed at the lower speed of 50 mm/s generally exhibited higher tensile strength compared to higher print speeds. The maximum tensile strength was achieved with a print speed of 50 mm/s. When printing at a lower print speed, the extruded material remains in contact with the already deposited layer for a relatively longer time, enabling the materials to be in better contact and to bond properly.

Hence, there is greater heat transfer, better polymer chain diffusion, and better interlayer bonding. This is particularly significant in the alternating ABS/PC structure. However, the faster print speed leads to the reduction in the amount of time available for heat dissipation and diffusion of molecules from one layer to another, and so more defects and poor bonding between the layers are expected. The slower print speed of 50 mm/s thus offers a conducive environment for bonding at the interlayers, which is why the tensile strength is improved.

However, the influence of shell layers on the tensile strength varied depending on other printing factors. Interestingly, SL = 2 resulted in the minimum value of tensile strength (22.98 MPa in Run 8) and in the maximum value of tensile strength (49.38 MPa in Run 22). It means that the number of shell layers is not an indicator of the tensile strength. The reason for high tensile strength despite two shell layers in Run 22 was the combination of 0.30 mm layer thickness, temperature of the nozzle - 255 °C and printing speed - 50 mm/s, which ensured the best material flow and temperature for good bonding of ABS and PC layers. At such printing parameters, the increasing the number of shell layers does not affect the tensile strength since the quality of bonding between the layers influences it more.

However, the low tensile strength in Run 8 illustrates that having just two shell layers does not necessarily imply that a high level of strength will be obtained. As such, the impact of shell layers is highly dependent on other printing parameters, especially temperature, layer height, and print speed. In general, the importance of proper bonding between ABS and PC layers seems to outweigh the importance of having many shell layers.

Bed Temperature (BT) showed a moderate effect on tensile strength over the range of 90-100 °C. The specimens printed at higher bed temperatures of 95-100 °C generally showed better tensile strength. A higher bed temperature improves the first layer's adhesion to the build platform and reduces the temperature difference between the printed material and the build surface. This helps reduce thermal stresses, warping, and the possibility of layer separation during printing. The effect is particularly important for PC because of its relatively high processing temperature and

greater tendency to develop thermal stresses. However, compared with Layer Thickness (LT) and Nozzle Temperature (NT), bed temperature had a relatively smaller influence on tensile strength in the present study.

4.3. ML Model Performance

The four models (Linear Regression, SVM, Gradient Boosting and AdaBoost) were trained with 80% data (21-22 samples) and the other 20% were tested upon (5-6 samples). The test set results are summarized in Table 3. Unlike other studies using larger datasets, Linear Regression was the best model in this study, with the highest test R² values. This result can be attributed to the bias-variance trade-off. In the case of ensemble models, there are many parameters to be estimated, but with just 27 samples, they cannot estimate all those parameters well, and they can overfit and hence, will not generalize well to unseen data. Near perfect training R² values were obtained for Gradient Boosting and AdaBoost, but poor test R² values, pointing to severe overfitting. In this data-limited regime, the simplicity of the model is a protective constraint and linear regression is the most stable predictor for this amount of data.

Figure 7 depicts a parity plot (also known as predicted vs. actual plot), evaluating the agreement of a model's predictions with the experimental measurements. The points represent individual specimens, with their x value being the measured tensile strength in the lab and their y value being the tensile strength predicted by the ML model. Every point would fall on the dashed diagonal line ($y = x$) if the model was perfect. Points on the line or above are overestimates; points below the line are underestimates. The scatter around the line represents the actual generalization error of the model for unseen data, especially for the test samples (diamonds). In all four models moderate scatter is noted, typical of a small sample of 27 runs

4.4. Comparative Analysis of ML Models

The side-by-side comparison of the four ML models in terms of the three popular regression metrics is shown in Figure 8. These metrics serve as different ways to describe the predictive performance of the models. R² shows the model's goodness of fit by showing the agreement between the predicted values and experimental ones, with a higher number closer to 1 indicating better agreement. RMSE and MAE show the prediction error in MPa, with smaller numbers showing a better prediction accuracy. RMSE is more sensitive to large errors since it consists of the squared errors while MAE consists of the magnitude of errors. The best-performing model was able to achieve an RMSE of 6.288 MPa within the range of experimental values of tensile strength of 22.98-49.38 MPa. The degree of this prediction error can be viewed as too large for any precise application where tolerances of design based on strength of materials are required. Hence, the current model can only be considered as a means of defining the general process-property dependencies and comparison of the effects of process parameters on each other but not as a highly

accurate prediction method for design purposes. A comparison of results of training and testing provides significant insights into the generalisation capabilities of the models. Small deviations between results on training and testing show that model has learned the relationship between process parameters and tensile strength without being dependent too much on the training data. On the other hand, significant decrease of R^2 between training and test sets along with high values of RMSE and MAE of test data show that there could be problems with generalisation of the model. In comparison to other algorithms, Gradient Boosting and AdaBoost exhibit better training results while having lower testing results. Such behavior implies overfitting when the models learn the fine details and fluctuations in the training set that are not necessarily reflected in the testing set. Such feature becomes especially relevant for the current research since the size of the dataset under consideration is only 27 experimental samples. In this case, the complexity of the models makes them even more sensitive to each observation. However, a model that shows less discrepancy between its training and testing performances will give better generalization, although its training R^2 will be a little bit lower. Thus, the choice of the models should not be made by only taking into consideration the highest training R^2 ; all the other factors mentioned should also be taken into account.

Overall, Figure 8 demonstrates that the predictive capability of the models depends not only on their ability to fit the experimental data but also on their ability to maintain reliable performance on previously unseen data.

4.5. Practical Engineering Implications and Limitations

Although the best model achieved a test-set R^2 of 0.4595, indicating limited predictive accuracy for precise engineering design, the experimental results provide useful practical guidance for dual-extrusion ABS/PC printing. The highest tensile strength in the present experimental study was obtained at a layer height of 0.30 mm, nozzle temperature of 255 °C, and printing speed of 50 mm/s. This combination can therefore be considered a favorable process window within the investigated parameter range. However, the present empirical models should not be considered a replacement for physical prototyping or experimental validation, particularly for applications involving strict strength or safety requirements. Instead, the results can be used as preliminary guidance for selecting suitable printing conditions and reducing the number of trial-and-error experiments. Further validation using a larger experimental dataset and additional process variables is required before the developed models can be applied for precise engineering design predictions.

Table 3. ML model performance metrics (test set, 80/20 split, random state=42)

Model	Train R^2	Test R^2	RMSE (MPa)	MAE (MPa)	5-Fold CV R^2	Best Param
Linear Regression	0.6336	0.4595	6.288	5.279	-0.16 ± 0.95	N/A
SVM (SVR-RBF)	0.6600	0.4211	6.507	5.838	0.40 ± 0.31	$C=100, \epsilon=0.1, \gamma=0.01$
Gradient Boosting	0.9611	0.3947	6.654	6.145	-0.12 ± 0.70	$LR=0.05, d=3, n=50$
AdaBoost	0.9985	0.4478	6.355	5.263	0.17 ± 0.35	$LR=1.0, n=200, d=4$

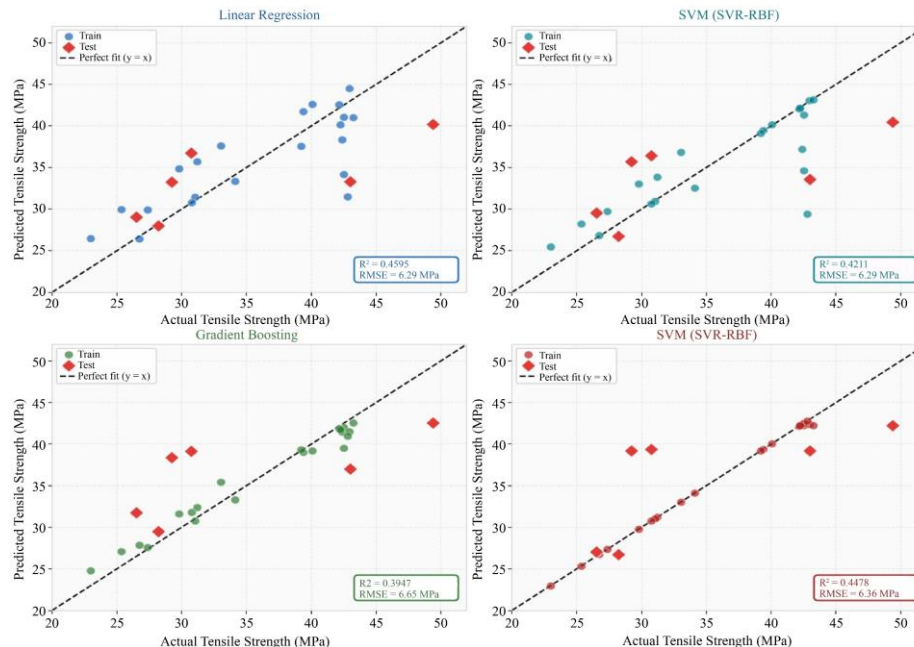


Fig. 7 Predicted vs actual tensile strength parity plots for all four ML models

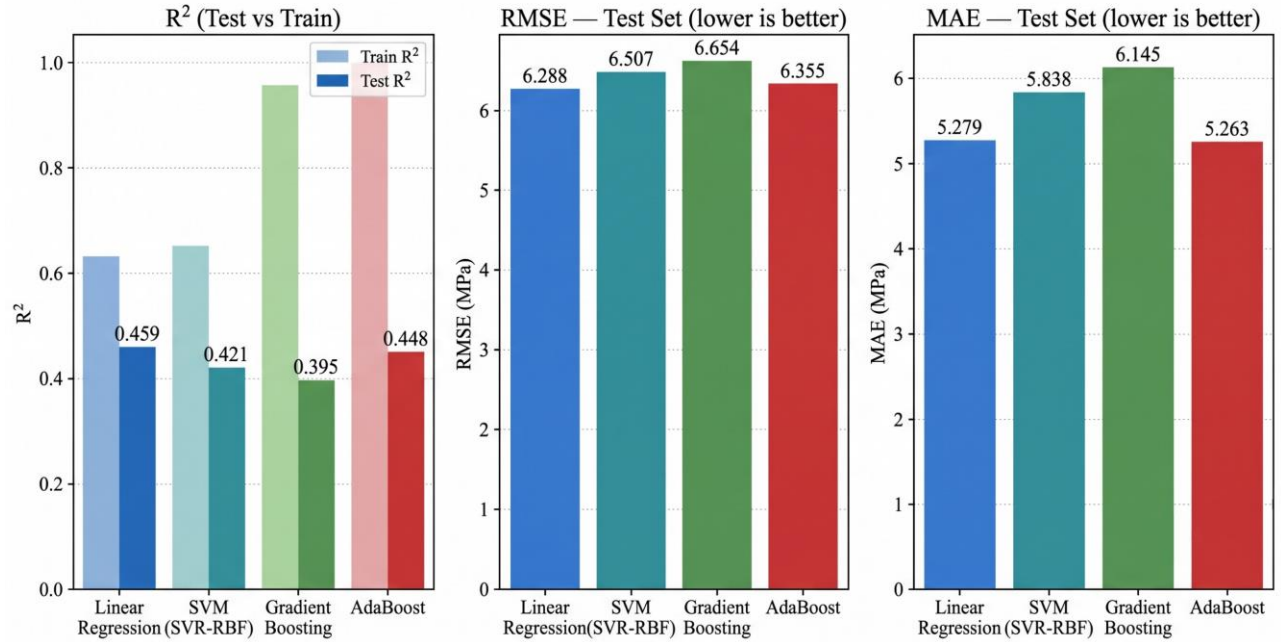


Fig. 8 Comparative bar charts of R² (test vs train), RMSE, and MAE for all four models

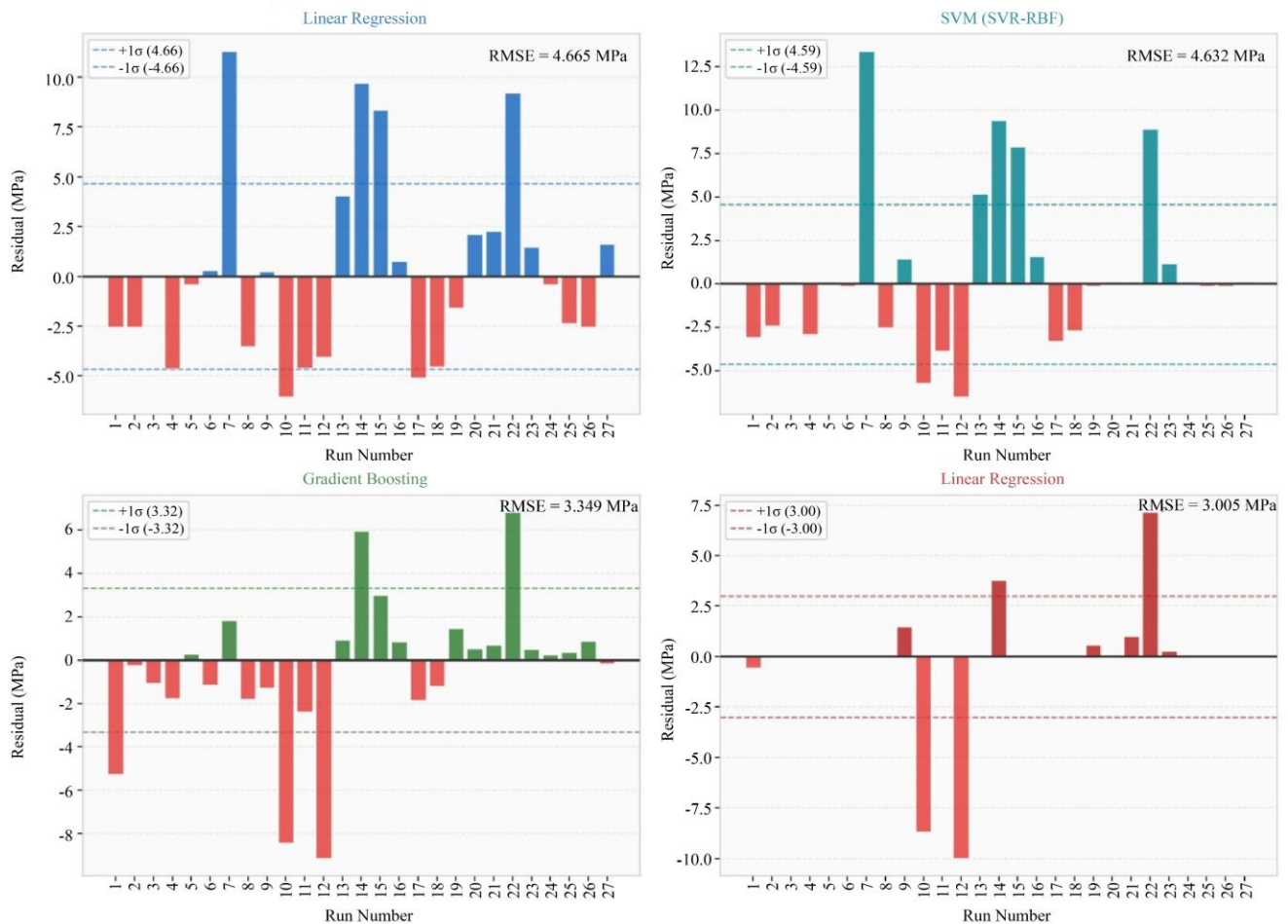


Fig. 9 Residual analysis: prediction error per Taguchi run for all four models

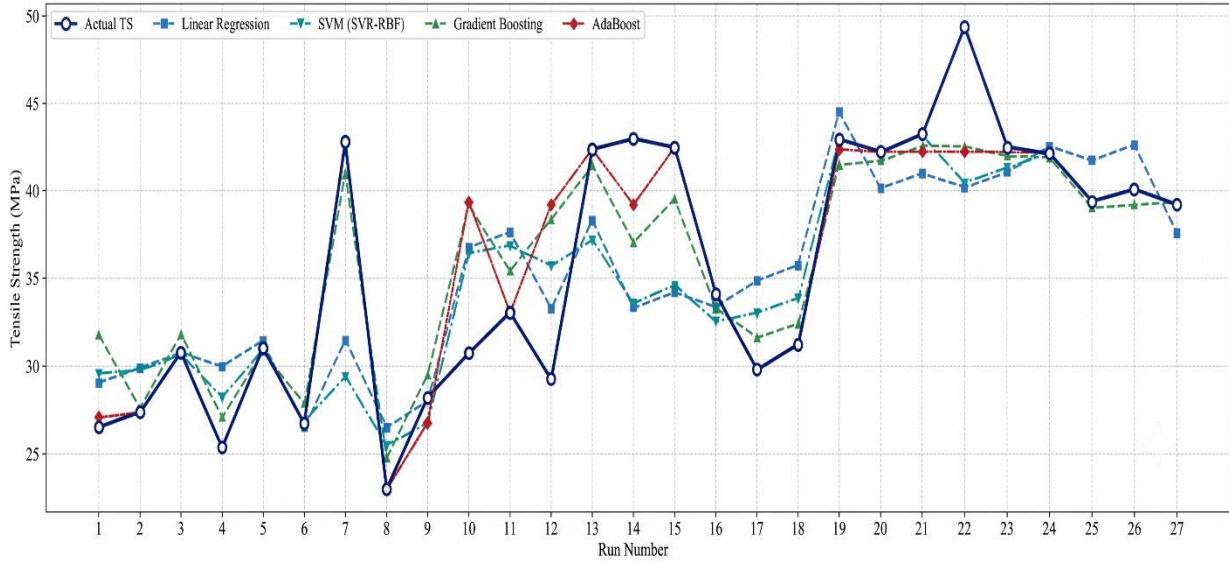


Fig. 10 Actual vs predicted tensile strength for all 27 Taguchi runs

The difference between the actual and the model's prediction is called a residual (Predicted - Actual). Residual analysis is performed to see whether the error is random and uniformly distributed or if there is a systematic pattern that indicates that the model is missing an important relationship. In Figure 9, each bar represents the error in prediction for one Taguchi run.

A good model will have bars fluctuating randomly without any trend. If some bars exhibit deviations of a certain kind for the same set of runs, e.g., the underestimations of Run 7 for all models, then the model has problems in dealing with certain combinations of parameters because of interactions that are not considered in its features. The dashed lines denote $\pm 1\sigma$ and act as a boundary; anything outside this boundary is an outlier and needs physical investigation. Figure 10 shows the plot for all four models together with their measured values.

4.6. Learning Curve Analysis

A learning curve shows the relationship between the predictive capability of a model and the number of training samples used. Learning curve analysis is effective in understanding the learning nature of the model and detecting any sign of either overfitting or underfitting. Normally, the closer the training and cross-validation performance become when the training samples increase, the better the predictive performance of the model.

Learning curve analysis has been carried out to determine how each of the four models performs depending on the number of training samples. Figure 11 displays the learning curves of the four models with the training R^2 and CV R^2 versus the number of training samples. The training R^2 is the measure of how well the model fits the training samples.

As seen from the results obtained, there is a distinct discrepancy in the learning pattern of the models. For the Gradient Boosting and AdaBoost algorithms, the training R^2 curve continues to be rather high, whereas the CV R^2 curve continues to stay significantly lower as the number of training instances increases. The constant discrepancy between the two curves implies that these models learn the training data very well, yet their ability to generalize is comparatively low. This means that these models exhibit an inclination towards overfitting, especially taking into account the rather small size of the data set which only consists of 27 experimental instances.

Unlike the other cases, the training and CV curves differ less in Linear Regression, and are much closer to each other. Although the model's train score significantly underperforms compared to the more complex algorithms, its generalization gap is considerably smaller.

This suggests that Linear Regression is less likely to be affected by the small sample size of the training set, making it potentially more reliable for the current task. Overall, the analysis of the learning curve illustrates the general trade-off between an algorithm's complexity and its generalization performance.

All things considered, the learning-curve study reveals a significant trade-off between generalization and model complexity. AdaBoost and Gradient Boosting's enhanced training accuracy may not always translate into improved performance on untested data. A simpler model may offer more dependable generalization than a highly flexible model for a small dataset like the current $N = 27$ experimental design, as evidenced by the narrower gap seen for Linear Regression, which implies more stability.

Fig. 11 — Learning Curves: Training R^2 vs 5-Fold CV R^2 as Training Set Size Increases
(Large gap = overfitting; Converging curves = good generalization!)

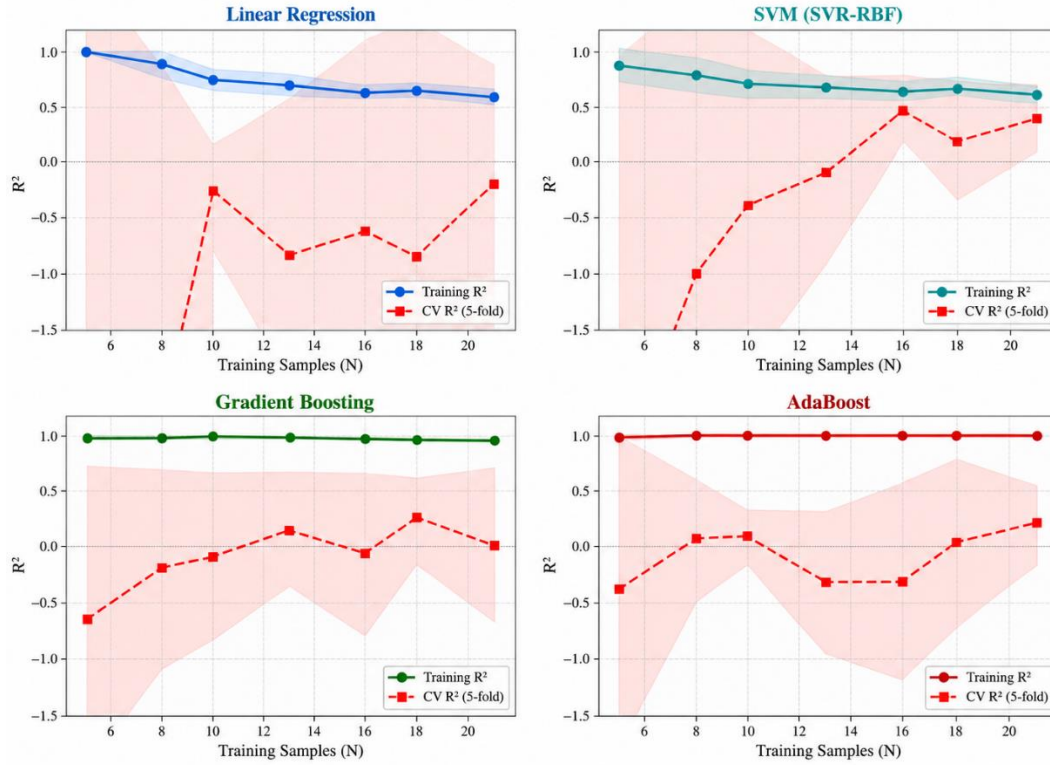


Fig. 11 Training R^2 (solid) and 5-fold CV R^2 (dashed) vs number of training samples: learning curves for each of the four models

Fig. 12 — Permutation Feature Importance (Mean R^2 Decrease $\pm$ Std, 30 Repeats)
(Larger bar = more important feature; Negative = feature adds noise)

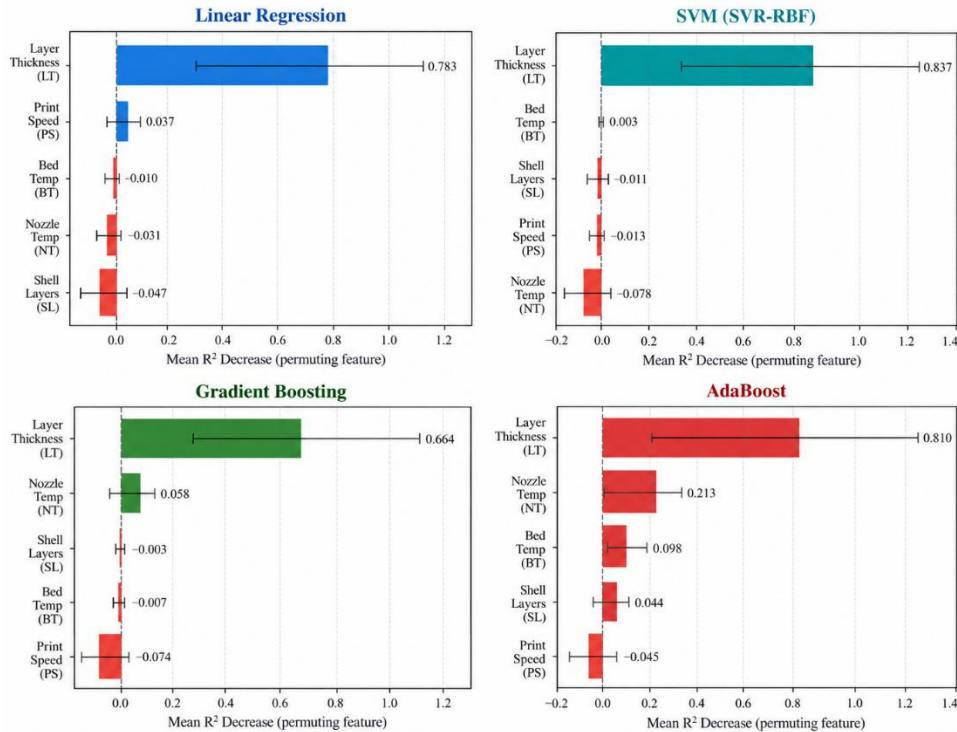


Fig. 12 Permutation feature importance for all four models (30 repeats, random_state=42)

4.7. Permutation Feature Importance

Permutation feature importance is a model-agnostic technique used to calculate the significance of individual features in predicting ML model's performance. It decides a feature's importance by quantifying the model's evaluation score drop when the values of that feature are randomly shuffled.

The values for each feature are randomly permuted across all samples, thereby disrupting the association between the values in that feature and the output and the decrease in the R^2 is noted. A large drop signifies the model being heavily dependent on that parameter, while a drop close to zero indicates that the feature contributed little.

This method is model-independent in that it does not assume anything about the internal structure of the model, therefore if it is applied to each of the four models and the same ranking is observed, it is a strong, algorithm independent evidence of physical primacy. The largest drop in R^2 across all 4 models was obtained for Layer Thickness (LT), as shown in Figure 12, this is due to the fact that layer thickness is the most important process variable, irrespective of the algorithm used.

5. Conclusion

This study aimed to perform a comprehensive experimental characterization and comparative ML evaluation of tensile strength of dual-extruded ABS/PC FDM composites, with the help of Taguchi L27 DoEs. The conclusions that can be drawn are as follows:

5.1. Tensile Strength Range and Parameter Sensitivity

The study resulted in tensile strengths ranging from 22.98MPa to 49.38MPa with ~26.4MPa difference between the lowest and highest tensile strength, showing that the performance of ABS/PC dual-extrusion FDM is highly sensitive to the five process parameters selected for this study, which is a good indicator of the reliability of the data for use in training ML models.

5.2. Dominant Role of Layer Thickness

Layer thickness was the most influential process parameter across all analyses (Taguchi main effects, correlation heatmap, permutation importance). Higher LT yielded higher tensile strength - a counter-intuitive finding for dual-material FDM, attributed to enhanced thermal inter-diffusion at the ABS-PC interface with thicker deposited beads.

5.3. Optimal Nozzle Temperature

Near-optimal Nozzle Temperature (NT = 255 °C) was found to be within the range of 250-260 °C, which was a

compromise between the preferred temperature windows of ABS (230-260 °C) and PC (260-300 °C) as reported in dual-material FDM literature.

5.4. ML Model Performance in the Small-Dataset Regime

Among the four models, with the test R^2 (0.4595), Linear Regression was the best model. The learning curves of ensemble methods were very high even after only small training sets, indicating an overfitting on both training and CV R^2 (AdaBoost Train R^2 =0.9985, Test R^2 =0.4478; GB Train R^2 =0.9611, Test R^2 =0.3947)

5.5. Model-Agnostic Feature Importance

LT was consistently the strongest predictor across all four models with mean R^2 decrease of 0.66-0.84, and permutation importance analysis was algorithm independent, giving strong evidence of its physical primacy.

Limitations and Future Work

The present study is subject to certain limitations. The experimental dataset contains only 27 observations based on the Taguchi L27 design, which restricts the ability of machine learning models to fully showcase the complex behaviour existing with the selected process variables and tensile strength. The present study gave the maximum test-set R^2 as 0.4595, pointing to a moderate predictive capability of the current models.

Furthermore, factors such as interfacial bonding quality, raster characteristics, internal porosity, material variability, and local thermal history were not explicitly included as model inputs. Future studies should therefore consider larger experimental datasets, additional process and material-related parameters, and advanced validation strategies to improve model generalization and predictive accuracy.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

The authors sincerely express their heartfelt gratitude to Chaitanya Bharathi Institute of Technology (CBIT) for the generous funding and continuous support provided under the major research project titled "A Comparative Analysis of Machine Learning Methods for Predicting Mechanical Properties of Dual-Extruded FDM 3D-Printed ABS / CF- PLA composite" as per the sanction order no. CBIT/PROJ-IH/1064/Mech/D016/2025, dated 15 April 2025. Due to some issues, the material - PLA had been replaced with PC and the change has been acknowledged while the name persists.

References

- [1] ASTM F2792-12a, ASTM International, West Conshohocken, 2012. [Online]. Available: <https://standards.iteh.ai/catalog/standards/astm/72f015d3-d2c5-4690-b1cf-d00d8fbe1e77/astm-f2792-12a>

- [2] Elif Aktepe, and Uçman Ergün, “Machine Learning Approaches for FDM-Based 3D Printing: A Literature Review,” *Applied Sciences*, vol. 15, no. 18, pp. 1-28, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [3] C. Wang et al., “Machine Learning in Additive Manufacturing: State-of-the-Art and Perspectives,” *Additive Manufacturing*, vol. 36, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] Cleiton Lazaro Fazolo De Assis, and Cleber Augusto Rampazo, “Assessment of the Mechanical Properties of PC/ABS Blends for Functional Prototyping by FFF 3D Printing,” *Rapid Prototyping Journal*, vol. 30, no. 2, pp. 214-227, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Prashant Anerao et al., “A Comparative Study of Machine Learning Techniques for Predicting Mechanical Properties of Fused Deposition Modelling (FDM)-Based 3D-Printed Wood/PLA Biocomposite,” *Mechanics of Advanced Composite Structures*, vol. 12, no. 2, pp. 261-270, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] Mohammad Hossein Nikzad et al., “Machine Learning-Driven Prediction of Tensile Strength in 3D-Printed PLA Parts,” *Expert Systems with Applications*, vol. 264, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Arda Pazarcıkçı, Koray Özsoy, and Bekir Aksoy, “Machine Learning-Driven Prediction of Manufacturing Parameters and Analysis of Mechanical Properties of PC-ABS Specimens Produced by the Fused Deposition Modeling Additive Manufacturing Method,” *Polymers*, vol. 18, no. 7, pp. 1-31, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] Mohd Nazri Ahmad, and Mohamad Ridzwan Ishak, “A Hybrid Taguchi – Machine Learning Framework in Optimizing FDM Printing Parameters,” *Next Materials*, vol. 13, pp. 1-15, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Mustafa Özgür Öteyaka, Kerem Aybar, and Hasan Candan Öteyaka, “Effect of Infill Ratio on the Tensile and Flexural Properties of Unreinforced and Carbon Fiber-Reinforced Polylactic Acid Manufactured by Fused Deposition Modeling,” *Journal of Materials Engineering and Performance*, vol. 30, no. 7, pp. 5203-5215, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] Syed Waqar Ahmed et al., “Mechanical Properties of an Additive Manufactured CF-PLA/ABS Hybrid Composite Sheet,” *Polymers*, vol. 34, no. 11, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Pui-Voon Yap, Ming-Yeng Chan, and Seong-Chun Koay, “Preliminary Study on Mechanical Properties of 3D Printed Multi-Materials ABS/PC Parts: Effect of Printing Parameters,” *Journal of Physical Science*, vol. 32, no. 2, pp. 87-104, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] Waqar Shehbaz, and Qingjin Peng, “Evaluation of Machine Learning Models in Predicting Mechanical Properties of Additive-Manufactured Parts,” *Transactions of the Canadian Society for Mechanical Engineering*, vol. 49, no. 4, pp. 769-784, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] Dinesh Yadav et al., “Optimization of FDM 3D Printing Process Parameters for Multi-Material Using Artificial Neural Network,” *Materials Today: Proceedings*, vol. 21, no. 3, pp. 1583-1591, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Mahmut Özkül, Fatma Kuncan, and Osman Ulkir, “Predicting Mechanical Properties of FDM-Produced Parts Using Machine Learning Approaches,” *Journal of Applied Polymer Science*, vol. 142, no. 20, pp. 1-17, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Catalin Fetecau, Felicia Stan, and Doina Boazu, “Artificial Neural Network Modeling of Mechanical Properties of 3D-Printed Polyamide 12 and Its Fiber-Reinforced Composites,” *Polymers*, vol. 17, no. 5, pp. 1-28, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Mahalingam Nainaragaram Ramasamy et al., “Characterization of PC-ABS and PETG Multi-Material Laminates Fabricated by MEX Method,” *Polymers*, vol. 18, no. 6, pp. 1-20, 2026. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Ram Kishore Shakya, Dharamvir Mangal, and Nagendra Kumar Maurya, “Evaluation of Mechanical Properties of Graphene-Reinforced PETG Filaments Fabricated by FDM: Influence of Reinforcement and Process Parameters,” *Journal of Computers, Mechanical and Management*, vol. 5, no. 2, pp. 11-24, 2026. [[CrossRef](#)] [[Publisher Link](#)]