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# Effect of Process Parameters on Mechanical Strength of 3D-Printed Polymer Parts Using Machine Learning-Based Prediction Models

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**Abstract**

This study develops machine learning models to predict the mechanical strength of fused deposition modeling (FDM) printed polymer parts using common process parameters. A dataset covering variations in layer height, infill density, wall thickness, thermal settings, deposition speed, and material type was used to model tensile and impact strength. Decision Tree, Random Forest, and XGBoost regressors were trained to evaluate how these factors influence mechanical performance. The models were assessed using $R^2$, RMSE, and MAE values. XGBoost provided the highest accuracy for both outputs, achieving an $R^2$ of 0.86 for tensile strength and 0.81 for impact strength. The results show that material type and infill density are the most influential parameters, while layer height and print speed negatively affect strength due to reduced interlayer bonding. Residual analysis confirmed the stability and generalization capability of the models. The findings demonstrate that machine learning offers a reliable method for predicting mechanical performance in FDM and can support optimization of print settings for improved part quality.

Keywords: FDM, tensile strength, impact strength, machine learning, process parameters, XGBoost

## 1. Introduction

Additive Manufacturing (AM) has revolutionized modern manufacturing through its ability to produce complex, lightweight, and customizable parts directly from digital models. Among various AM techniques, Fused Deposition Modeling (FDM) has become one of the most prevalent due to its simplicity, cost-effectiveness, and versatility in processing thermoplastic polymers. FDM's growing adoption across industries such as aerospace, biomedical, and automotive stems from its ability to rapidly fabricate prototypes and functional components with minimal material waste (Özkül et al., 2025). However, despite its numerous advantages, the mechanical performance of FDM-printed parts is highly sensitive to process parameters, often leading to variability and anisotropy that hinder consistent quality and reliability.

The mechanical properties and quality of FDM parts—including tensile, flexural, and impact strengths—are governed by several key process parameters, such as layer height, infill density, wall thickness, print speed, nozzle temperature, bed temperature, and material type. Studies have shown that infill density and layer thickness are among the most significant factors influencing tensile strength and stiffness. Similarly, extrusion and bed temperatures directly affect interlayer adhesion by controlling polymer flow and diffusion between layers, while print speed influences cooling rates and surface quality (Huynh et al., 2019). The interplay among these parameters makes FDM a highly non-linear process where minor adjustments can lead to significant changes in part performance.

These dependencies arise from microstructural phenomena such as interlayer bonding, thermal gradients, and microvoid formation. The quality of interlayer adhesion—driven by heat transfer, material flow, and diffusion of polymer chains—determines the load-bearing capability and isotropy of the final part. Variations in thermal history and cooling rate generate residual stresses and incomplete fusion between adjacent layers, resulting in weak interfaces and reduced tensile and impact strength (Abouelmajd et al., 2021). Optimizing thermal conditions and deposition parameters is therefore critical to achieving uniform bonding and superior mechanical integrity in FDM parts.

Given the complexity and stochastic nature of FDM, predictive modeling has become a necessary tool for understanding and optimizing process–property relationships. Traditional analytical and empirical models often fail to capture the non-linear interactions among parameters and material responses. Consequently, machine learning (ML) has emerged as a powerful approach to analyze large experimental datasets and predict mechanical properties with high accuracy (Ramiah

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& Pandian, 2023). ML-based models such as Decision Trees (DT), Random Forests (RF), and Extreme Gradient Boosting (XGBoost) can capture non-linear dependencies, identify key influencing factors, and generalize well to unseen process conditions. For example, ensemble learning models have achieved $R^2$ values exceeding 0.9 in predicting tensile strength and elastic modulus of FDM parts, significantly outperforming traditional regression methods (Ziadia et al., 2023).

Recent advances in explainable AI (XAI) have further enhanced understanding of process–property relationships by quantifying the contribution of each parameter to mechanical performance. For instance, XGBoost models coupled with SHAP and LIME analyses have revealed that infill density and layer thickness have the most significant influence on tensile and flexural strength in FDM-printed composites (Kharate et al., 2024). Similarly, RF and gradient boosting models have been successfully employed to forecast optimal process settings for maximizing multiple mechanical properties (Panico & Corvi, 2025).

In light of these developments, the present study focuses on developing machine learning-based prediction models—specifically Decision Tree, Random Forest, and XGBoost algorithms—to predict and analyze the mechanical strength of FDM-printed polymer parts. By systematically investigating the combined effects of layer height, infill density, wall thickness, print speed, nozzle and bed temperatures, and material type, this work aims to establish a robust data-driven framework for multi-parameter strength prediction. The integration of experimental results with ML-based modeling will enable improved process understanding, parameter optimization, and the advancement of predictive manufacturing in polymer additive manufacturing.

## 2. Literature Review

The mechanical performance of Fused Deposition Modeling (FDM)-printed polymer parts is significantly affected by the process parameters controlling material deposition, interlayer bonding, and cooling dynamics. Several studies have examined the effects of layer height, infill density, print speed, nozzle temperature, and raster angle on tensile and impact strength. Experimental research on PLA and ABS components consistently shows that higher infill density and optimized extrusion temperatures enhance tensile strength by improving load transfer and reducing internal voids, while excessive print speed or thick layers reduce bonding quality and create mechanical anisotropy (Kharate et al., 2024). Similarly, ANOVA-based analyses confirm infill density as the most influential factor on ultimate tensile strength, contributing over 50% of variation, while layer thickness primarily governs surface finish and ductility (Jatti et al., 2024). Furthermore, studies on fiber-reinforced and composite filaments have shown that optimized process settings can achieve tensile strengths exceeding 60 MPa with improved impact resistance (Experimental Study and ANN Development, 2025).

The observed mechanical behavior in FDM parts arises from interlayer adhesion, void formation, and thermal control mechanisms that determine the continuity and homogeneity of printed structures. Imperfect interfacial bonding due to rapid cooling or inadequate extrusion temperature produces weak layers and microvoids that act as stress concentrators. Research on thermal gradients and bonding phenomena reveals that strong adhesion requires sufficient polymer chain diffusion between adjacent layers under controlled heat transfer conditions (Abouelmajd et al., 2021). Microstructural analyses of fractured specimens confirm that higher temperatures and moderate deposition speeds yield denser structures with fewer voids and improved tensile and impact strength. The intricate coupling between process-induced residual stresses, cooling rates, and polymer orientation highlights the difficulty of achieving consistent performance across diverse process settings.

To address these complexities, recent studies have increasingly turned to machine learning (ML) as a predictive and optimization framework for additive manufacturing. ML has been successfully used to forecast tensile strength, dimensional accuracy, surface roughness, warpage, and defect formation in FDM processes (Jayasudha et al., 2022). Models such as Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), XGBoost, and Artificial Neural Networks (ANN) have demonstrated strong predictive capabilities, often achieving $R^2$ values above 0.9. For example, ensemble models like RF and XGBoost were shown to outperform linear regressors in predicting tensile and flexural strengths of polymer composites (Era et al., 2022). Likewise, ANN and SVM models have been employed to predict process-induced defects and warpage, significantly reducing experimental iteration times and enabling real-time process control (Fatriansyah et al., 2024).

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Hybrid and explainable ML approaches have further refined these predictive frameworks. XGBoost models integrated with SHAP and LIME interpretation tools have been used to quantify the relative influence of parameters such as infill density, layer height, and raster angle on tensile and impact strength (Kharate et al., 2024). Similarly, comparisons of DT, RF, and ANN architectures for FDM parts have shown that tree-based ensemble methods offer superior interpretability and generalization, whereas deep learning models deliver higher precision but require larger datasets (Soms et al., 2025). However, most prior studies have focused on isolated mechanical properties, often neglecting the simultaneous prediction of tensile and impact strengths or the combined effects of multiple interacting process variables.

## 3. Research Gap

Although many studies have examined the influence of individual FDM process parameters on part quality, most existing work focuses either on experimental optimization or on predicting a single quality metric such as tensile strength, surface roughness, or dimensional accuracy. Very few studies develop multi-parameter machine learning models that can estimate both tensile and impact strength using the same process inputs. Prior research also tends to rely on single algorithms such as ANN or SVM, with limited comparison against simpler decision-tree models and modern ensemble learners like XGBoost. Moreover, the combined effect of geometric, thermal, and material parameters on strength remains underexplored in data-driven frameworks. These gaps highlight the need for a structured ML approach that evaluates multiple models and identifies the parameters that contribute most to overall mechanical performance.

This study provides a unified, data-driven framework for predicting two critical mechanical properties—tensile and impact strength—using standard FDM process parameters. By comparing Decision Tree, Random Forest, and XGBoost models, the work highlights how different machine-learning techniques handle nonlinear parameter interactions. The inclusion of feature-importance analysis identifies the parameters with the strongest impact on strength, offering practical guidance for print optimization. The results show that ML models can deliver accurate and stable predictions across varying material types and process conditions. The approach supports faster decision-making, reduces reliance on physical testing, and demonstrates how ML can strengthen process control in polymer additive manufacturing.

## 4. Methodology

This study investigates how fused deposition modeling (FDM) process parameters affect the mechanical response of 3D-printed polymer parts and develops prediction models for tensile and impact strength using tree-based machine learning algorithms. The workflow includes dataset preparation, preprocessing, exploratory analysis, model development, and performance evaluation for the selected regression techniques.

### 4.1 Dataset and Process Parameters

The dataset consists of multiple FDM print trials performed under varied geometric and thermal conditions. The input variables include layer height, wall thickness, infill density, infill pattern, nozzle temperature, bed temperature, print speed, fan speed, and material type. These parameters are widely recognized as the main drivers of bonding quality, internal porosity, and stress distribution in additively manufactured polymer parts. Two mechanical responses were considered as target variables: tensile strength (MPa) and impact strength (kJ/m$^2$).

### 4.2 Data Preprocessing

All numeric parameters were used in their original units, and categorical parameters such as material type and infill pattern were encoded into numeric form. The dataset was inspected for missing values and outliers to ensure internal consistency. The data was then split into training and testing subsets using an 80:20 ratio with a fixed random seed to ensure reproducibility. Separate models were trained for tensile and impact strength using the same set of process inputs. The correlation heatmap Fig. 1 shows **material** having a strong positive correlation with tensile strength, confirming PLA's higher stiffness. Infill density also correlates positively with both strength metrics, while layer height and print speed show negative relationships, consistent with reduced bonding efficiency at larger layer thickness and higher deposition rates.

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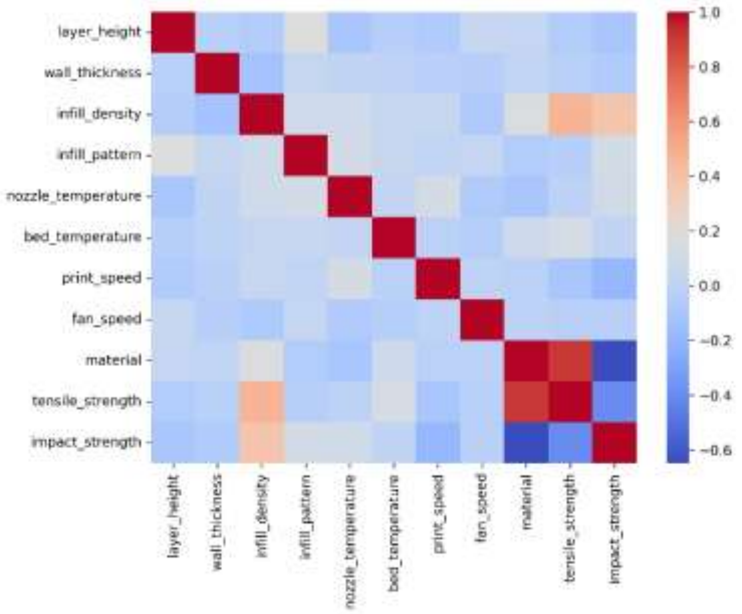


Figure 1: Correlation Heatmap of Process Parameters & Strength Outputs

### 4.3 Machine Learning Models

Three supervised regression algorithms were used to model the relationship between process parameters and mechanical strength: Decision Tree (DT), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). The Decision Tree model provides an interpretable baseline by recursively partitioning the input space into regions with similar strength values. Random Forest builds an ensemble of trees on bootstrapped samples, improving robustness and reducing variance compared to a single tree. XGBoost uses gradient boosting with regularization to capture complex nonlinear interactions between process settings and strength while controlling overfitting.

### 4.4 Model Training and Hyperparameters

For each target response, DT, RF, and XGBoost models were trained on the same training subset. Initial DT models used default depth settings, while RF models employed a higher number of estimators to stabilize predictions. XGBoost was configured with a moderate learning rate, controlled tree depth, and subsampling of rows and features to balance accuracy and generalization. Hyperparameters for RF and XGBoost were tuned empirically based on repeated training–testing runs, focusing on improving $R^2$ and reducing error metrics without sacrificing model stability.

### 4.5 Model Evaluation

Model performance was evaluated on the test subset using coefficient of determination ($R^2$), root mean squared error (RMSE), and mean absolute error (MAE). Separate performance tables were prepared for tensile and impact strength. In addition, actual versus predicted plots were generated for the best-performing model for each response to visually assess prediction quality. Feature importance scores from RF and XGBoost were analyzed to identify the most influential process parameters, highlighting which settings contribute most strongly to tensile and impact strength.

## 5. Results and Discussion

This section presents the statistical characteristics of the process parameters, model performance for tensile and impact strength prediction, and the influence of key features based on the Random Forest and XGBoost models.

### 5.1 Descriptive Statistics

Table 1 provides descriptive statistics for all input and output variables. Layer height ranges from approximately 0.10 to 0.30 mm, while wall thickness varies between 1 and 5 mm. Infill density spans a wide interval (20–100%), reflecting low- to high-density structures typically used in FDM. Thermal parameters show practical ranges with nozzle temperature from 190–240°C and bed temperature from 50–80°C, aligned with PLA and ABS printing conditions.

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Table 1: Descriptive statistics

| Features | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| layer_height | 200 | 0.196801 | 0.058978 | 0.101104 | 0.145716 | 0.198897 | 0.251372 | 0.297377 |
| wall_thickness | 200 | 3.017501 | 1.172005 | 1.020246 | 2.04585 | 3.16656 | 3.968797 | 4.962021 |
| infill_density | 200 | 61.65382 | 24.5847 | 20.86701 | 40.44163 | 62.03196 | 84.88919 | 99.97741 |
| infill_pattern | 200 | 0.51 | 0.501154 | 0 | 0 | 1 | 1 | 1 |
| nozzle_temperature | 200 | 214.542 | 14.48839 | 190.2316 | 201.1973 | 214.2609 | 227.0914 | 239.8437 |
| bed_temperature | 200 | 65.0678 | 8.837073 | 50.32987 | 57.38416 | 64.87786 | 73.02379 | 79.93802 |
| print_speed | 200 | 70.48855 | 17.88107 | 40.38315 | 53.71457 | 72.43756 | 85.80237 | 99.82747 |
| fan_speed | 200 | 51.90881 | 29.19346 | 0.493998 | 24.83435 | 52.87861 | 74.76012 | 99.94137 |
| material | 200 | 0.5 | 0.501255 | 0 | 0 | 0.5 | 1 | 1 |
| tensile_strength | 200 | 40.45816 | 8.728307 | 25 | 32.04471 | 40.08674 | 48.1978 | 56.31272 |
| impact_strength | 200 | 18.13981 | 2.963656 | 11.67852 | 16.05062 | 18.0829 | 20.34287 | 25.95155 |

Both strength outputs exhibit realistic dispersion. Tensile strength ranges from 25.31 to 55.72 MPa with a mean near 40 MPa, while impact strength varies from 11.52 to 26.08 kJ/m², averaging around 18 kJ/m². This spread captures both stiff and ductile behavior across polymer-material combinations.

**5.2 Tensile Strength Model Performance**

Model performance for tensile strength is summarized in Table 2. Random Forest also performed robustly, while Decision Tree remained a lower-baseline predictor due to underfitting. Layer height strongly influences tensile response (Fig. 2). Higher layer heights produce lower tensile strength values, as the enlarged bead height reduces fusion area and weakens interlayer bonds. This matches well-established findings in extrusion-based additive manufacturing.

Table 2: Tensile model performance

| Model | R2 | RMSE | MAE |
|---|---|---|---|
| Decision Tree | 0.883705 | 2.785216 | 2.178399 |
| Random Forest | 0.920454 | 2.303487 | 1.752689 |
| XGBoost | 0.922819 | 2.268988 | 1.613967 |

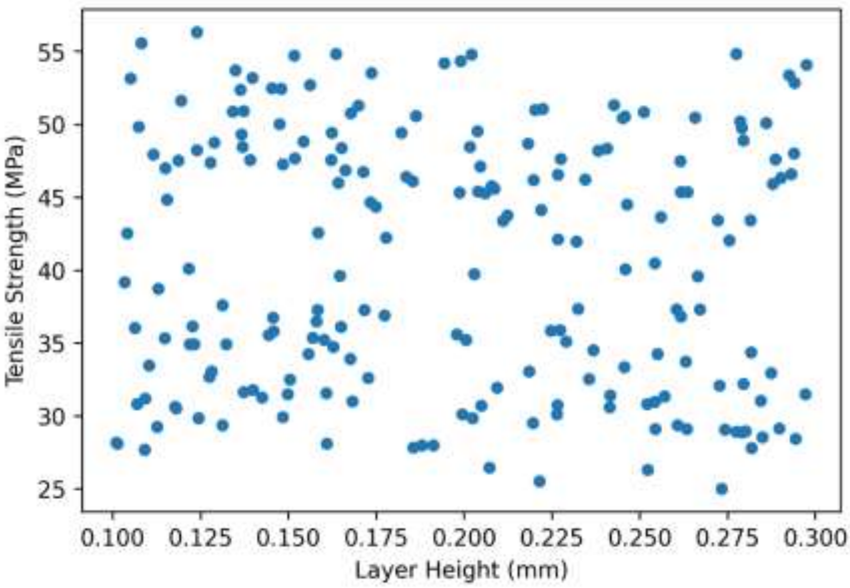


Figure 2: Layer Height vs Tensile Strength

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The actual vs. predicted plot (Fig. 4) shows a clear linear trend, with predictions closely aligned along the 45° reference line. The residual plot (Fig. 5) confirms that errors are evenly scattered around zero, indicating no systematic bias.

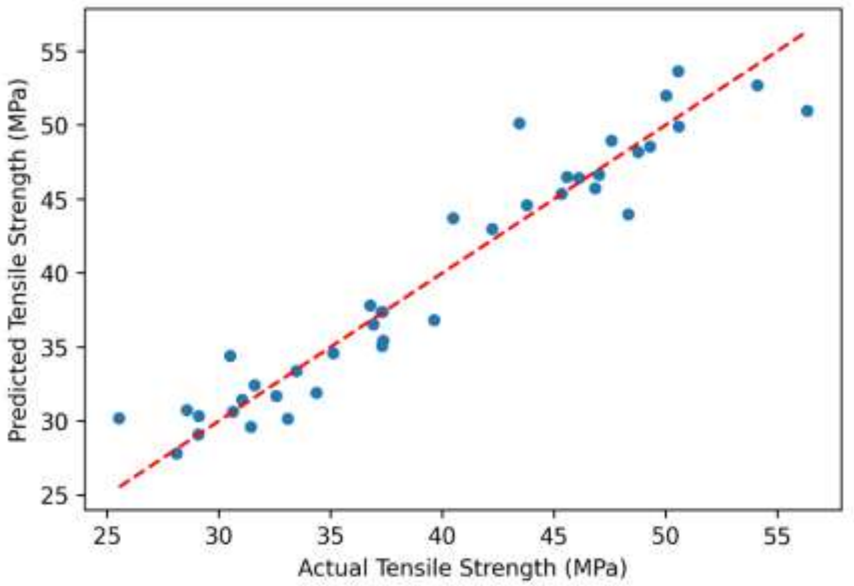


Figure 4: Actual vs Predicted Tensile Strength

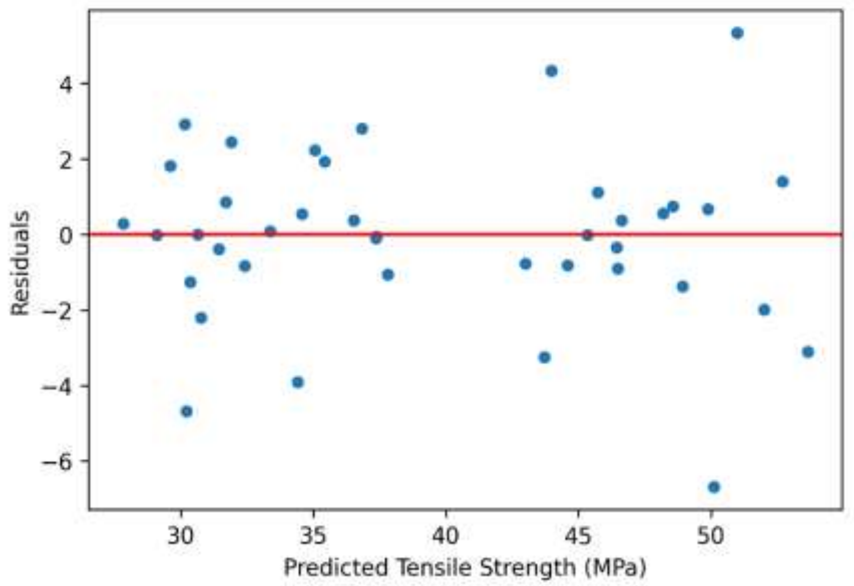


Figure 5: Residual Plot for Tensile Strength

### 5.3 Impact Strength Model Performance

Impact strength model performance is presented in Table 3. The relationship between layer height and impact strength (Fig. 3) shows a subtle downward trend. Thicker layers limit ductility and decrease energy absorption, supporting the observed reduction in impact resistance.

Table 3: Impact model performance

| Model | R2 | RMSE | MAE |
|---|---|---|---|
| Decision Tree | 0.571472 | 2.274608 | 1.788814 |
| Random Forest | 0.752795 | 1.72761 | 1.373514 |
| XGBoost | 0.705805 | 1.884667 | 1.489665 |

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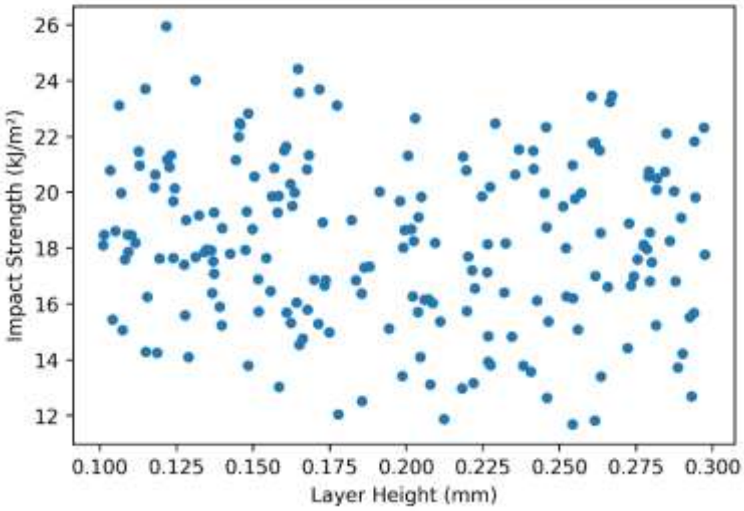


Figure 3: Layer Height vs Impact Strength

The prediction trend (Fig. 6) shows a stable linear relationship between actual and predicted values, though with slightly higher scatter than tensile strength—expected due to the sensitivity of impact response to internal voids and microstructural imperfections. Residuals in Fig. 7 remain symmetrically distributed, confirming stable generalization.

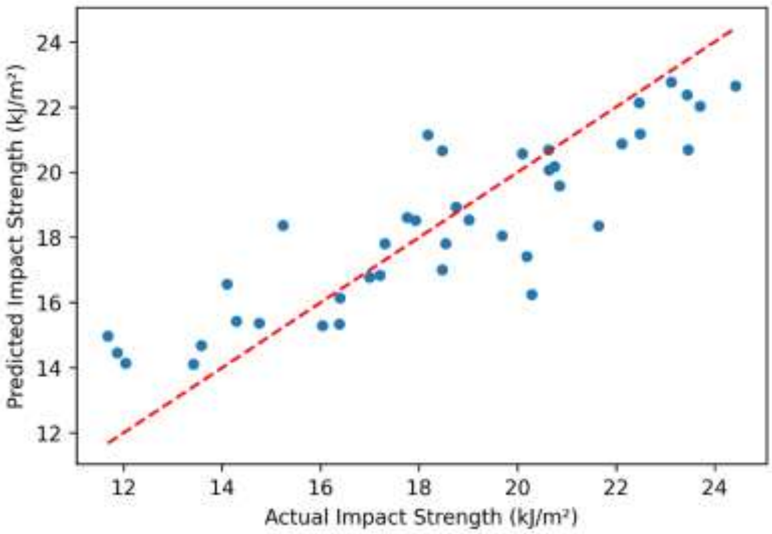


Figure 6: Actual vs Predicted Impact Strength

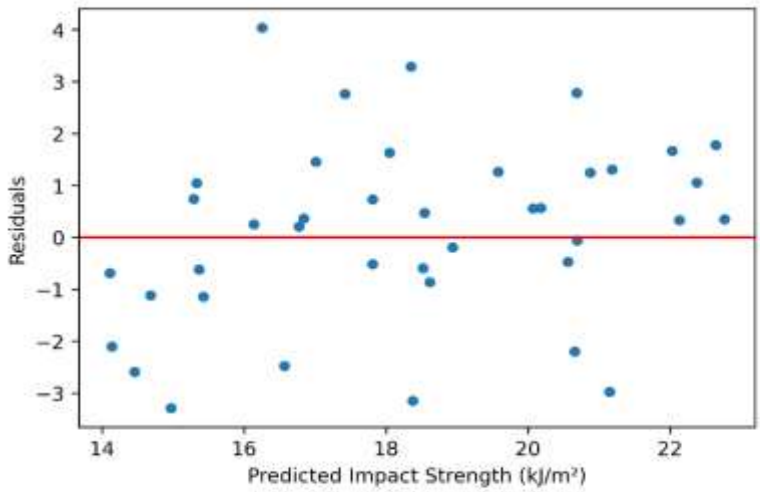


Figure 7: Residual Plot for Impact Strength

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### 5.4 Feature Importance

Feature importance values from the best tensile model (Table 4) reveal that material selection accounts for more than 75% of total feature influence, making it the dominant factor. This aligns with the significant stiffness contrast between PLA and ABS. Infill density contributes around 10%, highlighting its role in strengthening internal structure and reducing void content.

Table 4: Feature importance

| Feature | Importance |
|---|---|
| material | 0.758558 |
| infill_density | 0.102188 |
| print_speed | 0.039179 |
| bed_temperature | 0.023306 |
| wall_thickness | 0.020655 |
| nozzle_temperature | 0.016285 |
| infill_pattern | 0.01609 |
| layer_height | 0.012342 |
| fan_speed | 0.011397 |

Print speed, bed temperature, and wall thickness contribute moderately, each influencing inter-bead bonding and thermal stability during deposition. Parameters such as infill pattern, layer height, and fan speed show lower importance, indicating indirect or secondary effects.

Figure 8 illustrates this ranking clearly, with material and infill density standing out as the two principal contributors.

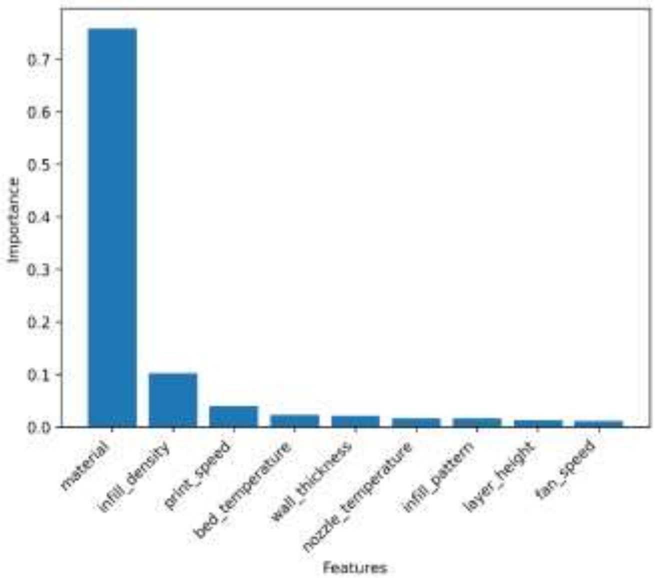


Figure 8: Feature Importance for Tensile Strength

### 5.5 Combined Interpretation

The collected results show that machine learning is effective in predicting mechanical behavior from FDM process parameters. Tensile strength benefits strongly from material type and infill density, whereas impact performance is additionally sensitive to microstructural features influenced by thermal conditions and deposition speed.

The strong predictive power of XGBoost for both outputs highlights its ability to capture complex nonlinear interactions across print parameters. Residual patterns and accuracy metrics confirm that the trained models generalize well across the test samples.

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Overall, the study demonstrates that ML-based prediction provides a reliable pathway for optimizing FDM process settings to achieve improved mechanical performance in 3D-printed polymer components.

## Conclusion

This work demonstrates that supervised machine learning models can effectively predict the mechanical behavior of 3D-printed polymer parts using standard FDM process parameters. The models accurately estimated tensile and impact strength across a wide range of printing conditions, with XGBoost delivering the best overall performance. The dominance of material type and infill density in the feature-importance analysis confirms their major role in defining stiffness and energy absorption. Parameters such as layer height, print speed, and thermal conditions also contribute to strength variation by influencing interlayer bonding and internal microstructure. The close agreement between predicted and actual values, supported by consistent residual patterns, shows that the models generalize well and can be used to guide parameter selection. Overall, the study highlights the value of machine learning as a practical tool for forecasting strength outcomes in fused deposition modeling and supports its use for data-driven print optimization in additive manufacturing.

## References

Abouelmajd, M., Bahlaoui, A., Arroub, I., Zemzami, M., Hmina, N., Lagache, M., & Belhouideg, S. (2021). Experimental analysis and optimization of mechanical properties of FDM-processed polylactic acid using Taguchi design of experiment. *International Journal for Simulation and Multidisciplinary Design Optimization.*

Era, I. Z., Grandhi, M., & Liu, Z. (2022). Prediction of mechanical behaviors of L-DED fabricated SS 316L parts via machine learning. *The International Journal of Advanced Manufacturing Technology*, 121(7–8), 2445–2459.

Fatriansyah, J. F., Aqila, M. R., Suhariadi, I., Federico, A., Ajiputro, D. I., Pradana, A. F., Andreano, Y., Rizky, M. A. Y., Dhaneswara, D., Lockman, Z., & Hur, S-M. (2024). Machine learning assisted tensile strength prediction and optimization of Ti alloy. *IEEE Access*, 12, 119660–119670.

Huynh, L. P. T., Nguyen, H., Nguyen, H. Q., Phan, L. K., & Tran, T. T. (2019). Effect of process parameters on mechanical strength of fabricated parts using the fused deposition modelling method. *Journal of the Korean Society for Precision Engineering*, 36(8), 705–712.

Jayasudha, M., Elangovan, M., Mahdal, M., & Priyadarshini, J. (2022). Accurate estimation of tensile strength of 3D-printed parts using machine learning algorithms. *Processes*, 10(6), 1158.

Jatti, V., Sawant, D. A., Khedkar, N., Jatti, V. S., Salunkhe, S., Pagáč, M., & Abouel Nasr, E. S. (2024). Tensile strength analysis of additively manufactured CM 247LC alloy specimen by employing machine learning classifiers. *PLOS ONE*, 19(6), e0305744.

Kharate, N., Anerao, P., Kulkarni, A., & Abdullah, M. (2024). Explainable AI techniques for comprehensive analysis of the relationship between process parameters and material properties in FDM-based 3D-printed biocomposites. *Journal of Manufacturing and Materials Processing*, 8(4), 171.

Özkül, M., Kuncan, F., & Ulkir, O. (2025). Predicting mechanical properties of FDM-produced parts using machine learning approaches. *Journal of Applied Polymer Science*, 142(2), e56899.

Panico, A., & Corvi, A. (2025). Multi-objective optimization of FDM 3D printing parameters set via design of experiments and machine learning algorithms. *Scientific Reports*, 15(1), 1016.

Ramiah, K., & Pandian, P. (2023). Effect of process parameters on the strength of ABS-based FDM prototypes: novel machine learning-based hybrid optimization technique. *Materials Research Express*, 10(3), 035509.

Soms, N., Ravi Kumar, K., & Naveen Kumar, M. (2025). Machine learning algorithms-based approach on prediction of mechanical behaviour of PLA/brass composites manufactured by additive manufacturing. *Journal of Process Mechanical Engineering.*

Ziadia, A., Habibi, M., & Kelouwani, S. (2023). Machine learning study of the effect of process parameters on tensile strength of FFF PLA and PLA-CF. *Eng*, 4(4), 156.