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Predicting Tensile Strength in FDM-Printed PLA Parts Using Machine Learning

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Abstract

Additive Manufacturing (AM) is transforming the manufacturing industry, with Fused Deposition Modeling (FDM) being one of the most widely used techniques due to its affordability and ease of use. However, the mechanical performance of FDM-printed parts is highly dependent on process parameters, making it essential to understand and optimize their influence. This study investigates the impact of six critical FDM parameters including extruder temperature, printing speed, infill density, infill pattern, layer height, and the number of wall layers, on the tensile strength of 3D-printed Polylactic Acid (PLA) parts. Using the dataset from Qian et al. (2024), which includes tensile strength values of 92 PLA samples fabricated under varied parameter settings, we extend their work by applying several machine learning (ML) models to predict and classify mechanical outcomes. Regression algorithms used include Polynomial Regression (PR), Gradient Boosting (GB), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB), while classification tasks employed Support Vector Classifier (SVC) and XGBoost (XGB). The XGBoost regressor outperformed other models with a test R^2 of 0.76 (RMSE:5.19, MAE:3.09), followed by Polynomial Regression (R^2:0.71, RMSE:5.60, MAE:3.17), Gradient Boosting (R^2:0.70, RMSE:5.78, MAE:2.83), and SVM (R^2:0.65, RMSE:6.18, MAE:3.19). In classification, the XGB classifier achieved perfect results on the test set with 100% accuracy, precision, recall, and F1-score, whereas the SVC model attained an accuracy of 84.21% and an F1-score of 0.8491. Pearson correlation coefficient analysis revealed infill density, printing speed and wall layers as the most influential parameters ($p<0.05$), with infill pattern showing moderate effects. While most existing studies have focused primarily on regression-based approaches to predict mechanical outcomes, this research fills a noticeable gap by also incorporating classification techniques to categorize part quality and enhance the mechanical performance of 3D-printed components.

Keywords
Additive Manufacturing, Fused Deposition Modeling (FDM), Machine Learning, Tensile Strength Prediction

1. Introduction
Additive Manufacturing (AM), or 3D printing, is becoming more important in engineering and education due to its many advantages, such as faster prototyping, lower costs, product customization, and better-quality control (Attaran 2017). Unlike traditional methods that cut away material, AM builds objects by adding material layer by layer from a digital 3D model (Boschetto et al. 2016). This allows for the creation of complex, single-piece parts that are difficult to make using conventional techniques (Adekanye et al. 2017). The ability to produce custom items in small quantities without expensive tools makes AM a powerful and flexible manufacturing option (Hasanzadeh et al. 2023; Hegab et al. 2023). AM is widely used in industries such as medicine, automotive, aerospace, food, fashion, and metalworking (Kalva 2015). There are various AM methods that use different materials and processes. Common techniques include Fused Deposition Modeling (FDM), Selective Laser Melting (SLM), Multi-Jet Modeling (MJM), Laminated Object Manufacturing (LOM), Stereolithography (SLA), and Selective Laser Sintering (SLS) (Husna et al. 2024; He et al. 2020; Rahman et al. 2023; Bikas et al. 2016).

FDM, also known as Fused Filament Fabrication (FFF), is one of the most popular methods because it is cost-effective, fast, and works with many types of thermoplastics such as PLA, ABS, ASA, and Nylon (Shakeri et al. 2021; Ford et al. 2022). In FFF, a plastic filament is heated and pushed through a nozzle to build an object layer by layer on a moving bed. However, despite its advantages, FFF has some drawbacks like lower mechanical strength, surface quality issues, and gaps between layers that affect durability (Yankin et al. 2023). One of the biggest challenges is ensuring consistent product quality. Problems like poor bonding between layers, material weakness in different directions, and warping due to uneven cooling can reduce the performance of the printed part (Goh et al. 2021). The outcome depends on many process settings such as infill density, layer thickness, nozzle temperature, print speed, build orientation, and pattern. Choosing the right material and process settings is important to improve strength, surface finish, accuracy, and print time (Ishraq et al. 2021).

Machine learning has become an important tool in additive manufacturing, helping to improve consistency and quality in 3D-printed parts. It can solve many challenges in AM, such as improving designs, fine-tuning printing settings, monitoring prints in real time, and controlling the manufacturing process (Meng et al. 2021). ML is also useful for predicting how printed parts will perform, as it can analyze large amounts of data and identify how different settings-like print speed, layer thickness, and nozzle temperature-affect strength, durability, and other key properties. By using ML, manufacturers can save time, reduce waste material, and cut down on energy use. One of the biggest advantages of machine learning is its ability to find hidden patterns in complex data, helping to predict outcomes without constant human input. This is especially helpful in 3D printing, where many factors interact in ways that are difficult to track manually. By using ML, companies can produce higher-quality parts at lower costs, making additive manufacturing more efficient and sustainable (Khalil et al. 2022; Özkül et al. 2025).

In this research, we investigate how six key FDM process parameters affect the tensile strength of 3D-printed PLA parts. Using the same dataset and experimental setup as Qian et al. (2024), we aim to extend the understanding of parameter influence through the application of machine learning techniques. While Qian et al. (2024) focused primarily on linear regression to identify sensitive parameters affecting tensile strength, our study explores a broader range of machine learning algorithms, including both regression and classification models. To model and predict tensile strength, multiple ML algorithms were employed, including Polynomial Regression (PR), Gradient Boosting (GB), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB) for regression tasks. Following the approach used by Roy et al. (2023), ABC analysis was used to classify the data based on Average Tensile Strength into different categories (A, B, and C). After that, machine learning algorithms, Support Vector Classifier (SVC) and XGBoost (XGB), were applied to perform the classification tasks. By comparing these methods, we evaluate their predictive accuracy and determine which models are most effective at forecasting tensile strength based on the selected process parameters. Additionally, a Pearson correlation coefficient analysis was conducted to quantify the relationship between each process parameter and tensile strength. Our goal is to provide a deeper insight into the relationship between FDM settings and mechanical performance, and to assess the potential of machine learning in building reliable, data-driven prediction systems for additive manufacturing.

2. Literature Review

Many researchers have investigated how Fused Deposition Modeling (FDM) process parameters influence the mechanical properties of 3D-printed parts. Chacón et al. (2017) studied PLA material and found that parameters such as build orientation, layer thickness, and feed rate had a noticeable effect on tensile and flexural strength. Their findings showed that upright orientation produced the weakest results, while flat and edge orientations offered better strength and stiffness. Similarly, Akessa et al. (2017) explored the mechanical performance of ABS-M30 by examining parameters like air gap, raster width, and raster angle. They concluded that reducing these parameters led to significant improvements in tensile and flexural properties. Deng et al. (2018) investigated the influence of parameters on the tensile strength of PEEK material and identified an optimal set of process parameters for achieving improved mechanical performance. Gebisa and Lemu (2018) conducted a comprehensive study on ULTEM 9085, analyzing five different parameters. Their results indicated that raster angle and raster width were the most critical factors affecting the flexural properties of the material.

Rodríguez-Panes et al. (2018) examined both PLA and ABS materials to assess the impact of layer height, infill density, and layer orientation on tensile strength. Among these, infill density had the strongest influence, while layer height had a minimal effect. Chokshi et al. (2022) studied PLA parts by varying layer thickness, infill pattern, and the number of contours. Their analysis showed that both layer thickness and the number of contours significantly influenced flexural strength. Mushtaq et al. (2023) took a broader approach, analyzing ABS parts with respect to mechanical strength, surface roughness, printing time, and energy usage and found that layer thickness played a key role in surface finish and print duration, while infill density had a major effect on tensile and flexural strength.

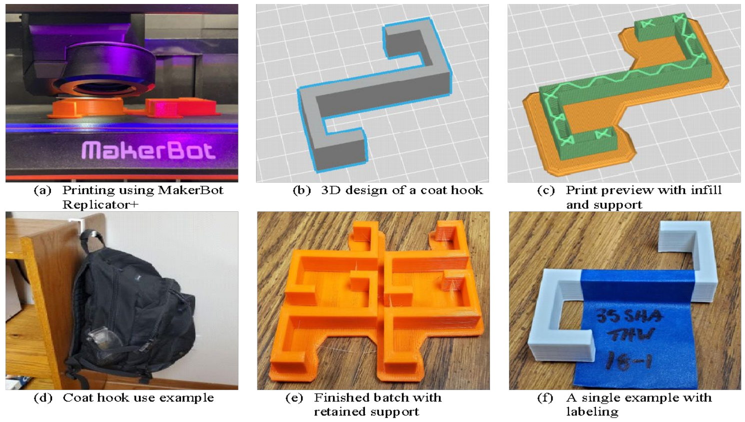
In recent years, machine learning (ML) has become an important tool in optimizing additive manufacturing (AM) processes. ML techniques are increasingly used to predict and improve the quality of 3D-printed parts by analyzing and fine-tuning process parameters. Hu et al. (2021) studied PLA composites reinforced with chopped carbon fiber and found that increasing fiber content improved tensile and flexural strength, hardness, and thermal conductivity. Using Gaussian process modeling, they predicted the optimal fiber content to be 6.7 wt.%, which closely matched their experimental data. Mishra and Jatti (2023) compared several machine learning algorithms to predict ultimate tensile strength (UTS) in PLA. The K-Nearest Neighbor (KNN) algorithm performed better than Logistic Regression, Gradient Boosting, and Decision Trees. Jayasudha et al. (2022) evaluated five different ML models for predicting tensile strength and concluded that XGBoost regression provided the most accurate results. Similarly, Deb et al. (2024) applied ensemble ML models to predict mechanical properties of PLA prints and found that Extremely Randomized Tree Regression gave the best results for tensile strength. Qian et al. (2024) developed a machine learning-based framework to identify and optimize key FDM process parameters that influence the tensile strength of 3D-printed PLA parts. Their study emphasized infill density, printing speed, infill pattern, and wall layers as the most impactful factors.

While many studies have used machine learning to optimize FDM parameters using regression models, the use of classification approaches is still limited. Most research focuses on predicting exact strength values, but few have explored classifying parts based on quality or strength ranges. Classification can be useful for quickly checking if a part meets certain standards. This study helps fill that gap by using both regression and classification, offering a more complete view of how process settings affect part quality.

3. Materials and Methods

3.1 Experimental Setup and Material

The experimental work was conducted using a MakerBot Replicator+ FDM 3D printer, a widely adopted system known for its reliability in additive manufacturing research. Standard polylactic acid (PLA) filament was selected as the printing material due to its favorable properties, including biodegradability, cost efficiency, and versatility in functional applications.



(a) Printing using MakerBot Replicator+ (b) 3D design of a coat hook (c) Print preview with infill and support

(d) Coat hook use example (e) Finished batch with retained support (f) A single example with labeling

Figure 1. (a) Printing process of the coat hook, (b-c) Digital design and slicing preview showing infill and supports, (d) Functional application example, (e-f) Printed part before and after support removal.

The test specimen- practical coat hook- was designed for organizational use on desks or chairs, serving as a representative example of a load bearing FDM-printed component. The printing process was documented in Figure 1(a), while Figures 1(b) and 1(c) provided detailed insights into the digital design phase, showcasing the infill structure and support material placement in the slicing software. This systematic approach ensured reproducibility and highlighted the interplay between design intent and manufacturing execution.The printed coat hook underwent standard post-processing to evaluate its real-world applicability. Figure 1(e) captured the object immediately after printing, with support structures still attached, demonstrating the raw output of the FDM process. Subsequent removal of these supports (Figure 1f)) revealed the final product, emphasizing the importance of post-processing in achieving functional parts. To validate its utility, Figure 1(d) illustrated the hook in a realistic usage scenario-mounted on furniture for organizational purposes.

3.2 Methods

We structure the overall process into three distinct phases. The flowchart in figure 2 presents a structured framework that integrates experimental design, machine learning for prediction and ABC Analysis for classifying each observation for optimizing the performance of Fused Deposition Modeling (FDM) processes.

In Phase 1, the process begins with designing a CAD model of the target part, which provides the foundation for subsequent fabrication and testing. Once the digital model is prepared, key process parameters are identified, including their operational levels and corresponding response metrics, such as tensile strength. This is followed by the use of a Design of Experiments (DoE) methodology, which systematically organizes test scenarios by varying process parameters to ensure statistically reliable results. Based on the designed experiments, test samples are fabricated using a 3D printer. These samples then undergo tensile testing to evaluate their mechanical properties. This phase ensures that high-quality, diverse, and controlled experimental data are generated for further analysis.

Phase 2 shifts the focus to data handling and modeling. The results from tensile testing are collected and preprocessed, involving tasks such as data cleaning, normalization, and encoding categorical variables to ensure compatibility with machine learning algorithms. After preprocessing, suitable machine learning models are selected based on the nature of the data and response variable. The dataset is then divided into training and testing subsets—typically using an 80/20 split—and the models are trained to learn the relationships between the input parameters and output response. Model performance is evaluated using metrics such as root mean squared error (RMSE), mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). The model that achieves the highest performance based on this evaluation is selected for further analysis. In Phase 3, The proposed flowchart presents a robust end-to-end methodology that integrates empirical experimentation, advanced data analytics, and ABC analysis tools. This approach effectively streamlines the process of identifying sensitive process parameters and determining their optimal or acceptable levels, making it highly applicable to additive manufacturing research.

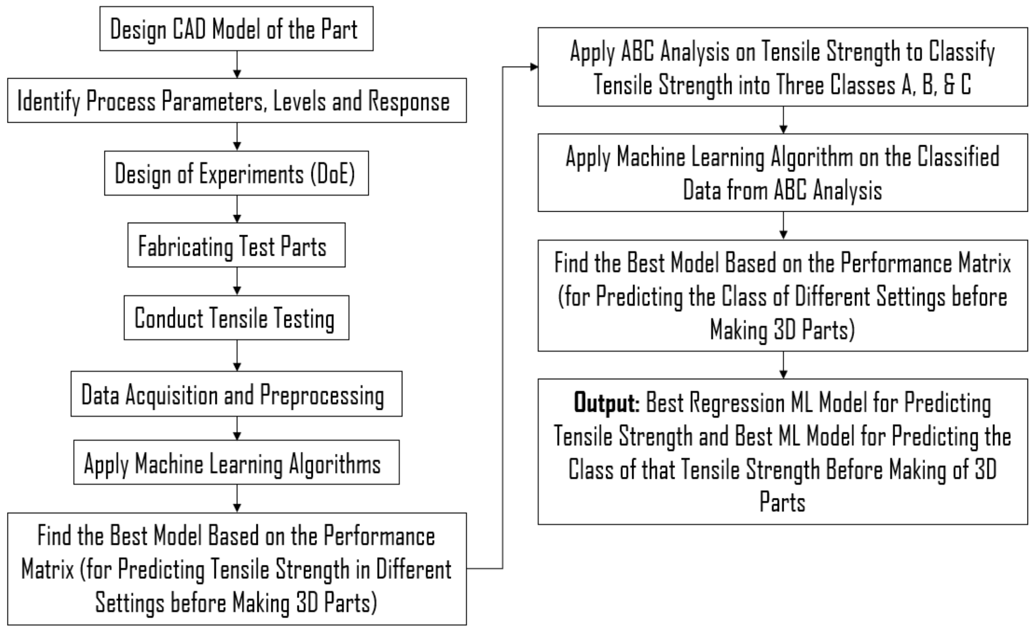


Figure 2. Overview of the research methodology across three phases

4. Data Collection

As described in the methodology section, Phase 1 of the study involved identifying potential Fused Deposition Modeling (FDM) process parameters and selecting those that are controllable. Among the many parameters associated with FDM, such as extruder temperature, infill density, infill pattern, wall layer thickness, and others, we selected six controllable parameters that are likely to influence the mechanical properties of the final printed product. These include extruder temperature, printing speed, infill density, infill pattern, layer height, and wall layer count. Once identified, the next step was to define appropriate levels or value ranges for each parameter, as summarized in Table 1. The dataset used for this phase was taken from the prior study of Qian et al. (2024), ensuring the reliability and relevance of the selected parameter values.

Extruder temperature, which determines how hot the printer's nozzle gets to melt the filament, generally ranges from 215°C to 250°C for PLA material. In our experiment, we selected three levels: 215°C, 220°C, and 225°C. Printing speed, defined as the rate at which the printer extrudes and deposits material, was tested at seven levels: 75, 80, 90, 100, 120, 125, and 150 millimeters per second (mm/s). Infill density, which represents the percentage of material filling the inside of the printed object, varied from 5% to 50% in 5% increments. In terms of infill pattern, which defines the internal structure within each printed layer, we tested several distinct geometries, including diamond, donut, and shark patterns. Additional patterns, such as hexagonal, cat, linear, Hilbert, and Moroccan star, were also included and grouped under a category labeled “other.” For layer height- the thickness of each deposited layer- we selected three commonly used values: 0.15 mm, 0.20 mm, and 0.25 mm.

Table 1. FDM processing parameters and range/level values

FDM Process Parameter	Description	Tested Levels / Values
Extruder Temperature (°C)	Temperature of the nozzle used to melt PLA filament	215, 220, 225
Printing Speed (mm/s)	Speed at which the printer deposits material layer by layer	75, 80, 90, 100, 120, 125, 150
Infill Density (%)	Percentage of the interior volume filled with material	5, 10, 15, 20, 25, 30, 35, 40, 45
Infill Pattern	Internal geometric structure of the printed part	Diamond, Donut, Shark, Other
Layer Height (mm)	Thickness of each printed layer	0.15, 0.2, 0.25
Wall Layer Count	Number of outer walls printed for structural strength	2, 3, 4, 5

Finally, the wall layer count, which affects the thickness of the printed object's outer shell, was tested at four levels: 2, 3, 4, and 5 layers. For each batch, a unique combination of parameter values was selected within the defined ranges. We printed four identical parts simultaneously in every batch (see Figure 2(e)), and the average tensile strength of these four parts was recorded as the representative value for that batch.

Since infill pattern and wall layer count are categorical variables, we applied One-Hot Encoding to convert them into numerical forms. This resulted in three dummy variables for infill pattern and three for wall layer count. To predict tensile strength based on the FDM process parameters, we constructed several machine learning models. The dataset was randomly divided into a training set (80%) and a testing set (20%). After training the model on the training data, its performance was evaluated using the test data. We assessed model accuracy using three metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2 score).

5. Results and Discussion

5.1 Numerical Results

5.1.1 Model Evaluation Metrics for Regression

The performance of four different regression models, PR, GB, SVM, and XGB, was assessed using standard regression metrics on both training and testing datasets. These metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R^2 (coefficient of determination), and Adjusted R^2.

Table 2 provides a comprehensive comparison of the models' performance. The coefficient of determination (R^2) provides critical insights into how well each machine learning model explains the variation in tensile strength based on FDM process parameters. Among the tested models, XGBoost demonstrated the strongest predictive performance with a test R^2 of 0.755, meaning it accounts for approximately 75.5% of the variability in tensile strength. This R^2 value indicates a good fit for the experimental data, as it captures most of the underlying relationships between printing parameters (e.g., infill density, extruder temperature) and mechanical performance. It also had the smallest prediction errors (RMSE=5.19, MAE=3.09). The Polynomial Regression model came second with decent results (R^2=0.71), while Gradient Boosting worked well on training data but didn't generalize as well to new data. The SVM model performed the worst across all measurements. These results help identify XGB as the best-balanced model in this setup.

Table 2. Performance metrics of regression models

Model	Train R2	Test R2	Train Adj R2	Test Adj R2	Train RMSE	Test RMSE	Train MAE	Test MAE	Train MSE	Test MSE	Test MAPE	Train MAPE
PR	0.7706	0.7148	0.7497	0.5722	4.0959	5.5988	2.9896	3.1686	16.7762	31.3465	13.8376	15.1161
GB	0.8579	0.6958	0.845	0.5437	3.2234	5.7823	2.2026	2.8268	10.3905	33.4355	21.3259	11.0644
SVM	0.8494	0.6529	0.8357	0.4794	3.3186	6.1761	2.0757	3.1906	11.0131	38.1442	25.1055	9.9785
XGB	0.8482	0.755	0.8344	0.6325	3.3323	5.1888	2.4567	3.0921	11.104	26.9239	26.3857	12.9198

The error metrics show all models predicted within about 3 units of the actual strength values on average (MAE). XGBoost's consistently strong performance across all metrics makes it the most reliable choice for this application. While other models like Polynomial Regression can give reasonable estimates, XGBoost handles the complex relationships between printing settings and strength better without memorizing the training data patterns. About 25% of the strength variations remain unexplained, likely due to factors we didn't measure.

The Pearson correlation analysis in Table 3 clearly identifies which 3D printing parameters most affect tensile strength. Infill density shows the highest correlation and the strongest impact ($r=0.738$, $p<0.001$), meaning higher density consistently increases strength.

Table 3. Top features based on Pearson correlation and p-value

Feature	Pearson Correlation	P-Value
Infill_density	0.7379	0.000000
Printing_speed	0.3090	0.002729
Wall_layer	0.2471	0.017550
Infill_pattern_Shark	0.1772	0.091055
Infill_pattern_Other	-0.1172	0.265867
Infill_pattern_Donut	0.0510	0.629076
Layer_height	0.0325	0.758228
Extruder_temperature	0.0307	0.771479

Printing speed ($r=0.309$, $p=0.003$) and wall layers ($r=0.247$, $p=0.018$) demonstrate statistically significant but weaker relationships. Infill pattern variations show marginal influence ($0.05<p<0.27$), while layer height and extruder temperature prove statistically insignificant ($p>0.75$). These results quantitatively confirm that mechanical strength is primarily governed by structural parameters (infill and walls) rather than thermal or resolution settings.

5.1.2 Model Evaluation Metrics for Classification

ABC analysis was implemented for classifying the data into three classes on the basis of Average Tensile Strength. Where ABC analysis works based on Pareto distribution (the 80/20 rule) it classified Average Tensile Strength 34.36 to 36.6 as Class A, 33.79 to 34.33 as Class B and 3.31 to 33.65 as Class C. Classification performance was evaluated using Support Vector Classifier (SVC) and XGBoost classifier. Key metrics include training and testing accuracy, precision, recall, F1-score, and F2-score. The SVC model achieves a good test accuracy of 84.21%, with good balance across precision (86.4%), recall (84.2%), and F1 (84.9%). However, the XGBoost classifier achieves perfect scores (100%) across all metrics, likely suggesting overfitting due to its complexity or a small test set. These results indicate XGBoost as the top-performing classifier in this context but warrant caution due to its suspiciously perfect results. The results are summarized in the following Table 4.

Table 4. Performance metrics of Classification models

Model	Train Accuracy	Test Accuracy	Precision	Recall	F1 Score	F2 Score
SVC	0.9315	0.8421	0.8640	0.8421	0.8491	0.8439
XGB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

5.2 Graphical Results

5.2.1 Graphical Results for Regression

Figure 3 illustrates the Pearson correlation heatmap for the dataset's features. Strong positive and negative correlations are clearly visible. Highly correlated features can influence model performance due to redundancy and multicollinearity. For instance, features with correlation coefficients above 0.8 or below -0.8 indicate a significant linear relationship, which may guide feature selection or dimensionality reduction processes. This visualization aids in understanding feature interactions and dependencies.

Figure 4 compares the goodness-of-fit (R^2 and Adjusted R^2) for four regression models (PR, GB, SVM, XGB) on both training and testing datasets. Higher values indicate better model performance in explaining variance. Figure 5 evaluates the same models using error metrics (RMSE, MAE, MSE, MAPE) for training and testing data, where lower values signify greater accuracy and lower prediction errors. Together, these figures provide a comprehensive overview of model performance.

Figure 6 presents scatter plots of actual versus predicted values for each regression model (PR, GB, SVM, XGB). Among the four, the XGB and GB models show the closest alignment with diagonal, indicating more accurate predictions. The PR and SVM models demonstrate more dispersion, reflecting their higher test errors. This visual comparison confirms the superior performance of XGB and GB, consistent with the quantitative metrics. Figure 7 visualizes residuals (the difference between actual and predicted values) versus predicted values for each regression model. Ideally, residuals should be randomly scattered around zero with no visible pattern. XGB and GB residual plots appear more homoscedastic and centralized around zero, indicating robust model performance. In contrast, PR and SVM show more variance and pattern in residuals, suggesting underfitting or non-linearity that the model failed to capture.

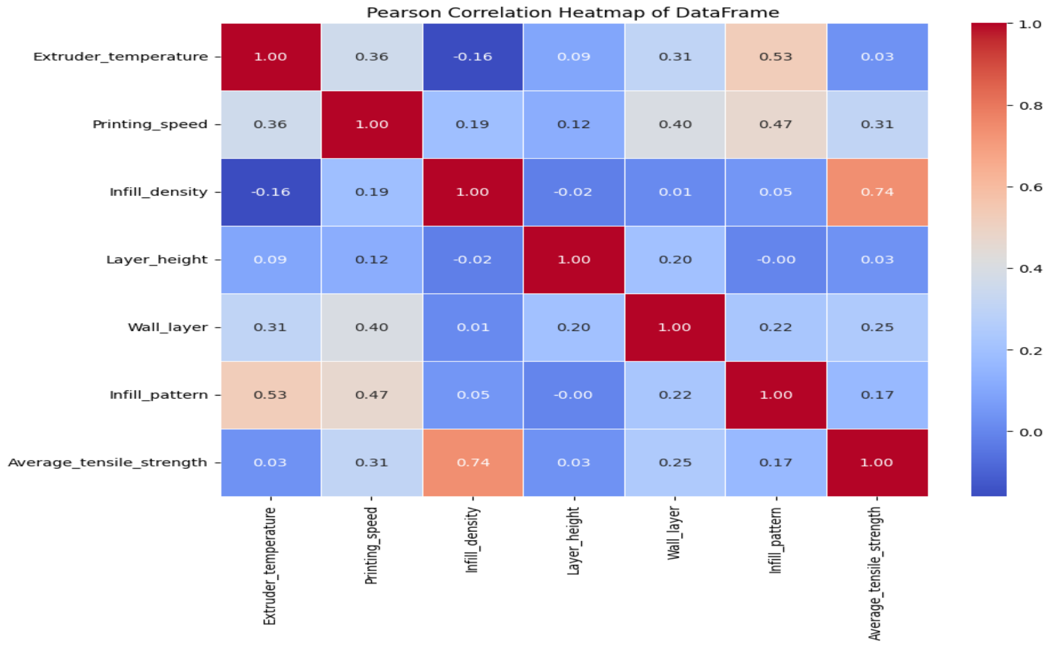


Figure 3. Pearson Correlation Heatmap showing linear relationships among features.

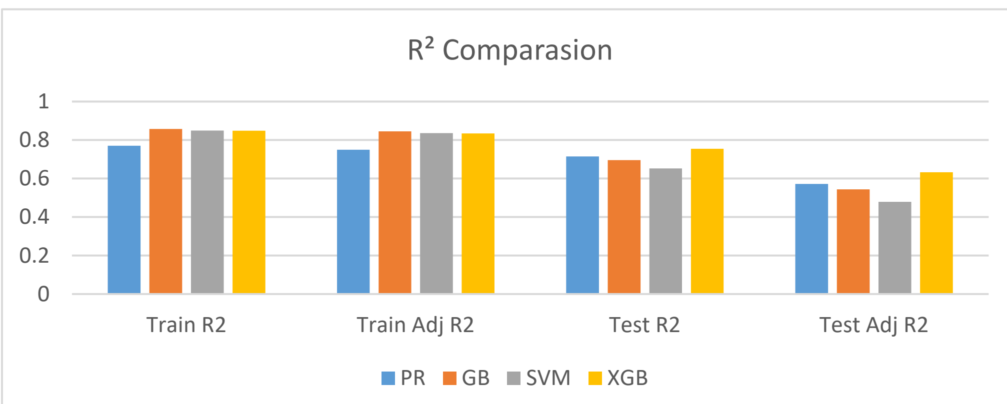


Figure 4. Comparison of R^2 scores across different regression models

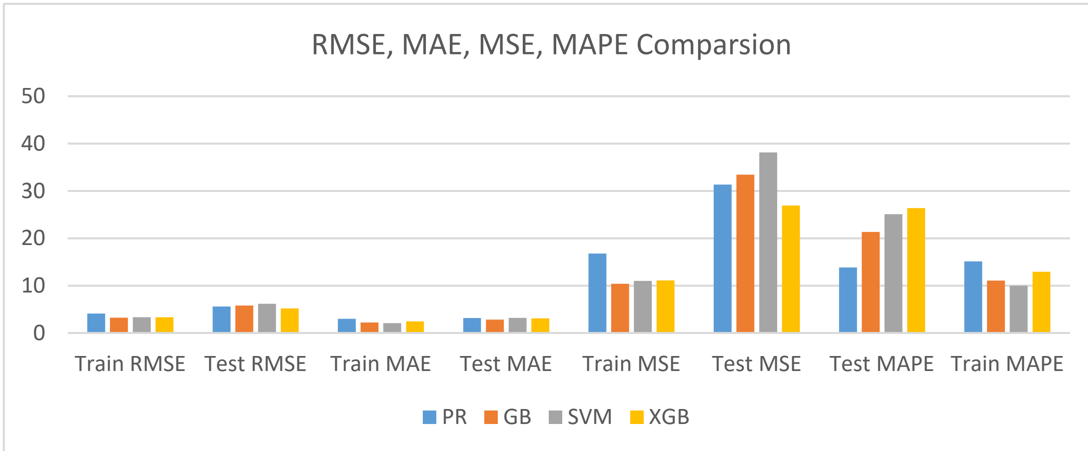


Figure 5. Comparison of RMSE, MAE, MSE, MAPEscores across different regression models

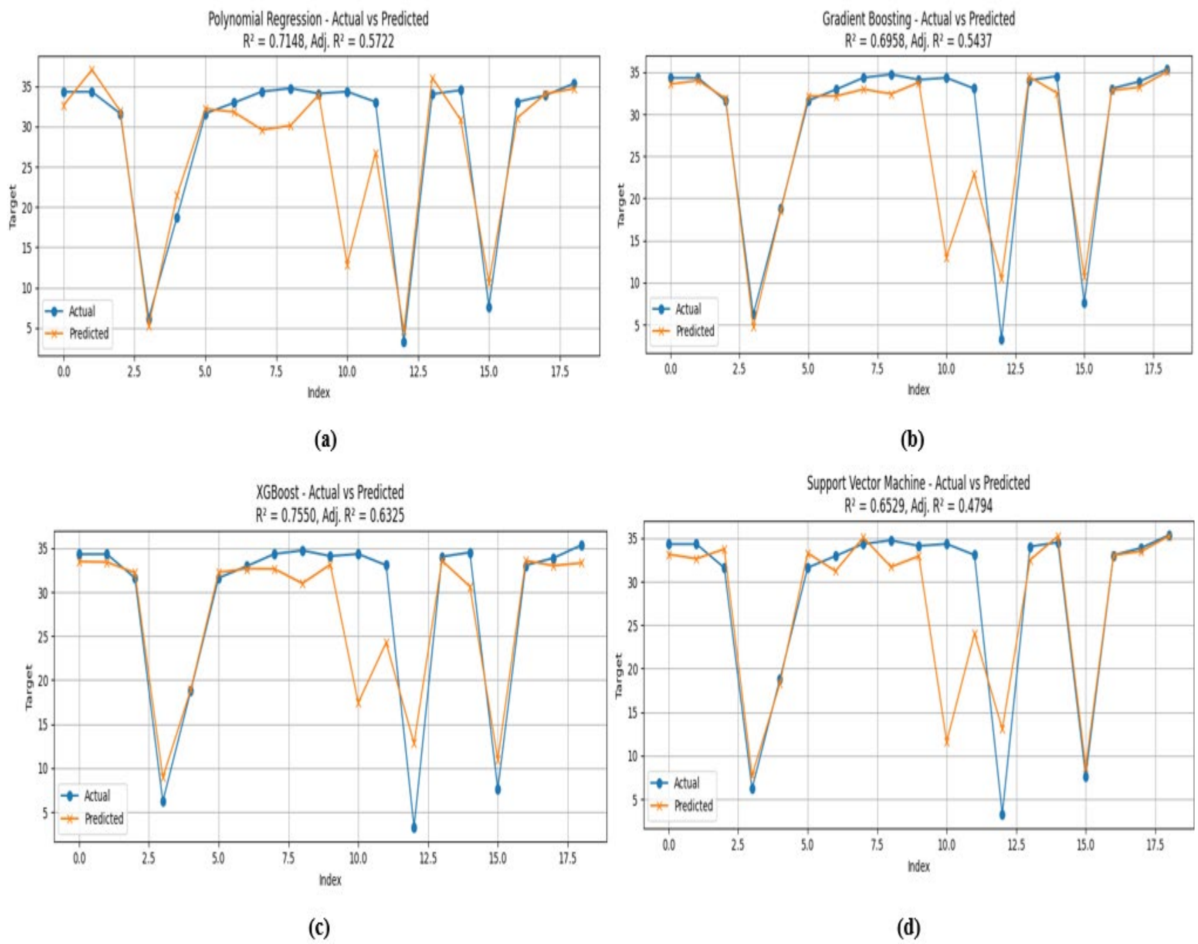


Figure 6. Scatter plots comparing actual values against predicted values for (a) Polynomial Regression, (b) Gradient Boosting, (c) XGBoost, and (d) Support Vector Machine (SVM)

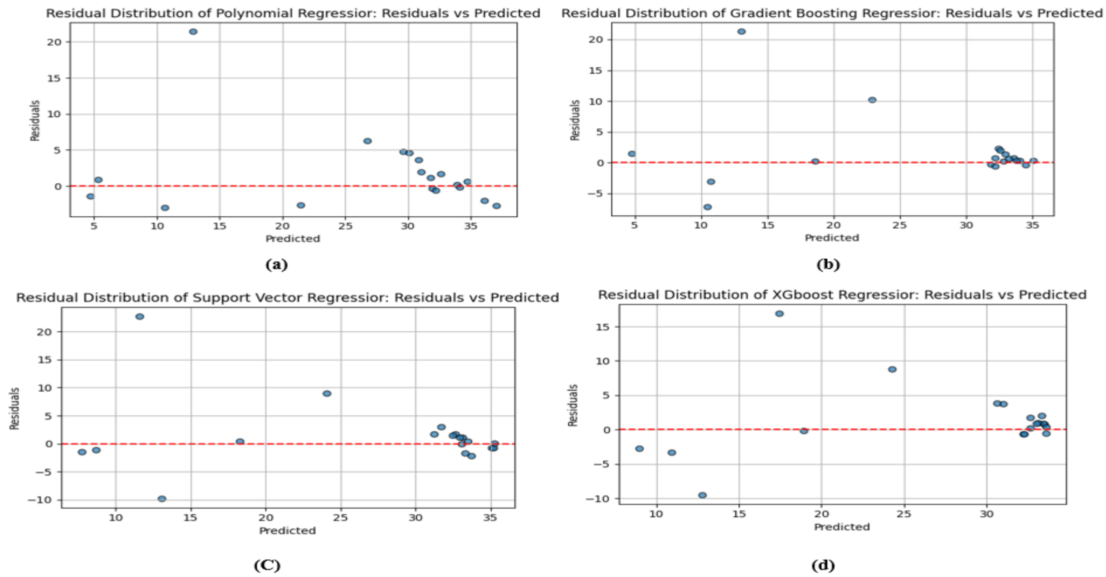


Figure 7. Scatter plots comparing residual values against predicted values for (a) Polynomial Regression, (b) Gradient Boosting, (c) Support Vector Machine (SVM), and (d) XGBoost

5.2.1 Graphical Results for Classification

Figure 8 shows confusion matrices for XGBoost and SVC classifiers on three classes: Zero (Class A), One (Class B), and Two Class C). XGBoost performs better with more correct predictions, while SVC misclassifies more, especially between Zero and One. Figure 9 illustrates the classification performance of two models: Support Vector Classifier (SVC) and XGBoost. The evaluation includes training and testing accuracy, precision, recall, F1-score, and F2-score. The SVC model demonstrates robust generalization with a test accuracy of 84.21%, along with well-balanced precision (86.4%), recall (84.2%), and F1-score (84.9%). In contrast, the XGBoost classifier achieves perfect scores (100%) across all metrics. While this suggests superior performance, such results may indicate overfitting probably due to model complexity or a limited test dataset. Figure 10 compares ROC curves of two models.

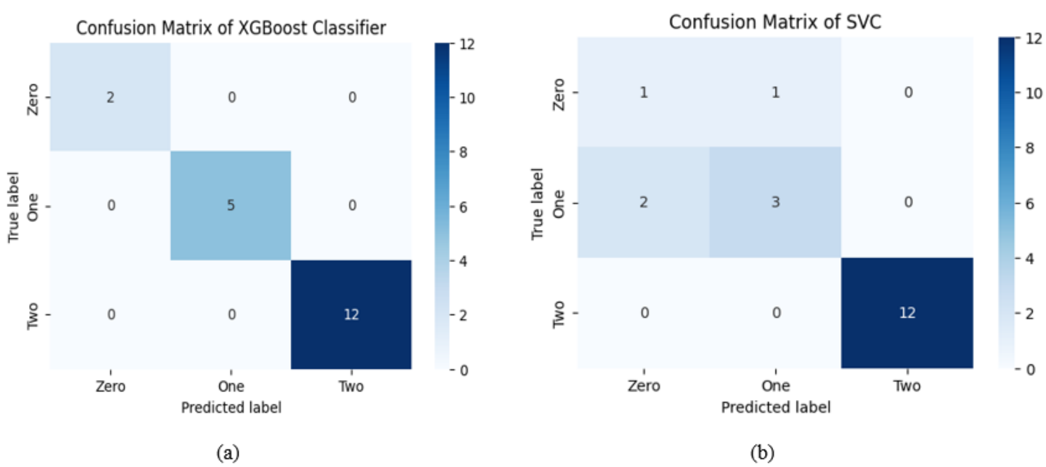


Figure 8. Confusion matrices for (a) XGBoost and (b) SVC classification models showing true vs predicted class

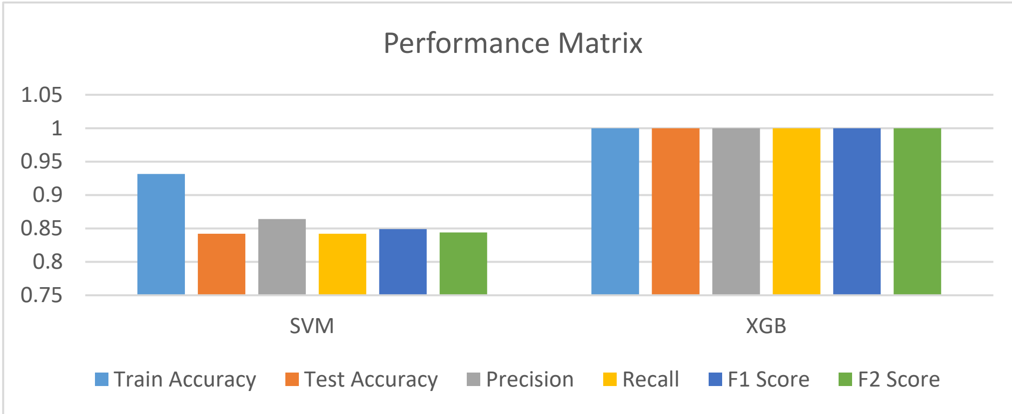


Figure 9. Comparison of performance metrics between two classification models

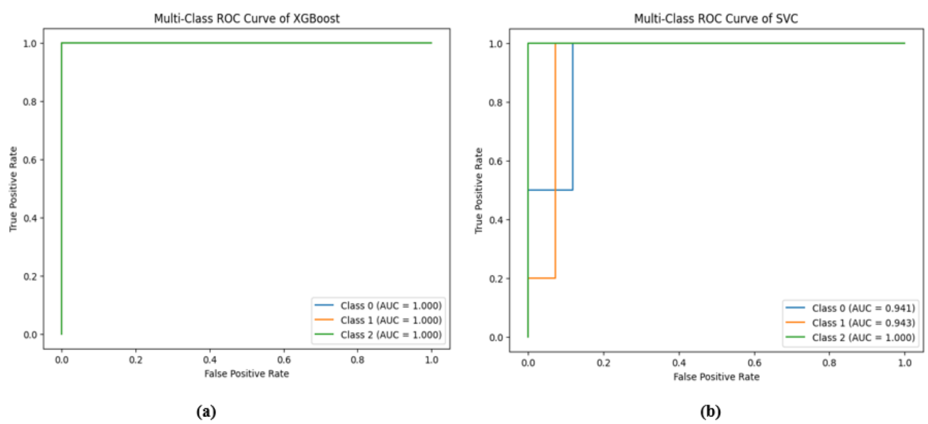


Figure 10. Comparison of performance metrics between two classification models

6. Conclusion

In this study, we investigated how six key FDM process parameters- extruder temperature, printing speed, infill density, infill pattern, layer height, and wall thickness- affect the tensile strength of 3D-printed PLA parts. Using the dataset from Qian et al. (2024), which contains tensile strength data for 92 PLA samples produced under varying process parameters, we extend their study by applying multiple machine learning models. Both regression (XGB, PR, GB, SVM) and classification (XGB, SVC) algorithms were employed to predict and categorize tensile strength outcomes. Additionally, a Pearson correlation analysis was conducted to determine the statistical significance of each parameter's effect.

This study shows that the mechanical strength of 3D-printed PLA parts using FDM technology is mainly influenced by structural parameters such as infill density, printing speed, and wall thickness. Through Pearson correlation analysis, these three parameters were found to have a statistically significant effect on tensile strength, with infill density showing the strongest positive correlation. In contrast, infill pattern had a moderate impact, while extruder temperature and layer height had negligible influence. These results highlight the importance of optimizing internal structure and wall settings when aiming for stronger printed components, rather than focusing solely on thermal or resolution parameters.

Our machine learning analysis revealed that the XGBoost regression model performed best among all regression algorithms, achieving the highest accuracy ($R^2 = 0.755$) and the lowest prediction errors (RMSE = 5.19, MAE = 3.09). In classification tasks, XGB also delivered perfect accuracy, though this may suggest overfitting due to the small dataset. The Support Vector Classifier (SVC) gave more balanced and realistic classification results, making it a reliable option for practical applications. Overall, the combination of ML models and statistical analysis provided meaningful insights into how different FDM settings influence part quality. These findings can help researchers and practitioners in optimizing print settings, improving mechanical performance, and reducing material and time waste in 3D printing workflows.

7. Future Work

This study focused only on tensile strength as the response variable, but future work should include other important mechanical and surface properties such as flexural strength, impact resistance, surface roughness, and surface finish. Including these responses would provide a more complete picture of part quality. Moreover, we did not consider all possible FDM parameters. Important factors like raster angle, raster width, build orientation, and nozzle diameter were not included and could be explored in future studies for a deeper understanding of their impact.

Additionally, we did not carry out optimization to find the best combination of parameters. Future research should apply multi-objective optimization techniques to balance strength, surface quality, and print time. Another key area for improvement is shifting from post-print analysis to real-time, in-situ parameter control. Monitoring and adjusting settings during printing could help improve part quality and reduce material and energy waste. Expanding the dataset will also be important to enhance model accuracy and ensure better generalization for real-world applications.

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