Enhancing Mechanical Property of Multi-material Printed Object Through Machine-Learning

Md.Hazrat Ali[1](✉), Nurbol Sabyrov[1], M. Hassan Tanveer[2](✉), Syuhei Kurokawa[3], and Essam Shehab[1]

[1] Department of Mechanical and Aerospace Engineering, School of Engineering and Digital Sciences, Nazarbayev University, Astana 010000, Kazakhstan
md.ali@nu.edu.kz
[2] Department of Robotics and Mechatronics Engineering, Kennesaw State University, Marietta, GA 30060, USA
mtanveer@kennesaw.edu
[3] Department of Mechanical Engineering, Kyushu University, Fukuoka, Japan

Abstract. Machine learning is gaining more popularity in the FDM process in the way of performance enhancement. The multi-functionality of multi-material printing and its rising employment makes the Machine-Learning (ML) tool more attractive as the diversity of process parameters involves many fabrication combinations. This paper describes the implementation of ML techniques in the production of multi-material objects to achieve a high mechanical outcome. A nozzle temperature of PLA and ABS extruders was chosen as an input feature for ML, whereas UTS was the target. 125 samples with additional 6 pieces for deviation cases printed for 25 temperature combinations. The decision Tree model exhibited improper prediction values. Although the next Random Forest model had a fairly good R^2-0.78, the 3D graph of UTS had a coarse curve. The highest R^2-0.81 belonged to the 5th degree Polynomial Regression model. According to this model, to acquire the highest UTS value-41.171MPa, extruding temperatures should be 216 C, and 246 C for PLA and ABS respectively.

Keywords: FDM · Multi-material · Machine learning

1 Introduction

The drawbacks of Additive Manufacturing (AM) over conventional like the low strength of structure or dimensional inaccuracy do not hinder it to surpass conventional machining. The complex geometry formation in a short amount of time with little waste [1] is still unattainable for an older opponent. The rapid progress of Fused Deposition Modeling (FDM) technologies gave impulse to penetration in different fields, from industrial to medicine and daily usage [2]. For the last decades, manipulations with process parameters, in the way to achieve the ideal final product quality were the main fields of researcher's interest [3]. Although optimizing process parameters for single-material

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printing was widely investigated, the development of multi-material (MM) component fabrication forced us to look for it from a new angle. Multi-material printing technology-enhanced functionality of printed objects by combining and merging specific properties of dissimilar filaments. Now, the printed model could be soft, hard, aesthetic, and colorful together. Despite the growing popularity of MM fabrication, the critical problem of adhesion is still open. The low level of mechanical strength caused by poor bonding between filaments could lead to the break or detachment of pieces [4]. Therefore, researchers trying to address this drawback and deeply analyze the behavior of MM products. It was proved that the key parameter for obtaining a high bonding degree is temperature. Adequate extrusion temperature and high-temperature value of platform give suitable bonding [5], while the heat treatment can improve tensile strength [6]. Machine learning (ML) is a perspective and powerful tool for observation, analysis, and optimization of multi-material 3D printing technology. The Heat Kernel Signature method [7] was applied to detect possible manufacturing defects of the CAD model. A double-Layered Extreme Learning Machine [8] was utilized for calculation and choosing the optimal orientation angle for eliminating support structure, whereas the convolutional neural network (CNN) technique was suitable for predicting final product mass and fabrication time [9]. The support vector machine (SVM) method with the aid of a camera can assess the quality of the model continuously and stop the process. Hence, it saves time and material [10]. Overall, ML is employed in numerous directions of AM, such as quality optimization, cloud 3D platform, and even cybersecurity. The review paper of G. D. Goh et al. [11] emphasized the unlimited potential of machine learning methods.

Although there are several methods of ML implemented in FDM technology, there are only a few studies carried out for multi-material technology. In this paper Decision Trees, Random Forest, and Polynomial Regression ML techniques are proposed to derive optimal process parameters (temperature) to acquire the high bonding degree between PLA and ABS materials.

2 Experimental Set-Up and Tensile Test

The scope of this research was to evaluate and measure the effect of different printing nozzle temperatures for each filament. Nozzle temperatures for PLA vary between 204–220C, while for ABS 240–256C. For each filament temperature step was 4C, which gave 25 total combinations. The standard ASTM D638, type 4 was chosen for the tensile test. To ensure effective influence observation of filament bonding at different nozzle temperatures special sample layer pattern was constructed (Fig. 1). Filament order alternates for getting several intersection layers.

3 Results

3.1 Tensile Test Results

The numbers of the main sample were 125. Figure 2 illustrated the Ultimate tensile strength (UTS) for each temperature combination of PLA and ABS in 3D view (average values of 5 printing cases indicated). Table 1 shows the results of tensile tests. Six

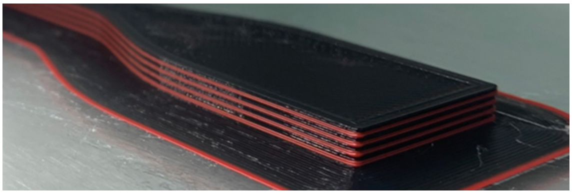

Fig. 1. Repetitive layer pattern

additional tests were conducted to replace tests that had a significant deviation from the average value. Replacedtest samples indicated with italic. The effect of the extra test, which replaced the failure sample, could be seen in the last column.

3.2 Machine Learning Programming

Three different ML algorithms were implemented on the gathered data (Table 2). To access the performance of each model Root-Mean-Square-Error (RMSE) and R^2 are measured. The general train and test data ratio in the model was 0.75–0.25.

Decision Tree Model. Initial observation and analysis of Fig. 2 showed nonlinearity of curve and classification algorithm decided to implement primarily. A decision tree algorithm was used to find the dependence between nozzle temperatures and UTS. This model has a tree structure decision-making algorithm and is listed in supervised machine learning algorithm types. The tunable parameter for this model is the depth of the tree. Figure 3 shows the structure of the depth concept. This parameter defines the split amount before prediction. The more split points have model, the easier to classify the target feature.

Figure 4 illustrates line graphs of RMSE and R^2 values that are affected by depth number. The values of RMSE start to decrease and R^2 increases with the rise of tree depth. At the optimal value of split points-3, RMSE and R^2 have approximately 0.6 and 0.8 for train data. However, when the model is implemented on test data, it exhibits poor results. The R^2value of test data is around 0.5, which is very low and unsatisfactory. So it was decided to implement another machine learning technique.

Random Forest Model. The second ML method was Random forest (RF). The RF method is a modified version of DT. The RF is capable of solving both classification and regression problems, which is suitable for our dataset case. The Random Forest consists of many Decision Trees. The single DT has high variance, but if the number of them is increased and the result is combined variance significantly falls. As each tree is trained by its own dataset portion, the final result does not depend on one single output. For classification, the final output takes the major value, while in regression it is equal to the average of all tree outputs. Figure 5 illustrates the algorithm of the RF model.

In this model number of estimators could be adjusted. The effect of this parameter on RMSE and R^2 could be observed in Fig. 6. The optimal parameter of estimators is 100, which shows a better result of RMSE on test data (0.71), compared to the Decision tree model. Moreover, the R^2 value for train data is very good (around 0.93), whereas for test data it is considered fairly good, 0.78. After tuning the RF model, the UTS of

Table 1. Tensile test results based on various printing head temperature combination

Filament temp		Main tests					Extra test	Avg UTS(Mpa)	Std. Deviation	
PLA	ABS	T1	T2	T3	T4	T5	T6		No Extra	with Extra
204	240	37,676	*35,245*	37,708	37,829	37,639	37,796	37,730	1106	0080
	244	38,486	38,338	38,542	38,361	38,384		38,422		0087
	248	39,093	38,838	38,917	38,926	38,875		38,930		0098
	252	39,481	39,509	39,380	39,431	39,347		39,430		0068
	256	38,708	*36,546*	38,718	38,796	38,671	38,676	38,714	0975	0050
208	240	36,412	36,634	37,051	*34,759*	37,181	37,148	36,885	0972	0343
	244	38,130	38,417	38,310	38,282	38,370		38,302		0110
	248	37,597	37,444	37,644	37,403	37,519		37,521		0101
	252	37,208	37,218	37,366	37,319	37,259		37,274		0067
	256	*35,231*	36,218	36,120	36,009	36,023	36,278	36,130	0394	0118
212	240	39,708	39,870	39,954	39,727	39,671		39,786		0120
	244	40,810	41,023	40,912	41,042	40,926		40,943		0094
	248	41,361	41,509	41,250	41,398	41,486		41,401		0104
	252	41,148	41,162	41,333	41,273	41,282		41,240		0081
	256	39,620	39,472	*40,250*	39,231	39,347	39,301	39,394	0399	0154
216	240	39,051	38,792	38,995	39,074	38,648		38,912		0185
	244	39,569	39,685	39,657	39,782	39,509		39,641		0106
	248	38,463	38,356	38,551	38,514	38,435		38,464		0075
	252	37,949	38,074	38,153	38,005	37,931		38,022		0092
	256	37,366	37,301	37,093	37,741	37,190		37,338		0248
220	240	39,250	39,269	39,495	39,375	39,589		39,396		0146
	244	39,032	38,898	39,009	38,824	38,750		38,903		0120
	248	*38,495*	39,556	39,481	39,611	39,306	39,435	39,478	0459	0118
	252	38,065	38,144	38,426	37,907	38,000		38,108		0198
	256	36,750	36,991	37,093	37,227	37,065		37,025		0176

the following numbers PLA: 214–220 (step = 1 °C) and ABS: 240–256 (step = 1 °C) were predicted by the model. The fine step allows getting a more precise value of UTS at different temperatures. The 3D view of UTS results depending on nozzle temperature shown in Fig. 7 (a) for experimental data. The 3D view of dependence became more accurate after RF implementation in Fig. 7 (b). However, there still exist sharp corners and falls.

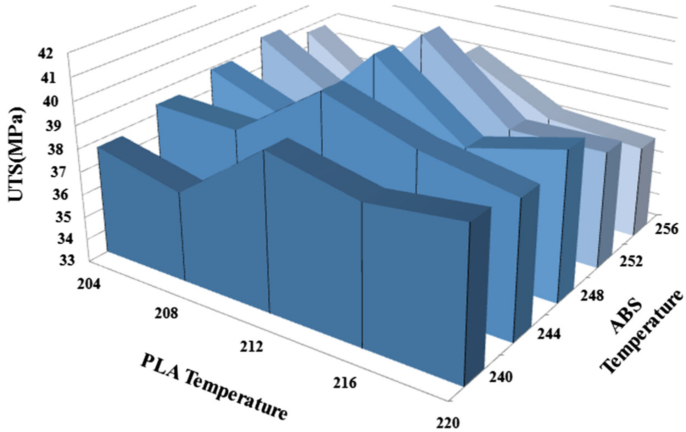

Fig. 2. Ultimate tensile strength at different PLA|ABS Nozzle temperatures.

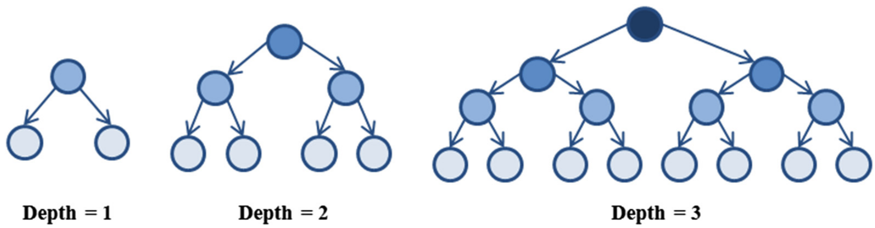

Fig. 3. Depth of decision tree

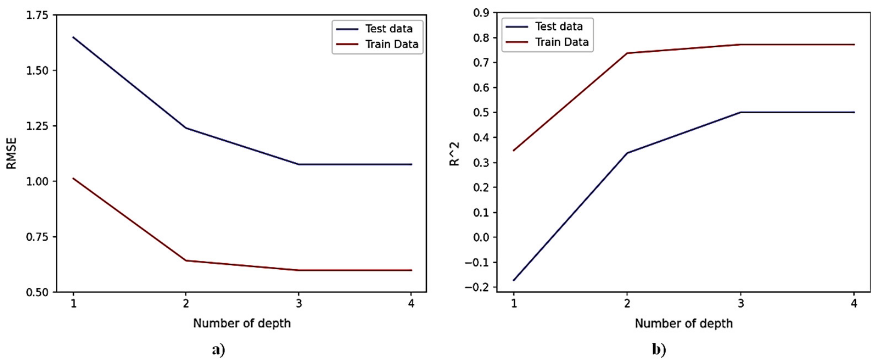

Fig. 4. Effect of decision tree model tree depth: **a)** on RMSE; **b)** on R^2.

Polynomial Regression Model. The third model was Polynomial regression (PR). The formula of PR is presented in Eq. 1, where the **y** is the predicted value, while **b** is the coefficient for the n^{th} degree of the polynomial. The PR regression builds dependence

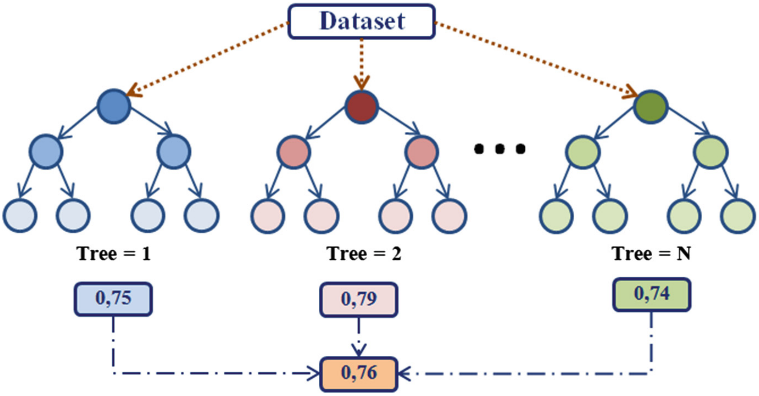

Fig. 5. Random forest algorithm

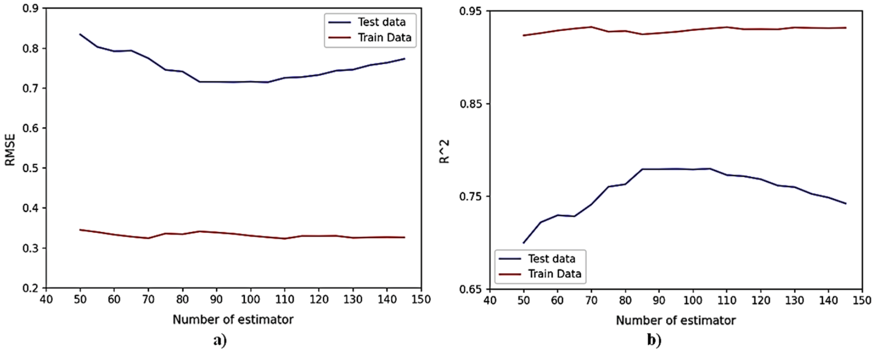

Fig. 6. Effect of random forest model estimator number: **a)** on RMSE; **b)** on R^2

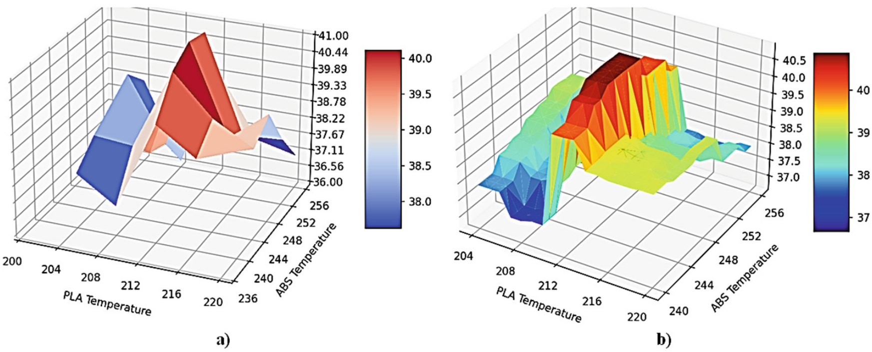

Fig. 7. 3D view of UTS according to **a)** experimental results **b)** RF model prediction results

between y and the independent variable.

$$y = b_0 + b_1x + b_2x^2 + b_3x^3 + \ldots b_nx^n \quad (1)$$

The control parameter was a degree of PR. It could be observed from Fig. 8 that the appropriate parameter for this model was 5th degree. From this point, the RMSE value started to rise, while R^2 started to fall for the test data. For the test data, the value of R^2 at this degree is 0.81, which is considered as a good correlation, while RMSE is equal to 0.59. In Fig. 9 (b) could be seen the smoother curve of 3D tensile results, obtained by the 5th degree PR model after uploading of fine testing data range of temperature (1 °C) for ABS and PLA.

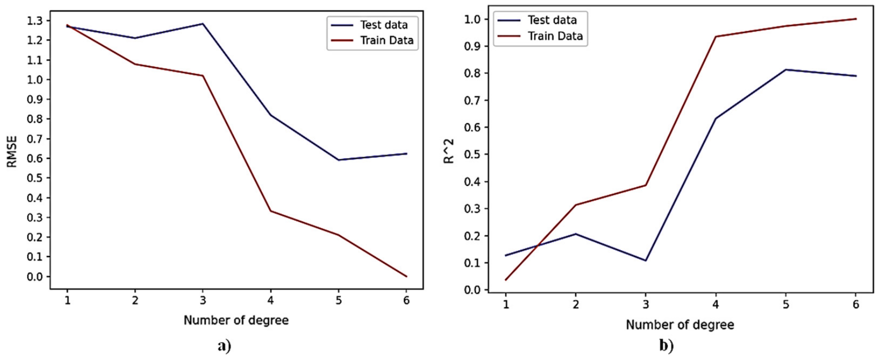

Fig. 8. Effect of PR model degree number: **a)** on RMSE; **b)** on R^2

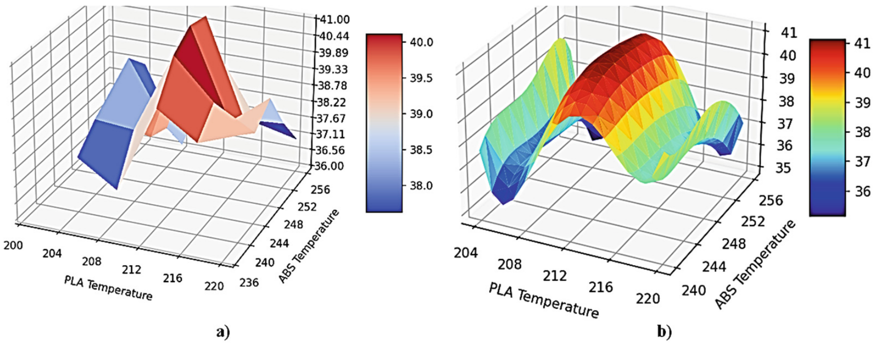

Fig. 9. 3D view of UTS according to **a)** experimental results **b)** PR model prediction results

Comparison of Models. Three different machine learning algorithms were implemented in this chapter. Comparative Table 2 indicates the superiority of the Polynomial regression model over Decision Tree and Random Forest models, both in RMSE and R^2 values for train and most importantly for test data.

4 Conclusion

The effect of different nozzle temperatures on the UTS value of PLA × ABS was experimentally investigated in this paper. Experimental results of tensile tests indicated

Table 2. Comparative analysis of Machine Learning algorithms

Model type	RMSE		R^2	
	Train data	Test data	Train data	Test data
Decision tree	0.6	1.1	0.8	0.5
Random forest	0.33	0.71	0.93	0.78
Polynomial regression	0.2	0.59	0.99	0.81

a non-linear relationship between nozzle temperatures and UTS. The machine learning approach was implemented to determine optimal process parameters for multi-material printing. Overall results are the following:

- The DT showed the worst result of R^2 and RMSE for test data, around 0.5 and 1.1 respectively.
- Although, the good value of R^2-0.78 and RMSE-0.71 for the RF model at an optimal number of the estimator, this method had a rough transition of the curve in small temperature steps in 3D view.
- The 5th-degree PR had the highest correlation value of test data R^2-0.81 and the lowest RMSE-0.59.
- The highest UTS of 41.171 MPa corresponds to PLA-216C and ABS-246C temperature values based on the PR model.

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