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Predictive Modeling and Optimization of Tensile and Flexural Strength in FDM 3D Printing Using Decision Trees and Bayesian Optimization

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Abstract

This research investigates predictive modelling and optimization technique for the tensile and flexural strength of PlA (Poly Lactic Acid) in Fused Deposition Modelling (FDM) 3D printing. Employing Decision Trees and Bayesian Optimization enhances comprehension and control of 3D printing process. Precise model predicts PLA material properties based on input parameters. Methodology involves rigorous data preprocessing, encompassing, cleaning, transformation, and normalization. Hyperparameter optimization via grid search systematically explores configurations, optimizing model performance. Bayesian Optimization further refines the model. Results exhibit significance, with the highest Tensile Mean Square Error at 5.5308 × 10^{-5} and a Tensile Root Mean Square Error of 0.007437, emphasizing findings' importance. The R-squared coefficient, at 0.94071, signifies substantial explanatory power. The optimized flexural model yields a notable best Flexural Mean Squared Error of 0.12583. With a respectable Flexural Root Mean Squared Error of 0.35472, the model demonstrates accuracy. A substantial R-squared value of 0.82573 indicates a robust correlation between predictor variables and observed flexural response.

Keywords: Additive manufacturing, Decision Trees, Bayesian Optimization, Predictive modeling, Mechanical performance

INTRODUCTION

In the field of cutting-edge manufacturing processes, FDM, which falls under the general heading of Additive Manufacturing, has attracted considerable interest due to its ability to produce three-dimensional objects with a high degree of accuracy and cost-effectiveness [1–3]. The process under consideration encompasses the sequential deposition of thermoplastic materials in a layer-by-layer manner, thereby facilitating its utilization in diverse domains such as product development, prototyping, and production [4–7]. However, the use of Poly Lactic Acid (PLA) within the field of FDM has gained significant attention due to its biodegradable and renewable properties [8, 9]. Nevertheless, within the framework FDM and PLA, ensuring accurate prediction and enhancement of the mechanical properties of 3D-printed elements holds significant significance. The accurate estimation of mechanical properties in FDM 3D printing with PLA material has significant importance for engineers, designers, and manufacturers [10, 11]. The mechanical characteristics play a crucial role in guaranteeing that the 3D-printed components adhere to performance standards and structural safety regulations, while also reducing the need for expensive trial-and-error iterations throughout the design and printing phases [12, 13].

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In response to this need, an approach is made for developing a predictive model for the tensile and flexural strength in FDM 3D printing with PLA material. This research is significant for its use of machine learning approaches, notably Decision Trees and Bayesian Optimization, to improve the predictability and optimization of mechanical properties of 3D-printed PLA components. The Decision Trees are an effective tool for modelling complex relationships between PLA material properties, printing parameters, and strength outcomes. This method improves the model's interpretability by offering useful insight into the parameter that influence the mechanical characteristics of 3D printed PLA components. Bayesian Optimization is smoothly integrated into the approach, building on the capabilities of Decision Trees. This technique optimizes and fine-tune the predictive model's performance, assuring accuracy and efficiency in capturing the complex relationship within the data. The interaction of Decision Trees with Bayesian Optimization improves the prediction models' overall reliability, Contributing to the precision and efficacy of additive manufacturing processes. Furthermore, the inclusion of Bayesian Optimization is a forward-thinking approach in our methodology. We position our research at the forefront of additive manufacturing developments by methodically researching the hyperparameter space and developing predictive models. This innovative combination has the potential to transform the potential to transform the predictability, efficiency, and cost-effectiveness of additive manufacturing processes, paving the path for increased product quality and performance.

Related Work

The investigation carried out by Arvind Kottasamy et al. [14] focused on examining the mechanical characteristics of composites made from copper-reinforced polylactic acid (Cu-PLA) using the FDM process. The researchers conducted an investigation on the impact of varying copper compositions (25% and 80%) and varied infill patterns on the resultant mechanical characteristics, encompassing tensile and flexural strengths. The investigation further integrated a prognostication technique employing response surface approach to evaluate the significant components and develop mathematical models for evaluating these qualities. This study aims to enhance the functionalities of FDM 3D printing through an investigation, modeling, and prediction of the mechanical properties of Cu-PLA composites

The study done by Ali et al. focused on the investigation of mix design issues associated with 3D-printed concrete. The researchers employed machine learning techniques, namely the Support Vector Machine (SVM), to construct predictive models for the estimation of flexural and tensile strength. The models incorporated various input parameters and data acquired from 25 distinct literature sources. The SVM model exhibited exceptional performance, exhibiting a robust link between the flexural strength of casted and printed concrete. This research paper presents a novel methodology to tackle the existing gap in machine learning-driven prediction models within the domain. The proposed strategy has the potential to minimize computational and experimental requirements in the design of 3D-printed concrete mixtures [15].

Rajpurohit and Dave [16] investigated Fused Deposition Modeling (FDM) in 3D printing, a versatile method that is constrained by weak mechanical performance. They employed the Adaptive Network-Based Fuzzy Inference System (ANFIS) to optimize construction settings and forecast the tensile strength of printed PLA pieces. This study showcases the application of ANFIS to enhance the mechanical properties of components produced using FDM printing. The user's text is a reference to a source or citation.

Zhang et al. [17] examined cooperative 3D printing, a distinctive approach in which mobile 3D printers collaborate to enhance printing speed and build volume. A data-driven prediction model was developed to ascertain the tensile strength of components produced utilizing this technology. The model accurately predicted tensile strength and identified crucial elements impacting mechanical qualities, filling a void left by the lack of systematic characterization for such components. This study adds to the improvement of the mechanical features of cooperative 3D printing for more efficient manufacture of bigger components.

Garzon-Hernandez et al. [16] investigated how 3D printing's FDM may be utilized to build components with configurable mechanical characteristics. A computational framework was developed by the researchers to incorporate production factors and filament qualities in order to predict mechanical properties and mesostructured characteristics. The investigation additionally incorporated a two-stage heating and sintering model to forecast the process of bond formation between filaments. The present study presents a valuable approach for the design of 3D printed polymeric components, wherein the desired qualities of the components can be tailored based on various production variables.

The study conducted by Samykano [19] employed a second-order mathematical model to evaluate the various tensile properties of 3D-printed polylactic acid (PLA) components manufactured using Fused Deposition Modeling (FDM). The mathematical models developed in this study were utilized to forecast several characteristics, such as ultimate tensile strength (UTS), fracture strain, elastic modulus, yield strength, and toughness. The models demonstrated minimal mistakes during the validation procedure, indicating their reliability in properly forecasting the tensile properties of 3D-printed PLA components.

The authors Sharma et al. [17] addresses the necessity of enhancing the dimensional quality in the context of FDM 3D printing. The researchers are studying how print elements affect dimensional accuracy in various geometries. They are using the Decision Tree Machine Learning Algorithm to predict changes in dimensions. The program generates accurate predictions, and the research achieves a validation score (R^2) of 0.67, indicating the potential for further industry-focused breakthroughs in enhancing the dimensional accuracy of FDM. Cerro et al. [21] employ machine learning methods to predict the surface roughness of polyvinyl butyral FDM-printed components. The researchers identify five input variables and utilize 3D printing technology to create a total of 16 components that display a wide range of surface characteristics. The most effective prediction model, Bagging and Multilayer Perceptron (BMLP), achieves a Kappa value of 0.9143. Wall angle and layer height are the two primary factors that influence the surface finish in FDM printing. These attributes offer valuable perspectives for enhancing the caliber of FDM-printed components. Zhang et al. [22] aim to tackle the issue of inconsistent product characteristics observed in the domain of Additive Manufacturing (AM). In order to address this problem, they suggest employing a data-driven predictive model that is specifically tailored for Fused Deposition Modeling (FDM). The researchers employ deep learning methodologies and leverage sensor data to accurately record the thermal and mechanical properties of several layers. The Long Short-term Memory (LSTM) network is employed to examine the interconnections between various layers in the printing process, facilitating the precise estimation of tensile strength. The results of this study suggest that the LSTM-based model outperforms other machine-learning methods. Layer-wise Relevance Propagation (LRP) aids in the understanding of the data, hence emphasizing the potential of deep learning in enhancing quality control for additive manufacturing. The study conducted by Meiabadi et al. [23] focuses on improving Fused Filament Fabrication (FFF) through the use of Polylactic Acid (PLA) 3D printing. The researchers employ the Response Surface Methodology (RSM) to optimize the controllable factors, including the extruder temperature, infill quantity, and layer thickness. An effort has been made to build artificial neural networks (ANN) and an ANN-genetic algorithm (ANN-GA) for the purpose of predicting toughness, component thickness, and manufacturing cost. The ANN-GA model exhibits improved performance in comparison to a single ANN, leading to a 7.5% improvement in modeling accuracy for toughness, an 11.5% improvement for component thickness, and a 4.5% improvement for production cost. This work emphasizes the capacity of machine learning to enhance the performance of fused filament fabrication (FFF) printing using polylactic acid (PLA) as the foundation material. The study conducted by Afonso et al. [24] aims to investigate the impact of different process parameters in Fused Filament Fabrication (FFF) on both the mechanical properties and mass characteristics of components made from Polylactic Acid (PLA). The parameter that had the most influence on the extrusion process was determined to be the temperature. This parameter exhibited distinct patterns that were closely associated with the thermal and rheological properties of the material. The research effectively constructed predictive models with minimal error rates, so showcasing the efficacy of systematic experimental design in producing precise mathematical equations for diverse outcomes.

Table 1. Overview of input parameters and output responses

S.N.	Print orientation	Print Speed (mm/s)	Infill density (%)	Print Temp. (°C)	Layer Height (mm)	Tensile strength (MPa)	Flexural strength (MPa)
1	90	50	40	210	0.2	0.175	6.7968
2	0	60	40	230	0.26	0.198	5.2439
3	135	55	60	220	0.23	0.168	6.6797
4	0	50	80	210	0.2	0.218	5.2146
5	90	60	40	210	0.26	0.168	6.533
6	45	55	100	220	0.23	0.263	7.6169
7	90	60	80	230	0.26	0.222	7.4411
8	45	55	60	200	0.23	0.164	5.7127
9	90	50	40	230	0.26	0.171	6.9138
10	0	50	40	230	0.2	0.186	5.0682
11	45	55	60	220	0.23	0.172	6.0642
12	45	65	60	220	0.23	0.177	6.0935
13	45	55	60	220	0.23	0.173	6.1228
14	90	50	80	210	0.26	0.227	7.4118
15	45	55	60	220	0.23	0.174	6.0642
16	0	50	40	210	0.26	0.216	5.3318
17	45	45	60	220	0.23	0.171	6.0056
18	45	55	20	220	0.23	0.119	4.1893
19	90	60	40	230	0.2	0.155	6.9138
20	90	60	80	210	0.2	0.235	7.8513
21	90	50	80	230	0.2	0.241	7.9099
22	-45	55	60	220	0.23	0.169	6.4451
23	0	50	80	230	0.26	0.256	5.8592
24	45	55	60	220	0.23	0.172	6.0349
25	0	60	80	230	0.2	0.229	6.1814
26	45	55	60	220	0.23	0.174	6.1228
27	0	60	80	210	0.26	0.244	5.6834
28	45	55	60	240	0.23	0.17	6.2986
29	45	55	60	220	0.23	0.17	6.3279
30	45	55	60	220	0.29	0.169	6.1521
31	45	55	60	220	0.17	0.173	6.6501
32	0	60	40	210	0.2	0.166	4.951

The study conducted by Bayraktar et al. [18] examined the use of Fused Deposition Modeling (FDM) in the production of 3D-printed plastic components. The researchers employed a 3D printer that was specifically constructed for this purpose. The experiment included manipulating melt temperatures, layer thicknesses, and raster pattern orientations, resulting in notable effects on the tensile strength. The use of artificial neural networks was applied in order to develop a precise mathematical model for the outcomes of tensile tests, with particular emphasis on the crisscross raster pattern as the most optimal approach.

The numerous investigations collectively contribute to enhancing the comprehension and refinement of 3D printing procedures. Each study examines several facets, ranging from the qualities of materials and challenges in designing mixes to optimizing building parameters and improving mechanical properties. The application of machine learning methodologies, such as Support Vector Machines (SVM), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and deep learning, showcases the adaptability and efficacy of these approaches in predicting and enhancing diverse results. The research findings, which have been confirmed through the use of mathematical models and accurate predictions, offer vital insights for enhancing 3D printing procedures. There is a significant research gap in the use of decision tree prediction models and Bayesian optimization approaches to improve the accuracy and efficiency of several elements of 3D printing. Subsequent research efforts should investigate the integration of decision tree models with Bayesian optimization to address this deficiency and propel the field forward.

DATA PREPROCESSING

Data preprocessing serves as essential to ensuring the accuracy and dependability of the predictive modeling and optimization process for tensile and flexural strength in FDM 3D printing, as investigated in this paper. The first phase involves importing the raw data and retrieving relevant input parameters, such as print orientation, print speed, infill density, print temperature, and layer height, along with the related output responses of tensile and flexural strength. In order to improve the performance and convergence of the model, the input features are normalized using the z-score approach, which is represented by the following mathematical equation:

$$Z = \frac{X-\mu}{\sigma} \tag{1}$$

In the provided information, X represents the unprocessed data, μ denotes the average, and σ represents the measure of dispersion known as the standard deviation. By normalizing the input parameters, any potential biases caused by variations in their scales are reduced. In addition, the dataset is divided into separate sets for training, validation, and testing using a stratified hold-out method. This method is mathematically expressed as:

$$Stratified\ Hold - Out: D = D_{train} \cup D_{valid} \cup D_{test}$$

$$D_{train}, D_{valid}, D_{test} = Partition(D, Ratio_{train,} Ratio_{valid,} Ratio_{test,}) \tag{2}$$

Where D Represents the complete dataset, and $Ratio_{train,} Ratio_{valid,} Ratio_{test,}$ denote the proportions allocated to the training, validation, and testing sets respectively. This guarantees that each subset maintains a representative distribution of input parameters and response variables. Additionally, the random seed S is established to ensure reproducibility between experiments, as determined by the equation:

$$S_{random} = 1 \tag{3}$$

This method guarantees consistent and reproducible outcomes, which enables a thorough assessment of the model's effectiveness and mitigates the risk of overfitting. The model's performance is evaluated using a comprehensive cross-validation approach, ensuring robustness. The generated datasets are systematically organized and preprocessed. This establishes the groundwork for the following phases of hyperparameter tweaking, model training, and optimization utilizing Decision Trees and Bayesian Optimization methodologies.

The rigorous data preprocessing methodology employed in this study greatly enhances the dependability and precision of the succeeding predictive modeling and optimization stages, thereby improving the comprehension and control of the FDM 3D printing process.

HYPERPARAMETER TUNING WITH GRID SEARCH

After carefully preparing the data, the next crucial step in this research is to fine-tune the hyperparameters utilizing the grid search approach. The performance of machine learning models is greatly affected by hyperparameters. In this case, we are specifically interested in the Decision Tree models utilized for predicting the tensile and flexural strengths in FDM 3D printing. The grid search method methodically investigates a pre-defined search area for hyperparameters, with a specific focus on the maximum number of splits ($MaxNumSplits$) and the minimum leaf size ($MinLeafSize$). The hyperparameters play a crucial role in setting the architecture and intricacy of the Decision Tree models.

The grid search methodology is employed to systematically evaluate models that have undergone training with different combinations of hyperparameters on a validation set. The comprehensive examination conducted ensures that the models are appropriately calibrated in order to achieve optimal performance, thereby resulting in a reduction of the mean squared error (MSE). The procedure involves the establishment of parameter ranges for hyperparameters, which are determined by considering the properties of the dataset and the intricacies associated with the 3D printing process.

The outcome of this study involves the identification of the most suitable hyperparameter values that effectively improve the dependability and accuracy of predictive models pertaining to both tensile and flexural strengths. The initial phase of this process establishes a crucial foundation for subsequent model training and optimization using Bayesian Optimization techniques. Graphical depictions, exemplified by Figure 1 (Tensile Strength & Flexural Strength MSE Heatmap) and Figure 2 (Tensile Strength & Flexural Strength MSE Contour Plot), serve as instrumental tools in comprehending the hyperparameter tuning procedure by providing significant elucidation regarding the impact of various hyperparameter configurations on the mean squared error pertaining to tensile strength. Each individual data point on the heatmap represents a unique set of hyperparameters, allowing for a comprehensive exploration and analysis of the search space. The plots presented in this analysis showcase the correlation between the variables $MaxNumSplits$ and $MinLeafSize$, shedding light on the intricate balance between these factors and their impact on the model's overall performance. The provided information serves as a valuable resource for informing the decision-making process in selecting hyperparameters that effectively minimize the Mean Squared Error. The hyperparameters that have been identified are subsequently utilized to train the model, establishing the foundation for further optimization through the application of Bayesian optimization in subsequent stages of the study. The optimal hyperparameter values for tensile strength, determined using grid search, are $MaxNumSplits = 1$ and $MinLeafSize = 1$. The best hyperparameter settings for flexural strength are $MaxNumSplits = 1$ and $MinLeafSize = 5$.

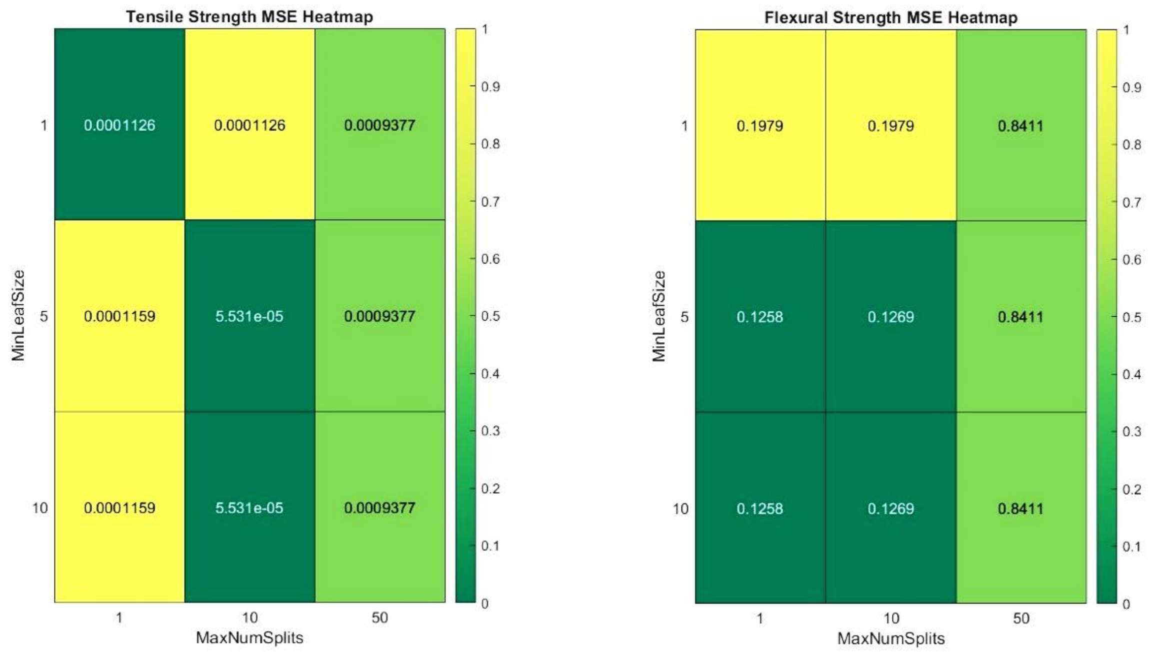

Figure 1. Tensile Strength &Flexural Strength MSE Heatmap.

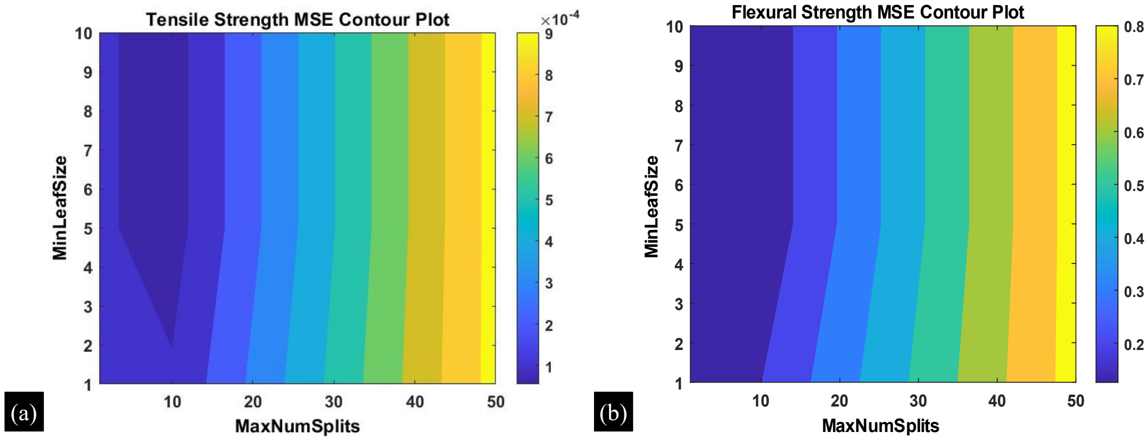

Figure 2. Tensile Strength & Flexural Strength MSE Contour Plot.

MODEL TRAINING AND PERFORMANCE EVALUATION

Following implementing an intensive hyperparameter tuning with grid search, the final models are trained utilizing the optimal hyperparameters determined by the exhaustive search method. The Decision Trees, which have been optimized particularly for predicting the tensile and flexural strengths in FDM 3D printing, are evaluated using the validation set. The Decision Tree graphics effectively illustrate the complexities of the decision-making process, offering a clear depiction of how the models make predictions by considering input parameters. These representations improve the capacity to understand and analyze the hierarchical structure of the models.

Additionally, the models' performance is thoroughly evaluated using industry-standard metrics such as Mean Squared Error, Root Mean Squared Error, and R-squared. The MSE is computed using the following mathematical expression:

$$MSE(m) = \frac{1}{card(R_m)}(y_i - y\bar{R_m})^2 \tag{4}$$

The region denoted as R_m is representative of the specific area associated with node m. The mean response within the population R_m is represented by the symbol $y\bar{R_m}$, Conversely, the specific response for a given observation i within the population R_m is denoted by y_i.

The model exhibits remarkable efficacy in the estimation of tensile strength, as evidenced by its best Tensile Mean Squared Error (MSE) of 5.5308 × 10^{-5}, a Tensile Root Mean Squared Error (RMSE) of 0.007437, and an outstanding coefficient of determination (R^2) value of 0.94071. Similarly, the enhanced model for flexural strength exhibits a Best Flexural Mean Squared Error (MSE) of 0.12583. Additionally, it achieves a Flexural Root Mean Squared Error (RMSE) of 0.35472, indicating the level of deviation between the predicted and actual flexural strength values. Notably, the model also demonstrates a high R-squared value of 0.82573, which signifies the proportion of the variance in the flexural strength that can be explained by the model. The diagram presented in Figure 3 illustrates the Regression Tree model for both Tensile Strength and Flexural Strength. The inclusion of this visual representation within the context of the model serves as a valuable instrument for comprehending the underlying decision-making process. Furthermore, it significantly enhances the comprehensive assessment of the model's predictive capacities.

BAYESIAN OPTIMIZATION FOR MODEL ENHANCEMENT

Following a rigorous process of data preprocessing, hyperparameter tuning, and model training, the subsequent and crucial step entails the evaluation of the models' performance and their predictive capabilities. The models, which have been trained using the optimal hyperparameters determined through the grid search and Bayesian Optimization phases, undergo thorough evaluation on a validation dataset. The Bayesian Optimization process, a crucial step in improving the accuracy and effectiveness of predictive models for both tensile and flexural strengths in FDM 3D printing, is executed with

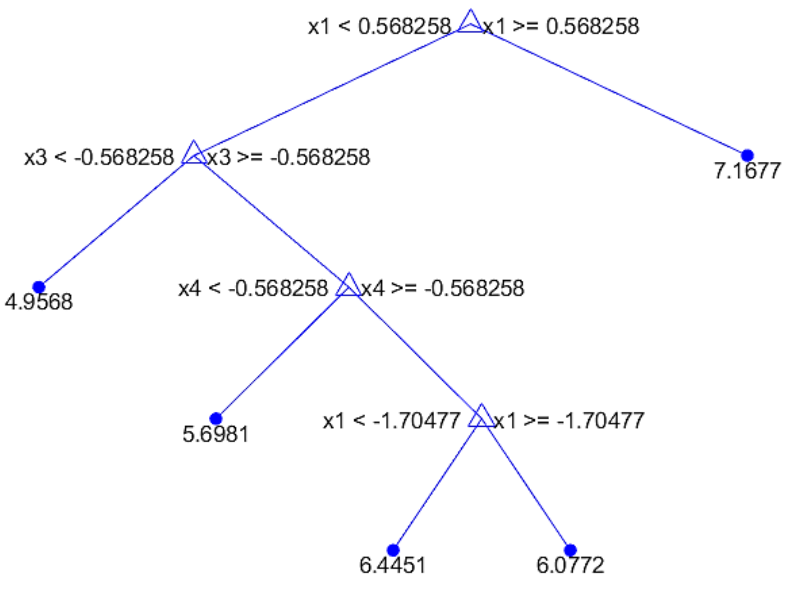

Figure 3. Regression tree for tensile and flexural strength models.

meticulousness and efficiency. The hyperparameter search space, indicated as Θ, is defined as $\Theta = \{MaxNumSplits, MinLeafSize\}$. The optimization approach improves the models' performance by iterative enhancements. The goal functions for tensile (Θ) and flexural $(\Theta)$are intended to optimize the strengths under tension and flexure, respectively, by minimizing the MSE.

$$f_{tensile}(\Theta) = MSE_{tensile}(\Theta)$$
$$f_{flexural}(\Theta) = MSE_{flexural}(\Theta) \quad (5)$$

Here, Θ represents the mean squared error for tensile strength (MSE tensile) and Θ represents the mean squared error for flexural strength (MSE flexural). The optimization results demonstrate the algorithm's versatility and effectiveness. The most accurately measured point for tensile strength is at $\{MaxNumSplits = 49\ MinLeafSize = 2\}$, with an observed objective function value of -0.238. Bayesian Optimization identifies the optimal feasible point as $\{MaxNumSplits = 1\ MinLeafSize = 4\}$ with an estimated objective function value of -0.238. Regarding flexural strength, the optimal values observed for the parameters are $MaxNumSplits = 44\ MinLeafSize = 6$, resulting in an objective function value of -7.1677. The estimated optimal values for the parameters $MaxNumSplits = 50\ MinLeafSize = 5$, with an estimated objective function value of -7.1677. Bayesian Optimization ultimately aims to determine the most favorable hyperparameter values, which greatly enhance the accuracy and reliability of predictions concerning tensile and flexural strength. The optimized models demonstrate exceptional performance, with the highest tensile strength having a mean squared error (MSE) of 5.5308×10^{-5}, a Tensile root mean squared error (RMSE) of 0.007437, and a remarkable R-squared value of 0.94071. The model for flexural strength demonstrates a noteworthy performance, as indicated by the achieved Best Flexural Mean Squared Error (MSE) of 0.12583, a Flexural Root Mean Squared Error (RMSE) of 0.35472, and a substantial R-squared value of 0.82573. These metrics suggest that the model is able to accurately predict flexural strength with a relatively low level of error and a high degree of explained variance. The obtained results provide compelling evidence that Bayesian Optimization exhibits a notable impact on enhancing the precision of prediction models within the context of Fused Deposition Modeling (FDM) 3D printing.

RESULT AND DISCUSSIONS

The present research study aims to explore the utilization of predictive modeling and optimization techniques in order to improve the tensile and flexural strength of objects produced through Fused

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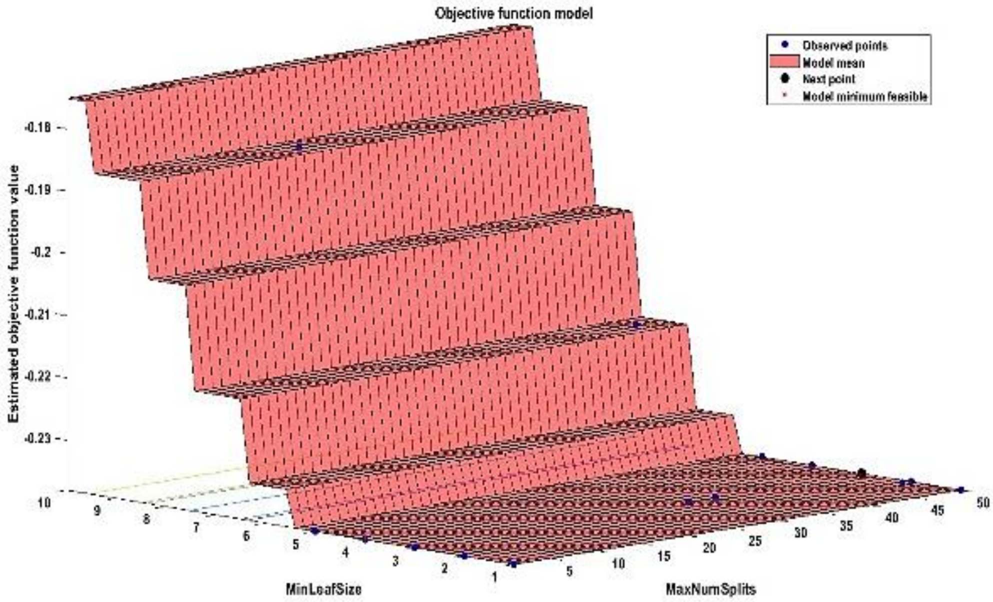
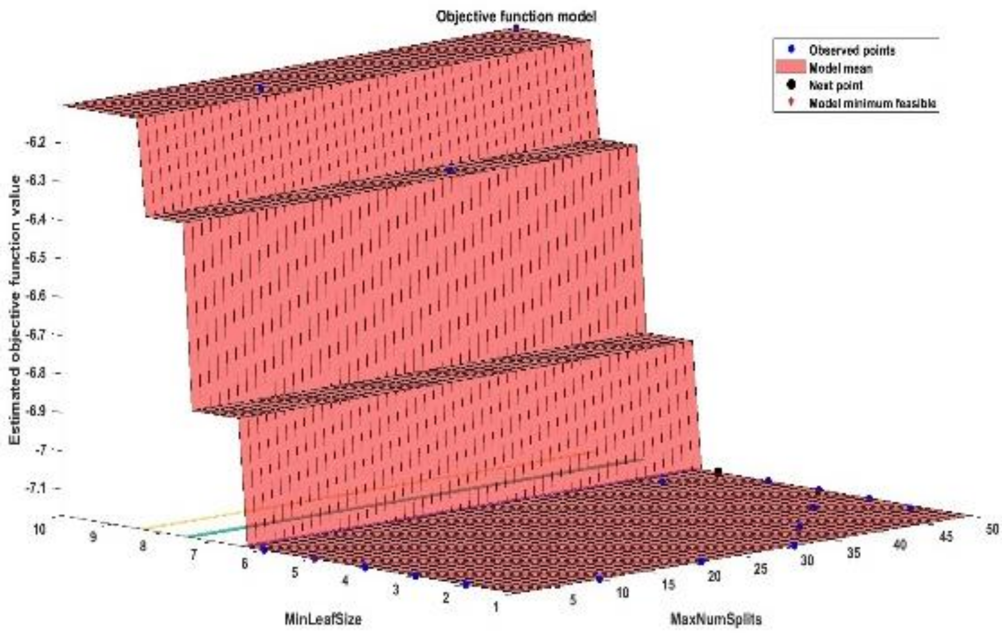
Deposition Modeling (FDM) 3D printing. The research employs the utilization of Decision Trees and Bayesian Optimization techniques in order to improve the understanding and management of the 3D printing procedure. The methodology employed in this study involves several key steps. Firstly, data preparation is conducted to ensure the dataset is suitable for analysis. This includes tasks such as data cleaning, feature engineering, and data transformation. Next, hyperparameter modification is performed using grid search. This technique systematically explores different combinations of hyperparameters to identify the optimal configuration for the model. By exhaustively searching the hyperparameter space, we aim to find the settings that yield the best performance. Once the hyperparameters have been determined, the model training phase commences. During this stage, the model is trained on the prepared dataset using the selected hyperparameter values. The goal is to optimize the model's ability to learn patterns and make accurate predictions. To further enhance the model's performance, Bayesian Optimization is employed. This technique leverages Bayesian inference to iteratively refine the model by intelligently selecting the next set of hyperparameters to evaluate.



(a)



(b)

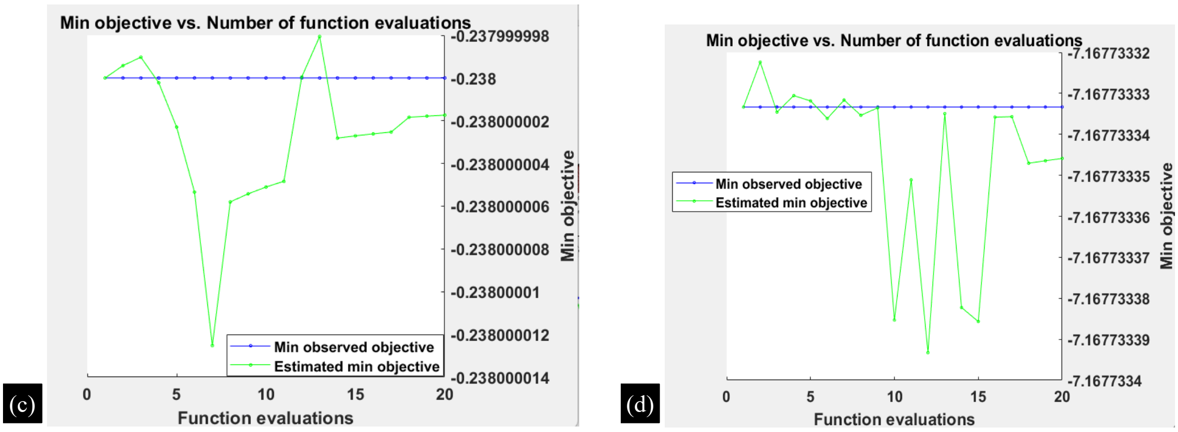


Figure 4. Optimization analysis for tensile and flexural strength models.

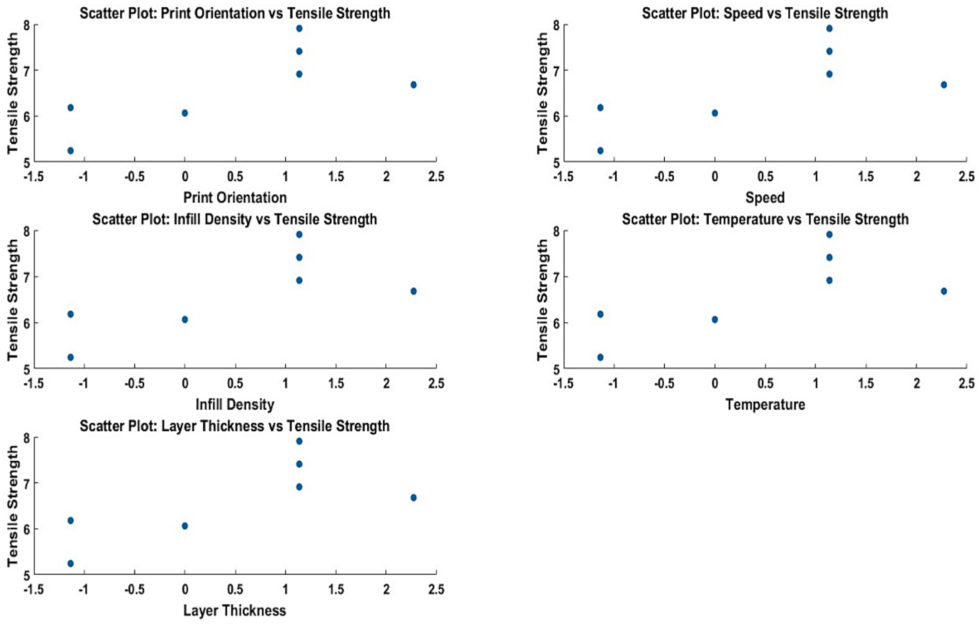


Figure 5 Design variables and objective functions (Tensile Strength) scatter plot

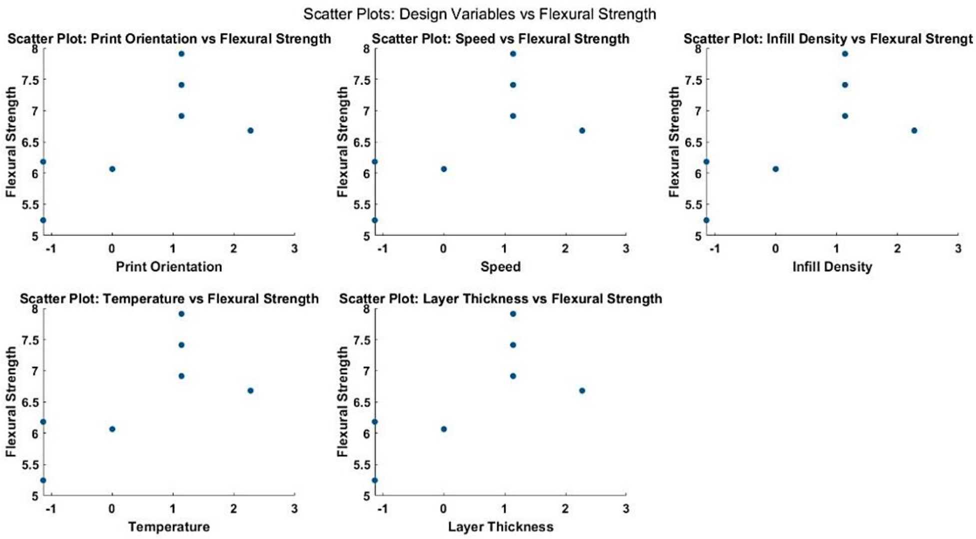


Figure 6. Design variables and objective functions (Flexural Strength) scatter plot.

The findings of this study indicate significant and noteworthy results. The obtained results indicate that the optimal Mean Squared Error (MSE) value is 5.5308×10^{-5}. Additionally, the corresponding Root Mean Squared Error (RMSE) for the tensile property is calculated to be 0.007437. Moreover, the coefficient of determination (R-squared) value is determined to be 0.94071, indicating a high level of correlation between the predicted and actual values. The enhanced Flexural model yields a noteworthy Best Flexural Mean Squared Error (MSE) of 0.12583. Additionally, it demonstrates a respectable Flexural Root Mean Squared Error (RMSE) of 0.35472 and an R-squared value of 0.82573. The phase of Bayesian Optimization, which plays a crucial role in the refinement of predictive models, progresses with a high degree of precision. The primary objective of the optimization algorithm is to achieve maximum values for both tensile and flexural strengths. This is accomplished by minimizing the mean squared error (MSE) through the establishment of a defined hyperparameter search space (Θ). The findings illustrate the algorithm's ability to adapt and excel, as indicated by the observed and predicted optimal points, providing valuable insights into the optimal hyperparameter configurations.

The efficacy of these findings is augmented by the utilization of visually informative graphical representations. The study is enhanced by the incorporation of an objective function model, which allows for a systematic evaluation of the problem at hand. By minimizing the objective, the researchers are able to identify the optimal solution that best satisfies the given criteria. Additionally, the utilization of scatter plots to depict the correlation between the number of function evaluations and the design factors provides valuable insights into the relationship between these variables. Overall, these methodological choices contribute to the rigor and comprehensiveness of the study. The visual representations presented in these plots offer a valuable means of delving into the intricacies of the optimization process, thereby shedding light on the intricate relationships that exist between design variables and material strengths. By combining these illustrative depictions with comprehensive numerical data, a thorough investigation into the realm of predictive modeling and optimization within the domain of FDM 3D printing is achieved.

CONCLUSIONS

In summary, the conducted investigation pertaining to the utilization of predictive modeling and optimization techniques for Fused Deposition Modeling (FDM) 3D printing, specifically employing Decision Trees and Bayesian Optimization, yielded noteworthy outcomes. Through a rigorous process of meticulous preprocessing and careful hyperparameter modification, the research team was able to achieve remarkable numerical accomplishments. Notably, they were able to attain the lowest Tensile Mean Squared Error (MSE) of 5.5308e-05, indicating a high level of accuracy in their predictions. Additionally, the team obtained outstanding R-squared values, further validating the effectiveness of their approach. These achievements highlight the importance of thorough data preprocessing and thoughtful hyperparameter tuning in obtaining superior results in this research endeavor. The models underwent a successful fine-tuning process utilizing Bayesian Optimization, which effectively showcased their adaptability and versatility. The utilization of the Objective Function Model and Scatter Plots has facilitated the acquisition of lucid insights pertaining to the intricate interrelationships existing between design variables and material strengths. The present study significantly contributes to the academic domain by introducing a robust methodology for enhancing the optimization process of 3D printing. The results not only enhance theoretical comprehension but also provide practical guidance for optimizing printing procedures. This study establishes a strong basis for future research in the field of 3D printing, offering guidance for enhancing material durability and optimizing printing techniques with efficiency.

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