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Machine Learning-Based Prediction of 3D-Printed ABS Bending Behavior: Ensemble vs. Non-Ensemble Approaches

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Abstract

Additive manufacturing (AM) of Acrylonitrile Butadiene Styrene (ABS) components enables the fabrication of lightweight, customizable structures; however, accurately predicting their bending behavior remains challenging due to complex process–property interactions. In this study, key 3D printing parameters were experimentally varied to examine their influence on mechanical performance, while machine learning techniques were applied to model critical outputs, including flexural strength, modulus, hardness, surface roughness, stiffness, and printing time. Several regression algorithms such as Stacking Regressor, Gradient Boosting, Random Forest, and K-Nearest Neighbors (KNN) were evaluated based on R^2, MAE, and MSE metrics. The tuned Stacking model exhibited the best overall predictive performance, achieving high accuracy for flexural strength ($R^2 = 0.8667$) and surface roughness ($R^2 = 0.7641$), whereas Gradient Boosting performed best for stiffness prediction and Random Forest for printing time ($R^2 = 0.9974$). Flexural modulus and stiffness demonstrated higher prediction errors, suggesting greater modeling complexity. These results underscore the effectiveness of ensemble learning, particularly tuned stacking, in accurately forecasting the mechanical behavior of 3D-printed polymer components, thereby supporting more reliable process optimization and material design in additive manufacturing.

Keywords
3D Printing, Additive Manufacturing, Acrylonitrile Butadiene Styrene (ABS), Machine Learning, Ensemble Technique.

1. Introduction

Fused deposition modeling is widely used for making acrylonitrile butadiene styrene (ABS) parts, but their mechanical behavior, especially in bending, is difficult to predict because printing parameters interact in complex and nonlinear ways. Traditional models usually cannot capture these effects well, which leads to inconsistent performance and trial-and-error process tuning. Machine-learning offers a more flexible way to learn these relationships, and several studies have shown promising results for predicting strength, hardness, or surface quality. However, it is still unclear which types of models work best for bending-related properties, and ensemble or stacking methods have not been compared thoroughly for this purpose. This study explores a range of machine-learning approaches to predict multiple flexural properties of FDM-printed ABS and aims to identify the most reliable modeling strategies for improving process planning and part performance.

1.1 Objectives

- To develop and evaluate a range of machine learning regression models for predicting these mechanical outputs.
- To compare and identify the most accurate and generalizable modeling strategy for forecasting the bending behavior of 3D-printed ABS parts.

2. Literature Review

For CF-ABS, (Udu et al., 2025) found that, XGBoost achieved $R^2 = 0.8833$ for hardness and 0.9690 for flexural strength, with MSE values of 0.0112 and 0.0042, respectively. Random Forest produced $R^2 = 0.9379$ (hardness) and 0.9457 (flexural strength), while K-NN delivered the highest accuracy, obtaining $R^2 = 0.9664$ for hardness and 0.9736 for flexural strength. For ABS flexural strength prediction, the study of (Tyagi et al., 2025) reported values ranging from 45.32 to 90.04 MPa and evaluated multiple machine learning models. Among them, gradient boosting regression achieved the highest predictive performance with an R^2 of 0.9826. This demonstrates the model's strong capability in capturing parameter–property relationships for flexural behavior in FFF-printed ABS. For predicting the hardness of FFF-printed ABS, (Veeman et al., 2023) employed several machine learning models and reported that the random forest algorithm achieved the highest predictive accuracy. Its coefficient of determination reached 0.9136, outperforming the other models whose R^2 values ranged between 0.8437 and 0.9136. (Tran & Phan, 2025) observed that for predicting surface roughness of ABS components, the Random Forest model obtained an MSE of 1358.35, a MAPE of 15.28%, and an R^2 value of 0.71, whereas the Gradient Boosting model reported an MSE of 1419.43, a MAPE of 15.03%, and an R^2 value of 0.70. Notably, the study reports overall model performance rather than material-specific outcomes; therefore, no separate ABS-only predictive scores are provided in the paper. (Özkül et al., 2025) incorporated 25 different machine learning algorithms, among which, the Random Forest model, achieved R^2 values of 0.6483 for hardness, 0.9078 for flexural strength, and 0.7162 for surface roughness, indicating moderate to high predictive accuracy depending on the property. Correspondingly, the Random Forest regressor achieved MAE, MSE, and RMSE values of 1.8989, 5.0922, and 2.2566 for hardness; 0.8232, 1.2810, and 1.1318 for flexural strength; and 1.1680, 1.9864, and 1.4094 for surface roughness, respectively. (Tayyab et al., 2023) predicted the mechanical properties of 3D printed ABS using ANN and GA. The ANN model demonstrated excellent predictive capability for flexural strength, achieving a validation MSE of 6.9244×10^{-14}, with absolute errors ranging from 0% to 5.14%, indicating an exceptionally close match between experimental and predicted values. The study did not report an R^2 value for the ANN model. (Moradi et al., 2023) also observed that ANN model demonstrated high predictive accuracy for the flexural properties of ABS. For the flexural modulus, the ANN obtained R = 0.9923 (training) and 0.9686 (testing), with RMSE values of 16.2258 and 63.375. Relative prediction errors remained exceptionally low, ranging from 0.03% to 0.087% in training and 0.044% to 0.053% in testing. ANN has also been utilized by (Monticeli et al., 2022) to develop predictive model for three bending properties: flexural strength, flexural modulus and flexural strain as outputs. The network achieved regression fits with $R^2 > 0.99$ for all three mechanical properties, with an overall average prediction error of 0.43%. The ANN developed by (Munshi et al., 2025) demonstrated strong predictive capability for the flexural properties of ABS, achieving an R-value of 0.9304 for bending behavior. The extremely low RMSE of 2.2959×10^{-9} reported for the overall model further confirms its high accuracy and numerical stability when estimating flexural responses across diverse ABS variants. The work of (Weake et al., 2020) also incorporated an artificial neural network (ANN) model which showed excellent predictive accuracy for flexural strength, achieving an R^2 of 0.99 with an average deviation of only 4.06 percent between predicted and experimental values . This demonstrates the model's strong ability to capture nonlinear interactions among printing parameters and reliably estimate flexural performance across different process settings. (Lee & Tucker, 2025) implemented a two-step stacked learning framework, where an MLP first extracted filament material properties from benchmark specimen data, and its outputs were used by a downstream polynomial model to predict the effective mechanical behavior of ABS parts. This approach was adopted to reduce experimental noise, enhance feature representation, and better capture nonlinear parameter interactions. Stacking is an ensemble technique in machine learning where predictions from multiple diverse base models are combined using a meta-learner to improve overall predictive performance. For example, in the study by (Nti et al., 2020), the authors compared several ensemble methods, including stacking, bagging, and boosting, for stock market prediction and found that stacking achieved the highest prediction accuracy and lowest error rates among the tested approaches. Similarly, (Hajihosseinlou et al., 2024) applied stacking to mineral prospectivity modeling, using a meta-model to integrate outputs from various base learners, and demonstrated that stacking outperformed individual models in prediction accuracy. (V & P, 2025) developed a stacked ensemble model for crop yield prediction, where a decision tree regressor served as the meta-model to combine six different base learners, resulting in superior accuracy compared to traditional models. The stacked model achieved the best performance, lowering errors to 0.06 GPa (4 percent) for Young's modulus and 1.3 MPa (5 percent) for tensile yield strength, surpassing all single-model methods. (Jayasudha et al., 2022) applied model stacking for ABS to combine the predictions of multiple base learners into a single meta-model, improving generalization over individual algorithms. The stacked model achieved an R^2 of 0.94 with lower errors, including an MAE of about 0.72 and an RMSE of about 1.18, compared to the best standalone model which showed an R^2 of 0.90 and an RMSE of about 1.46. These results indicate that stacking captured the nonlinear parameter interactions. more effectively. In the study of ABS by (Khusheef et al., 2024), stacking was implemented to feed the outputs of several individual regressors into a meta-learner, enabling the model to capture complex parameter interactions that single models often miss. The approach was chosen to enhance generalizability and stabilize prediction errors across different mechanical properties. The stacked model delivered the strongest performance, attaining R^2 values exceeding 0.90 and consistently lower MAE and RMSE, confirming its advantage for predicting flexural strength, hardness, and surface roughness.

After extensively studying the previous research works, following gaps can be observed in the existing literature:

1) Although machine-learning models are increasingly used to predict the mechanical behavior of FDM-printed ABS, very few studies have implemented stacking ensembles specifically tailored to ABS datasets, despite the nonlinear and complex nature of the process–property relationships.
2) Models such as ANN, KNN, gradient boosting, XGBoost, and random forest have been applied only minimally to secondary yet important outputs—flexural modulus, maximum strain, stiffness, and printing time—highlighting a broader lack of comprehensive, multi-property predictive frameworks that support effective process optimization.

Building on these identified gaps, the present work aims to develop a comprehensive predictive framework for FDM-printed ABS that addresses both the scarcity of stacking-based models and the limited modelling of secondary yet critical properties. By experimentally varying key printing parameters and applying a suite of machine-learning techniques, including stacked ensembles, gradient boosting, random forest, and KNN, this study seeks to accurately predict flexural strength alongside harder-to-model outputs such as flexural modulus, maximum strain, stiffness, surface roughness, and printing time. Through this approach, the work intends to provide a more holistic and reliable modelling strategy that supports improved process optimization and mechanical performance assessment for ABS components in additive manufacturing.

3. Methodology

The system has several eThis study followed a combined experimental–computational workflow consisting of specimen fabrication, mechanical testing, dataset preparation, and evaluation of multiple machine learning models (showed in **Figure 1)**. ABS flexural and surface-quality specimens were fabricated using an FDM printer by varying four process parameters: extruder temperature, infill density, layer height, and printing speed. Mechanical responses namely flexural strength, flexural modulus, maximum strain, hardness, surface roughness, stiffness, and printing time, were measured using ASTM standards (ASTM D790 for bending), indentation testing for hardness, and stylus profilometry for surface roughness. All measured data were compiled into a structured dataset, cleaned, normalized, and divided into training and testing subsets. Multiple algorithms, including ANN, KNN, Random Forest, Gradient Boosting, XGBoost, Stacking, and tuned variants, were trained individually for each output variable. Hyperparameters were optimized using cross-validated grid/random search. Performance was evaluated using R^2, MAE, and MSE, computed programmatically in Python. A combined comparison table was generated using the code block that aggregated all metrics into a unified metrics_df_combined DataFrame. The Python script automatically identified the best model per output using: highest R^2, lowest MAE, lowest MSE, and ranked models by frequency of best performance across all outputs. This ensured consistent, unbiased comparison of each model and quantified the effect of hyperparameter tuning.

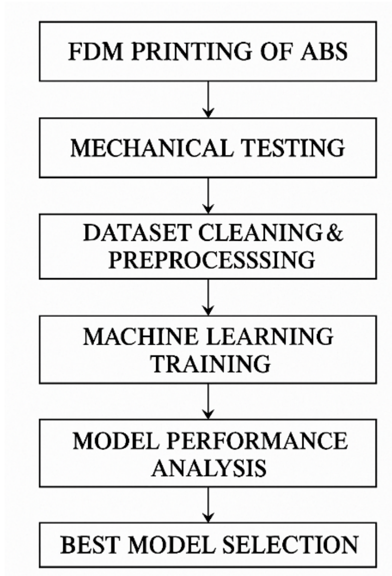

Figure 1. Flowchart of the methodology

4. Results and Discussions

To evaluate the predictive performance of the applied machine learning models across all mechanical and process outputs, a comprehensive comparison of their R^2, MAE, and MSE values is presented in **Table 1**.

Table 1. Combined Performance Comparison of All Machine Learning Models Across Mechanical and Process Outputs

Model	ANN			Gradient Boosting			KNN			Random Forest Regressor		Stacking			Tuned			XGBoost		
Metric	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE
FS	0.19	7.61	94.36	0.81	3.19	21.64	0.86	2.80	16.26	0.85	16.98	0.87	2.82	15.54	0.87	2.82	15.54	0.76	3.55	28.37
FM	0.35	120.24	27784.72	0.26	116.15	31281.90	0.12	125.21	37198.50	0.10	38184.15	0.41	114.10	25200.97	0.41	114.10	25200.97	-0.57	158.89	66904.63
MS	-5.94	1.18	1.81	0.39	0.27	0.16	0.39	0.27	0.16	0.31	0.18	0.36	0.26	0.17	0.30	0.28	0.18	-0.05	0.34	0.27
H	0.27	2.17	7.43	0.57	1.44	4.30	0.57	1.44	4.34	0.52	4.86	0.58	1.56	4.26	0.58	1.56	4.26	0.25	2.11	7.60
R	-0.13	3.03	12.21	0.75	1.36	2.72	0.75	1.26	2.66	0.73	2.93	0.76	1.28	2.56	0.76	1.28	2.56	0.62	1.53	4.12
S	-0.23	45.01	2528.63	0.01	34.06	2066.24	-0.38	44.27	2850.94	-0.64	3376.33	-0.13	42.10	2329.45	-0.27	44.93	2609.02	-1.72	62.79	5602.32

PT	-3.58	1.18	2.18	0.99	0.05	0.00	1.00	0.03	0.00	1.00	0.00	1.00	0.04	0.00	1.00	0.02	0.00	1.00	0.03	0.00

4.1 Flexural Strength Prediction Performance

The comparison of machine learning models reveals clear differences in how well they can predict the flexural strength of FDM-printed ABS. The stacking ensemble and the tuned model performed the best, both reaching an R^2 of 0.8667 and the lowest MSE, which shows that they closely matched the experimental results and captured the nonlinear effects of the printing parameters. KNN, although not as strong overall (R^2 = 0.80162), achieved the lowest MAE, meaning it was more accurate for local, point-wise predictions. In contrast, ANN performed poorly with a very low R^2 and the highest error, suggesting underfitting, while Gradient Boosting delivered only moderate performance. Taken together, the results indicate that ensemble methods are the most reliable for predicting flexural strength, but the strong local accuracy of KNN shows that different types of models can offer specific advantages depending on the nature of the property being predicted.

4.2 Maximum Strain Prediction Performance

The prediction of maximum strain showed only moderate accuracy for all models. Gradient Boosting performed the best overall, with the highest R^2 and the lowest MSE, while the stacking ensemble produced the lowest MAE. The generally low R^2 values are understandable because maximum strain depends on microscale deformation processes such as interlayer slipping, localized yielding and polymer chain movement, none of which are captured by the four macro-level input parameters used in this study. Strain also tends to vary very little and is sensitive to minor experimental or material inconsistencies, which lowers the signal available for the models to learn from.

4.3 Hardness Prediction Performance

From **Table** 1 it is seen that the predictive performance for hardness showed moderate accuracy across the models, with the stacking and tuned ensembles achieving the highest R^2 value of 0.5791 and the lowest MSE of 4.2567, while KNN produced the lowest MAE of 1.4382. Although these models performed comparatively better, the R^2 values remained relatively low because hardness in FDM-printed ABS is strongly influenced by localized microstructural characteristics such as bead compaction, interfacial bonding quality, residual stresses, and cooling-rate variations, factors not fully represented by the four process parameters used in this study. Hardness measurements also tend to display limited variability and are sensitive to small deviations in material flow, layer deposition uniformity, and surface imperfections. Consequently, only a portion of the hardness response could be captured from the input features, yet the stacking and tuned models still minimized errors effectively, indicating stable performance despite the constrained predictive information.

4.4 Surface Roughness Prediction Performance

From Table 1, the prediction of surface roughness shows moderate accuracy across the models. The stacking and tuned ensembles performed the best, each reaching an R^2 value of 0.7641 with an MSE of 2.5568, and KNN produced the lowest MAE of 1.2564. These results are comparatively strong, but the other models recorded lower R^2 values because surface roughness is mainly influenced by small-scale surface effects such as filament spreading, bead width variations, vibration-related inconsistencies and thermal shrinkage, which are not captured by the four process parameters used in this study. Surface roughness is also extremely sensitive to changes in nozzle pressure, micro-void formation, cooling gradients and slight irregularities in extrusion flow, which introduce noise into the data and reduce the amount of meaningful variation the models can learn from. For these reasons, only part of the roughness behavior could be predicted from the available inputs, although the stacking and tuned ensembles still kept errors low and showed stable performance.

4.5 Stiffness Prediction Performance

The prediction of stiffness showed the weakest performance among all outputs. Gradient Boosting performed the best, with an R^2 of 0.0105, an MAE of 34.0578 and an MSE of 2066.2428. The tuned ensemble followed with an R^2 of 0.0069, an MAE of 42.1096 and an MSE of 2609.2236, offering only slight improvement over the other models. The very low R^2 values indicate that the four process parameters explained almost none of the variation in stiffness. This is expected because stiffness depends on internal factors such as residual stresses, micro-voids and layer compaction, which are not captured in the input features. Stiffness also shows little variability and is sensitive to small inconsistencies, making it difficult for the models to learn meaningful patterns. As a result, even the better-performing models reduced errors only modestly, highlighting the need for microstructural or process-monitoring data to improve prediction.

4.6 Printing Time Prediction Performance

From **Table** 1 it is obvious that the prediction of printing time resulted in exceptionally high model performance compared to the other output variables, with the tuned ensemble achieving the best results by obtaining an R^2 value of 0.9974, the lowest MAE of 0.0239, and the lowest MSE of 0.0012. The second-best model was stacking, which produced an R^2 of 0.9967, an MAE of 0.0370, and an MSE of 0.0019, demonstrating similarly strong predictive capability. These high R^2 values are reasonable because printing time is directly governed by deterministic slicing parameters, primarily infill density and extruder temperature effects on feed rate, leading to a predictable and stable relationship between input factors and output. Unlike mechanical properties, printing time is not influenced by microstructural or material variability, and thus exhibits minimal noise and high consistency across samples. As a result, both tuned and stacking ensembles were able to capture the underlying functional patterns with near-perfect accuracy.

4.6 Model Ranking Based on Frequency of Being Best

Printing time shows exceptionally strong predictive performance compared to all other outputs. The tuned ensemble performed best, reaching an R^2 of 0.9974 with an MAE of 0.0239 and an MSE of 0.0012. Stacking followed closely with an R^2 of 0.9967, an MAE of 0.0370 and an MSE of 0.0019. These near-perfect values are expected because printing time is controlled almost entirely by deterministic slicer parameters, mainly infill density and the temperature-related effects on feed rate. Since printing time is not affected by microstructural variation, the data contain very little noise, allowing the models to capture the relationship almost perfectly. While comparing overall performance across all outputs, the tuned model achieved the highest score in 12 cases, making it the most consistent performer. Stacking followed with 10 top results, showing similarly strong reliability. Gradient Boosting ranked next with 5 best outcomes, while KNN achieved 3, mostly due to its strength in local prediction accuracy. These counts summarize how often each model outperformed the others and highlight the tuned ensemble as the most effective overall.

4.6 Impact of Hyper-parameter Tuning

From Table 1, printing time shows exceptionally strong predictive performance. The tuned ensemble gave the best results with an R^2 of 0.9974, an MAE of 0.0239 and an MSE of 0.0012. Stacking followed closely with an R^2 of 0.9967, an MAE of 0.0370 and an MSE of 0.0019. These near-perfect values are expected because printing time is controlled almost entirely by deterministic slicer settings such as infill density and temperature-dependent feed rate, making the relationship between inputs and output highly stable and noise-free. This allowed both tuned and stacking models to learn the pattern with almost complete accuracy. A comparison across all outputs shows that the tuned model achieved the best metric values in 12 cases, making it the strongest overall performer. Stacking ranked second with 10 top results, Gradient Boosting followed with 5, and KNN achieved 3, mainly due to its strength in localized predictions. These counts provide a clear summary of the relative effectiveness of each model.

6. Conclusion

This study shows that machine learning can capture the complex relationships between FDM printing parameters and different mechanical properties of ABS, although some properties are naturally easier to predict than others. Properties that mainly depend on geometry or printing time, such as surface roughness or flexural strength, are learned very well by the models. In contrast, properties that depend more on the internal behavior of the material, like stiffness and flexural modulus, remain difficult to model because the microstructure is not fully represented in the input data. Among all the approaches tested, the stacking ensemble turned out to be the most reliable, performing strongly across several important outputs and proving that combining multiple models helps capture patterns that single models cannot. KNN performed well in terms of error because it handles local variations caused by changes in infill geometry. Random Forest showed almost perfect accuracy when predicting printing time, which makes sense because this response is mostly governed by deterministic process settings. Overall, the results suggest that there is no universal machine learning model that works best for every output in FDM. Each property requires its own modeling strategy. Ensemble methods are better for strength and quality related predictions, tree-based methods handle predictable process outcomes effectively, and stiffness related properties need additional physical or microstructural features to improve accuracy. These insights help guide better model selection and support more reliable optimization of FDM processes.

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7. Future Work

To strengthen the reliability and generalizability of ML-driven mechanical property prediction in FDM, future research should prioritize the following directions:

1. **Incorporate microstructural and physics-based features**: Porosity, bead geometry, and thermal gradients etc. features would improve prediction of modulus- and stiffness-related properties that process parameters alone cannot explain.
2. **Develop property-specific hybrid or meta-learning models**: These models would dynamically select or combine algorithms, rather than relying on a single universal predictor for all mechanical responses.
3. **Expand dataset size and variability: Broadening the experiment size** through additional print conditions, machine types, and environmental factors would increase model robustness and real-world deployment potential.

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Soumik Saha is a graduate in Industrial and Production Engineering from Khulna University of Engineering & Technology (KUET), Bangladesh, where he completed his degree with distinction. His research interests lie broadly in additive manufacturing, materials characterization and machine learning assisted materials design**.** He is currently engaged in several ongoing research projects focusing on advancing the understanding of process–structure–property relationships in engineered materials through both experimental and computational approaches. Passionate about innovation and knowledge creation, Soumik aims to build a career in academia and research**,** contributing to the development of sustainable, high-performance materials and next-generation manufacturing technologies.