Machine Learning-Based Prediction of Surface Roughness in Fused Deposition Modeling Using Multi-Parameter Process Data

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Abstract

Surface roughness is a key indicator of printed-part quality in fused-deposition modeling (FDM) and is strongly influenced by geometric and thermal process parameters. This study investigates the predictive behavior of surface roughness using a multi-parameter dataset consisting of layer height, wall thickness, infill density, infill pattern, nozzle temperature, bed temperature, print speed, material type, and fan speed. Categorical parameters were label-encoded and fed into four machine-learning models: Generalized Linear Model (GLM), Gradient Boosting Machine (GBM), Deep Learning (MLP), and a Stacked Ensemble combining GBM and MLP with GLM as the metalearner. All models were trained directly on raw data without normalization to preserve parameter scale effects. Layer height and nozzle temperature emerged as the most influential parameters, contributing over 85% of total predictive importance. Model comparison showed that GLM achieved the highest accuracy (R^2 = 0.789), producing stable predictions with well-behaved residuals, while nonlinear models underperformed on unscaled features. Diagnostic results confirmed that surface roughness is governed mainly by geometric resolution and melt-flow behavior. The findings provide a robust, data-driven understanding of roughness formation and offer a reliable prediction framework for optimizing FDM print settings.

Keywords: Surface roughness, FDM, additive manufacturing, machine learning, process parameters, predictive modeling

1. Introduction

Fused Deposition Modeling (FDM) has emerged as one of the most widely utilized additive manufacturing (AM) technologies due to its cost efficiency, material versatility, and capability to fabricate complex geometries with minimal waste. It plays a crucial role across industries such as aerospace, biomedical, and consumer products, offering rapid prototyping and functional part production flexibility (Borah & Chandrasekaran, 2025). However, despite these advantages, FDM is often constrained by poor surface quality caused by its layer-by-layer deposition process. Surface roughness is a critical quality metric that directly impacts not only the aesthetic appeal but also the mechanical performance, dimensional accuracy, and post-processing requirements of printed parts (Abas et al., 2023). The interplay of geometric factors such as layer height, wall thickness, infill density, and infill pattern, along with thermal and dynamic parameters including nozzle temperature, bed temperature, print speed, and cooling fan speed, strongly influences the final surface texture (Alam et al., 2021). Small variations in these parameters can lead to substantial differences in roughness, complicating process optimization.

Traditional approaches for surface quality enhancement in FDM, such as empirical testing and trial-and-error parameter tuning, are time-consuming, material-intensive, and lack generalizability across different machines, materials, and geometries (Maidin et al., 2022). As a result, these heuristic methods fail to provide predictive insights necessary for process automation or adaptive control. In contrast, the advent of machine learning (ML) has transformed additive manufacturing by enabling predictive modeling and quality forecasting. ML algorithms such as decision trees, support vector regression, artificial neural networks (ANN), and random forests have been successfully implemented to predict warpage, tensile strength, melt flow, and surface roughness trends in AM processes (Boschetto et al., 2013); (Wei & Wu, 2019). For instance, random forest and ANN models have demonstrated remarkable accuracy in predicting surface roughness when trained on multi-sensor or parameter datasets (Wu et al., 2018); (Tura et al., 2021). Yet, despite the proliferation of these models, most existing studies focus on single or limited parameters, overlooking the complex multi-factor interactions that govern surface quality in FDM. Moreover, the lack of standardized datasets and real-time adaptive prediction frameworks further limits the robustness and scalability of current models (Wei & Wu, 2023); (Mishra & Jatti, 2023). Therefore, a comprehensive, data-driven approach integrating both geometric and thermal process parameters is essential for the accurate prediction and optimization of surface roughness in FDM. Such a model would not only bridge the existing gap in multi-parameter quality prediction but also support intelligent process planning and real-time control, significantly enhancing surface finish and production efficiency (Soundararajan et al., 2025). A robust machine-learning-based prediction framework can thus serve as a cornerstone for smart manufacturing systems, facilitating sustainable and adaptive additive manufacturing practices in the Industry 4.0 era.

Surface roughness is one of the most important quality metrics in FDM because it directly influences the functionality, appearance, friction characteristics, and post-processing requirements of printed parts. Manufacturers often rely on empirical parameter tuning, trial-and-error adjustments, or operator experience to achieve acceptable surface finish, leading to inconsistent output and increased production time. With the growing adoption of FDM in automotive, biomedical, tooling, and consumer-product sectors, there is a strong need for a data-driven approach capable of predicting roughness accurately before printing. Machine learning offers a powerful alternative by enabling models that learn complex interactions among multiple process parameters and provide actionable insights for parameter optimization. Developing such a model not only ensures more predictable print outcomes but also supports automation, reduces waste, and enhances process reliability.

2. Literature Review

Machine learning (ML) has become a pivotal tool in enhancing the quality control of additive manufacturing (AM), particularly in Fused Deposition Modeling (FDM), where surface roughness remains a primary limitation affecting mechanical performance, aesthetics, and post-processing needs. Early investigations demonstrated that process parameters such as layer height, nozzle temperature, infill pattern, and print speed critically influence the surface finish of printed components. For instance, higher layer heights and faster print speeds tend to increase surface roughness, whereas optimized nozzle temperatures and infill patterns can reduce irregularities and improve surface smoothness (Abas et al., 2023). ML-driven approaches have thus been developed to capture these nonlinear parameter–response interactions. Random Forest and decision tree models have demonstrated strong predictive capabilities in quantifying roughness in PLA-based FDM parts, with key influencing variables identified as print speed, layer height, and nozzle temperature (Soundararajan et al., 2025). Artificial neural networks (ANN) have also been shown to predict surface roughness effectively, achieving less than 5% error in average roughness values for ABS specimens (Tura et al., 2021).

A wide range of ML models have been explored for surface-quality prediction in AM, including linear regression, support vector regression (SVR), gradient boosting, and deep neural networks. Among these, ensemble and hybrid models have exhibited the best generalization and interpretability. For instance, a coupled Genetic Algorithm–Decision Tree model achieved an R^2 of 0.9378 for FDM surface roughness prediction, indicating robust performance in optimizing both feature selection and model parameters (Mishra & Jatti, 2023). Similarly, explainable AI (XAI) frameworks incorporating models like XGBoost and CatBoost have reached accuracies above 96%, with XGBoost providing the most precise predictions for PLA specimens (Mishra et al., 2023). Deep belief networks and hybrid optimization algorithms such as Adaptive Cuckoo Search have further improved the accuracy and stability of surface and tensile property predictions, achieving validation accuracies above 95% (Dong et al., 2021). In addition, emerging studies on quantum and physics-informed ML approaches have extended predictive modeling to more complex datasets, offering high-dimensional insights into surface integrity and process–structure–property relationships (Mishra & Jatti, 2023); (Zeng & Pi, 2023).

Beyond surface roughness, ML has also been instrumental in predicting other quality metrics in AM. Deep and ensemble models have been applied to forecast warpage, dimensional accuracy, and mechanical properties such as tensile strength and hardness. For instance, ANN and SVR models have accurately predicted tensile strength and surface quality in fiber-reinforced nylon composites with R^2 values exceeding 0.99 (Ulkar & Kuncan, 2025). Similarly, ML-assisted frameworks in selective laser melting have predicted porosity and surface hardness of AlSi10Mg parts, highlighting scan speed and layer thickness as dominant parameters influencing surface texture and density (Alamri & Barsoum, 2025). Hybrid sensing and vision-based models have also enabled real-time defect detection in FDM, demonstrating improved accuracy when fusing vibration and temperature data with visual feedback (Li et al., 2023). These advancements underscore the growing reliance on ML for predictive quality assurance across multiple AM platforms, from polymer extrusion to metal powder bed fusion.

Despite these promising results, several gaps persist in the literature. Most existing models rely on small, material-specific datasets that limit generalizability and fail to capture complex interdependencies between geometric and thermal parameters (García-Martínez et al., 2023). Furthermore, validation practices vary widely, with many studies using limited cross-validation or single-material experiments, which restricts real-world applicability. The modeling of multiparametric relationships remains weak, particularly under dynamic process variations. The current research addresses these deficiencies by developing a robust multi-parameter ML framework for surface roughness prediction in FDM, integrating both geometric and thermal variables into a unified predictive model. By employing ensemble learning and data-driven optimization, this work aims to enhance predictive accuracy, improve interpretability, and establish a scalable foundation for intelligent print-quality control in modern additive manufacturing systems.

3. Research gap

Despite considerable progress in additive manufacturing research, the prediction of surface roughness in fused-deposition modeling (FDM) remains limited by the lack of robust, multi-parameter machine-learning frameworks. Existing studies often analyze the effect of single parameters such as layer height or nozzle temperature, but very few incorporate a comprehensive set of geometric, thermal, and process-related variables within a unified predictive model. Moreover, most published work relies on small datasets or simplified experimental conditions, resulting in models that perform well only under controlled environments and fail to generalize across real-world variations. Several studies employ machine learning for defect detection, dimensional accuracy prediction, or mechanical-property estimation, yet the literature offers very limited evidence of accurate, raw-data-based modeling for surface roughness. The absence of reliable, data-driven models that can capture the combined effects of layer resolution, melt-flow behavior, and thermal interaction represents a clear research gap in the field of AM quality prediction. This study provides a systematic, machine-learning-driven framework for predicting surface roughness in FDM using a rich set of geometric and thermal process variables. By incorporating multiple influential parameters—including layer height, wall thickness, infill density, nozzle temperature, bed temperature, material type, and print speed—the model captures a more realistic representation of printing conditions compared to traditional single-parameter studies. The use of multiple regression, boosting, deep learning, and ensemble approaches allows the identification of the most effective predictive architecture under raw, unnormalized conditions. The findings not only validate the dominant role of layer height and thermal conditions but also demonstrate how predictive analytics can support consistent quality control in additive manufacturing. This contributes to the broader vision of intelligent, automated AM systems aligned with Industry 4.0 goals, offering manufacturers a reliable pathway for optimizing print parameters and minimizing manual intervention.

4. Methodology

This study evaluated the influence of key FDM printing parameters on surface roughness and developed machine-learning models for predictive analysis. The workflow included dataset preparation, preprocessing, exploratory analysis, correlation evaluation, feature selection, and model development using linear, tree-based, and ensemble learning methods.

4.1 Dataset Preparation

The dataset contained 50 printing trials extracted from the printer. Each entry included major 3D-printing parameters such as layer height, wall thickness, infill density, infill pattern, nozzle temperature, bed temperature, print speed, material type (ABS/PLA), and fan speed. Surface roughness (µm) was used as the target variable. These parameters represent the dominant geometric and thermal factors governing surface texture in FDM.

4.2 Data Preprocessing

Categorical fields such as infill pattern and material were converted into numerical form using label encoding. The dataset was divided into training (80%) and testing (20%) partitions using a fixed random seed to ensure reproducibility.

4.3 Exploratory Data Analysis

Histograms of key variables showed wide variation across layer height, print speed, and infill density, ensuring a broad representation of printing conditions. Roughness values displayed moderate spread with several outliers, indicating substantial variability linked to geometric and thermal settings.

4.4 Correlation Analysis

A correlation heatmap as shown in figure 1 was generated to understand relationships between process parameters and roughness. Layer height exhibited the strongest positive correlation with roughness, while nozzle temperature showed moderate influence. Other parameters, such as wall thickness and infill density, had weak associations.

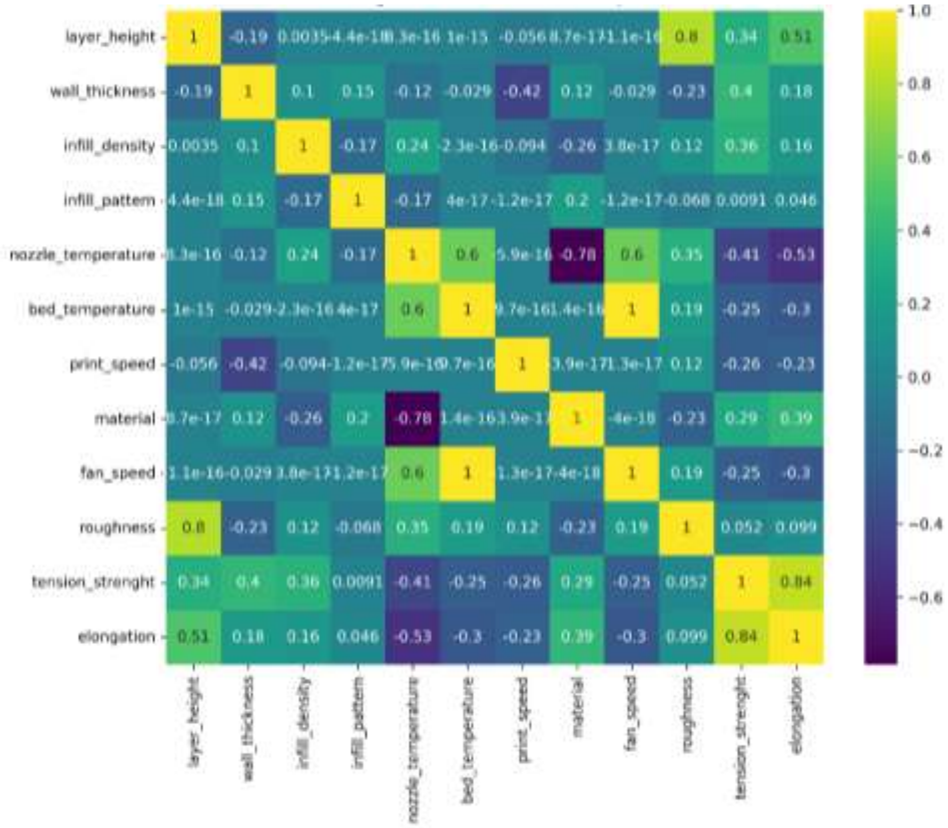

Figure 1. Correlation heatmap for process parameters.

4.5 Feature Selection

Gradient Boosting Machine (GBM) feature-importance ranking identified layer height and nozzle temperature as the most influential parameters. Feature-subset experiments confirmed that two- and three-parameter combinations yielded the highest R^2 performance for GBM models. Wall thickness, infill density, and fan speed contributed minimally and their exclusion did not degrade model accuracy.

4.6 Model Development

Four models were developed: GLM (Linear Regression), Gradient Boosting (GBM), Deep Learning (MLP), and a Stacked Ensemble combining GBM and MLP with GLM as the metalearner. Models were trained on raw features, and their performance was evaluated using R^2, MSE, RMSE, and MAE.

5. Results and Discussion

5.1 Descriptive Statistics and Initial Observations

Descriptive statistics for all process parameters and roughness are summarized in Table 1. Roughness values ranged from 21–368 µm, indicating significant variation across samples. Layer height spanned from 0.02–0.20 mm, covering fine to coarse layer deposition. Thermal parameters such as nozzle and bed temperature varied across typical ABS/PLA ranges. Initial inspection showed that roughness increases with layer height and decreases with optimized nozzle temperature.

Table 1. Descriptive statistics of process parameters and surface roughness

Parameter	Count	Mean	Std. dev.	Min	25%	50%	75%	Max
Layer height (mm)	50	0.106	0.0644	0.02	0.06	0.10	0.15	0.20
Wall thickness (mm)	50	5.22	2.92	1.00	3.00	5.00	7.00	10.0
Infill density (%)	50	53.40	25.36	10.0	40.0	50.0	80.0	90.0
Infill pattern (–)*	50	0.50	0.51	0.00	0.00	0.50	1.00	1.00
Nozzle temp. (°C)	50	221.50	14.82	200	210	220	230	250
Bed temp. (°C)	50	70.00	7.14	60	65	70	75	80
Print speed (mm/s)	50	64.00	29.69	40	40	60	60	120
Material (–)**	50	0.50	0.51	0.00	0.00	0.50	1.00	1.00
Fan speed (%)	50	50.00	35.71	0	25	50	75	100
Roughness (µm)	50	170.58	99.03	21	92	165.5	239.25	368

5.2 Distribution Analysis

Histograms showed that layer height and print speed had wide distributions, while roughness exhibited a slightly right-skewed pattern due to high-value outliers caused by coarse layers or low thermal flow. These observations align with known FDM behavior, where layer resolution and melt fluidity dominate surface characteristics.

5.3 Pairwise Trends

Pairwise scatter trends are shown in Figures 2 and 3. A strong increasing trend was observed between layer height and roughness, confirming that thicker layers increase the staircase effect. Nozzle temperature showed a mild inverse relation with roughness, reflecting improved melt flow and surface smoothing at higher temperatures.

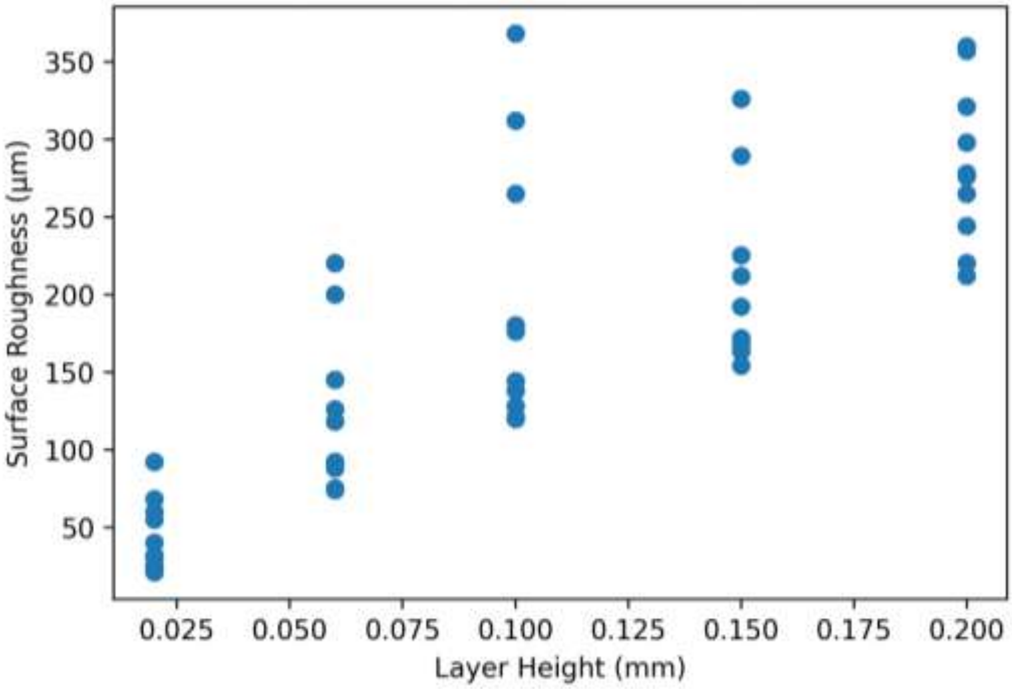

Figure 2. Scatter plot of layer height vs roughness.

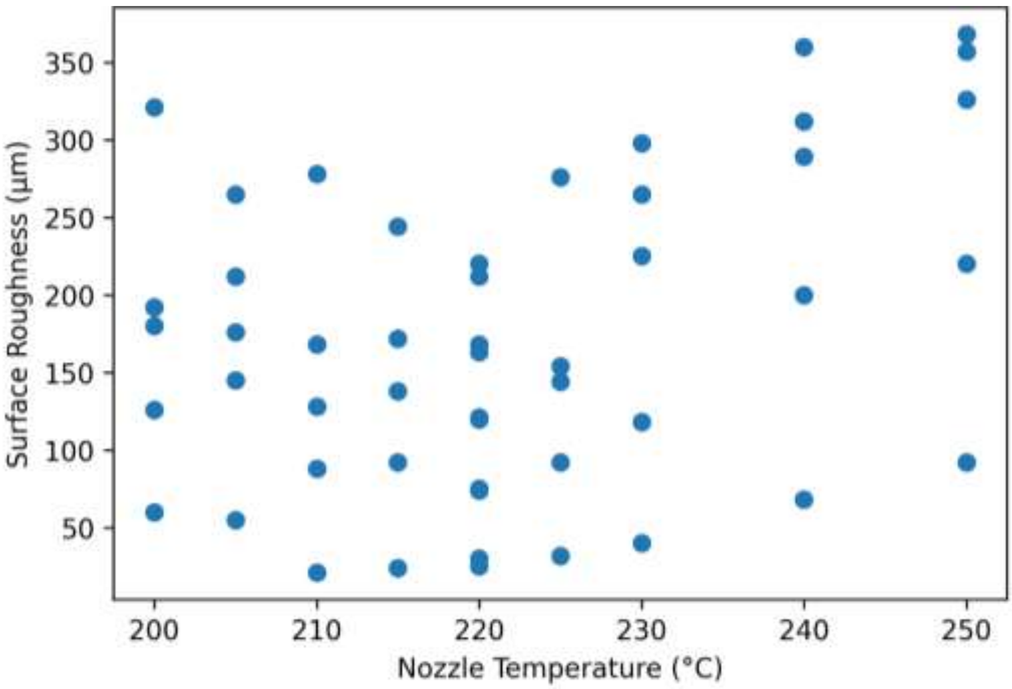

Figure 3. Scatter plot of nozzle temperature vs roughness.

5.4 Model Performance Comparison

Model performance metrics are presented in Table 2. Linear Regression achieved the highest accuracy with $R^2 = 0.789$, outperforming nonlinear models under raw-data conditions.

Table 2. Performance comparison of roughness-prediction models

Model	R^2	MSE	RMSE	MAE
GLM (Linear Regression)	0.7891	978.36	31.28	23.07
Gradient Boosting (GBM)	0.5226	2214.89	47.06	36.98
Deep Learning (MLP)	−0.0484	4864.34	69.74	51.86
Stacked Ensemble (GBM+MLP, GLM metalearner)	0.4901	2365.98	48.64	39.09

GBM and the Stacked Ensemble showed moderate performance, with residual errors suggesting nonlinear variations not fully captured without feature scaling. The MLP model performed poorly on raw data due to sensitivity to unnormalized input ranges.

5.5 Best Model Evaluation

Figures 4–6 present evaluation results from the best model (GLM). The actual vs predicted plot shows points clustering near the diagonal, confirming good alignment between predicted and actual roughness. Residual scatter exhibited no obvious funneling, and residual distribution showed a near-normal shape, confirming the model's stability and lack of strong bias.

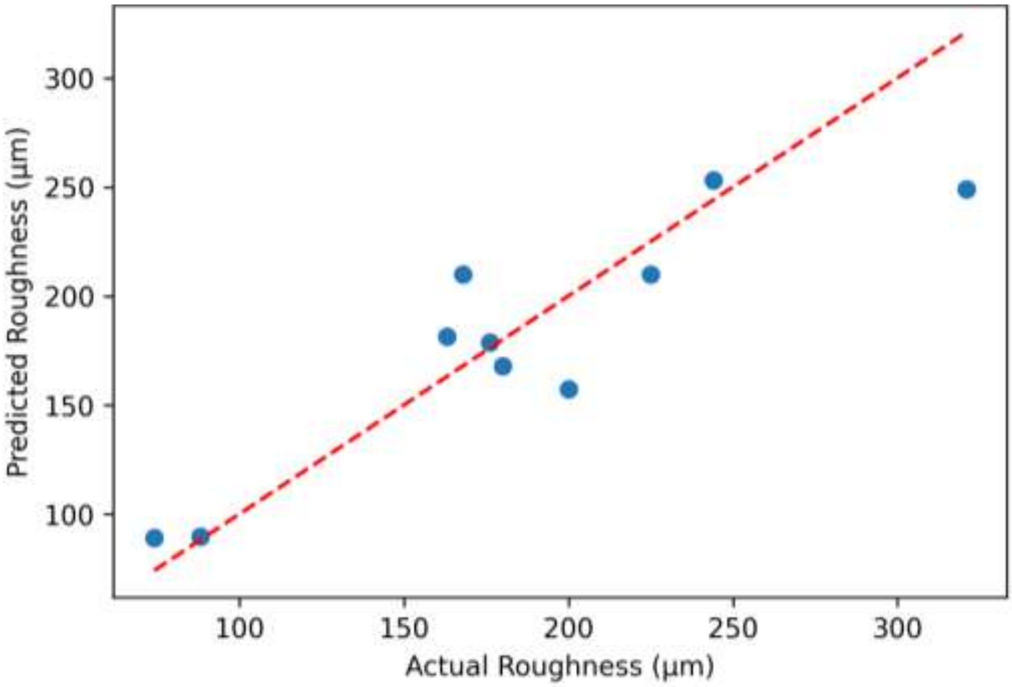

Figure 4. Actual vs predicted roughness.

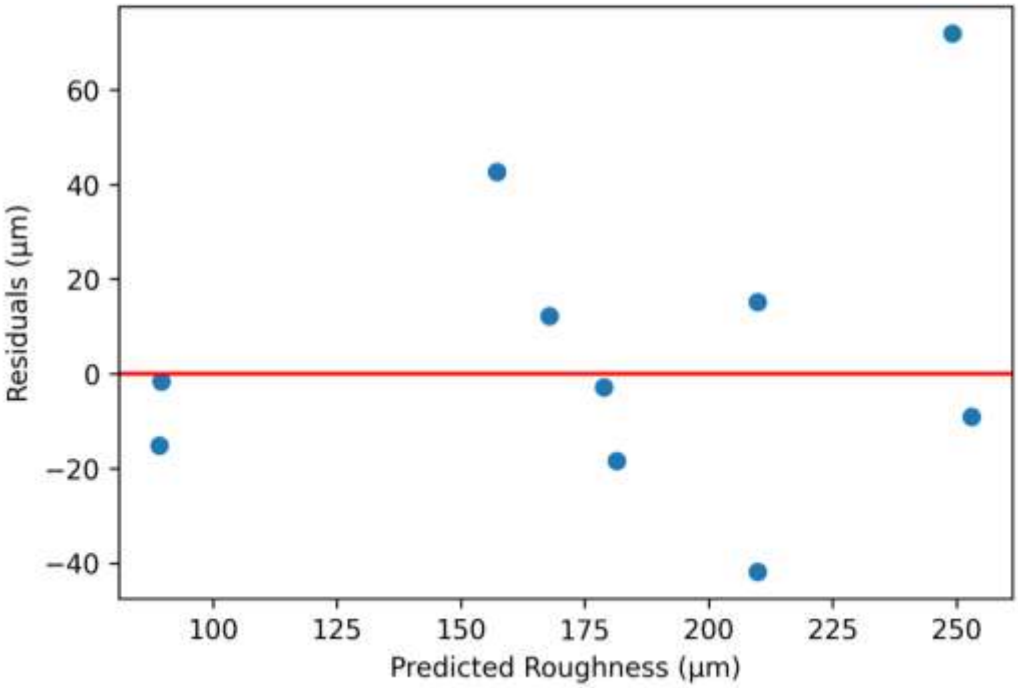

Figure 5. Residual scatter.

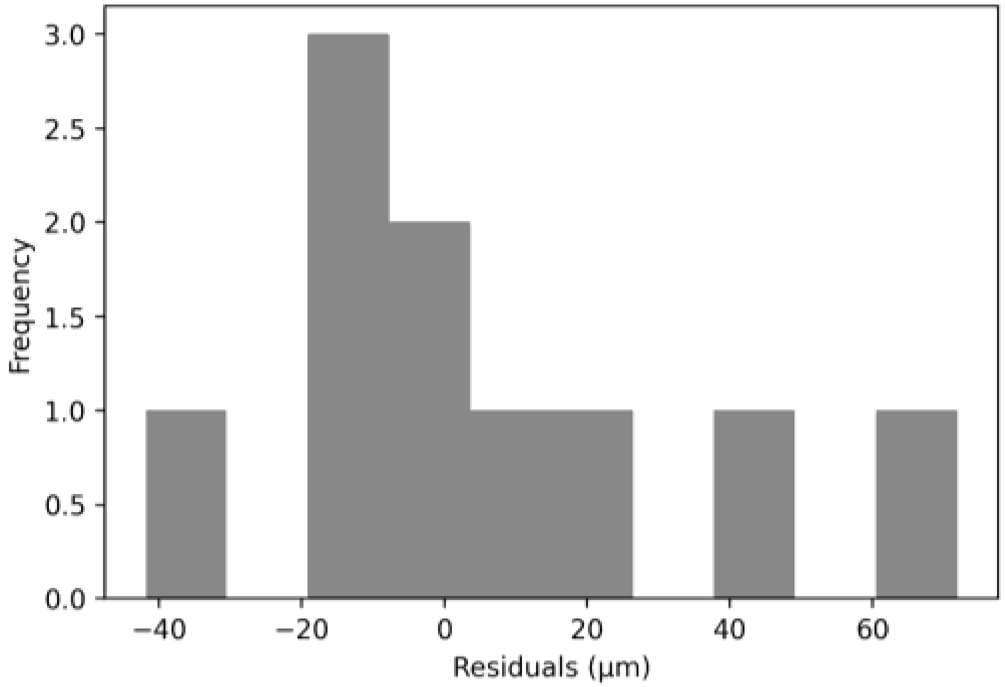

Figure 6. Residual distribution.

5.6 Interpretation of Variable Influence

Feature-importance analysis as shown in Table 3 shows that layer height contributed 60.4% of predictive influence, followed by nozzle temperature with 25.4%. These findings confirm that geometric resolution and melt-flow behavior dominate surface roughness in FDM. Fan speed, wall thickness, and infill density contributed minimally.

Table 3. Top feature combinations for GBM-based roughness prediction

No. of features	R^2	Selected features
2	0.7396	layer_height, nozzle_temperature
3	0.7466	layer_height, nozzle_temperature, print_speed
4	0.6863	layer_height, nozzle_temperature, print_speed, infill_density
5	0.5062	layer_height, nozzle_temperature, print_speed, infill_density, fan_speed

These results are consistent with physical printing behavior, where finer layers improve surface finish and thermal parameters control flow uniformity during deposition.

Conclusion

This study analyzed the effect of key FDM printing parameters on surface roughness and developed machine-learning models capable of predicting roughness with high reliability. The dataset covered a wide range of geometric and thermal conditions, ensuring realistic representation of FDM process behavior. Correlation analysis showed that layer height has the strongest influence on roughness, followed by nozzle temperature, while other parameters contributed only marginally. Model evaluation revealed that GLM produced the most accurate predictions under raw-data conditions, achieving an R^2 of 0.789 and well-distributed residuals. Nonlinear models such as GBM, MLP, and the Stacked Ensemble performed moderately but did not surpass the linear model due to sensitivity to unnormalized feature ranges. Overall, the results confirm that surface roughness is controlled primarily by layer resolution and melt-flow dynamics during deposition. The developed predictive framework provides a practical tool for selecting optimal printing parameters and can support real-time quality control in FDM production environments. Future work may explore feature scaling, larger datasets, and hybrid models to further enhance predictive accuracy.

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