Machine Learning-Based Prediction of Mechanical Properties in Fused Deposition Modeling Through Optimization of Process Parameters

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Abstract

Additive Manufacturing (AM), particularly Fused Deposition Modeling (FDM), has gained significant attention due to its ability to fabricate complex geometries with reduced material waste and production time. However, the mechanical properties of FDM-manufactured components are highly influenced by process parameters such as nozzle temperature, infill density, layer height, printing pattern, and material type. Determining the optimal combination of these parameters through conventional experimental approaches is time-consuming and costly.This study presents a Machine Learning-based framework for predicting the mechanical properties of FDM-printed components manufactured using PLA+ and PLA Pro+ materials. A comprehensive experimental dataset was generated by varying critical process parameters and conducting standardized mechanical tests to evaluate Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. Advanced feature engineering techniques and data preprocessing methods were applied to improve model performance.Multiple machine learning algorithms, including Random Forest Regressor, XGBoost Regressor, Gradient Boosting Regressor, Extra Trees Regressor, and CatBoost Regressor, were developed and evaluated using R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Experimental results demonstrate that ensemble learning models provide reliable prediction capability, with the best-performing model achieving an R^2 score of approximately 0.67 for multi-output mechanical property prediction. The developed system enables rapid estimation of mechanical properties without extensive physical testing, thereby reducing experimental cost, material consumption, and development time.The proposed approach offers an effective decision-support tool for process optimization, material selection, and quality enhancement in additive manufacturing environments. The integration of machine learning with FDM process parameter optimization contributes toward intelligent manufacturing and Industry 4.0 applications.

Keywords: Additive Manufacturing, Fused Deposition Modeling (FDM), Machine Learning, Mechanical Property Prediction, Random Forest, XGBoost, CatBoost, Process Parameter Optimization, PLA+, PLA Pro+, Multi-Output Regression, Industry 4.0, 3D Printing

I. Introduction

Additive Manufacturing (AM), commonly known as 3D printing, has emerged as a revolutionary manufacturing technology capable of producing complex geometries with reduced material waste, shorter production cycles, and increased design flexibility. Among various additive manufacturing techniques, Fused Deposition Modeling (FDM) is one of the most widely adopted methods due to its low cost, ease of operation, and compatibility with a wide range of thermoplastic materials. FDM has found extensive applications in aerospace, automotive, biomedical, consumer products, and rapid prototyping industries.

The mechanical performance of FDM-manufactured components is significantly influenced by several process parameters, including nozzle temperature, layer height, infill density, printing pattern, printing speed, and material composition. Variations in these parameters can lead to substantial differences in mechanical properties such as Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. Traditionally, determining the optimal combination of process parameters requires extensive experimental testing, which is both time-consuming and costly.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have provided new opportunities for process optimization and predictive modeling in manufacturing systems. Machine learning algorithms can learn complex relationships between process parameters and output responses from historical experimental data, enabling accurate prediction of mechanical properties without performing repeated physical experiments. This approach reduces manufacturing costs, minimizes material consumption, and accelerates product development cycles.

In this study, a Machine Learning-based framework is proposed for predicting the mechanical properties of FDM-printed components fabricated using PLA+ and PLA PRO+ materials. Experimental datasets were collected by varying critical process parameters such as nozzle temperature, infill density, layer height, material type, and printing pattern. Advanced data preprocessing, feature engineering, and multi-output regression techniques were employed to develop predictive models. Several machine learning algorithms, including Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, Extra Trees Regressor, and CatBoost Regressor, were implemented and compared using performance metrics such as R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

The primary objective of this research is to develop an intelligent prediction system capable of accurately estimating multiple mechanical properties simultaneously while identifying the most influential process parameters. The proposed framework contributes to the advancement of smart manufacturing and Industry 4.0 by integrating machine learning techniques with additive manufacturing process optimization. The developed system can assist researchers, engineers, and manufacturers in selecting optimal printing parameters, improving product quality, and reducing the need for extensive experimental trials.

II. Literature Survey

The rapid growth of Additive Manufacturing (AM) has attracted significant research interest in understanding the influence of process parameters on the mechanical performance of fabricated components. Among various additive manufacturing techniques, Fused Deposition Modeling (FDM) has been extensively studied due to its affordability, accessibility, and suitability for rapid prototyping and functional part production.

Ahn et al. investigated the effect of layer thickness, raster angle, and air gap on the tensile properties of FDM-manufactured parts. Their study revealed that process parameters significantly affect mechanical strength and dimensional accuracy. The researchers concluded that optimizing process parameters is essential for achieving superior mechanical performance.

Sood et al. applied Response Surface Methodology (RSM) to analyze the relationship between process parameters and mechanical characteristics of FDM components. Their findings demonstrated that nozzle temperature, layer thickness, and raster orientation have a considerable impact on tensile strength and surface quality. However, the experimental optimization process required extensive testing and computational effort.

Chacón et al. evaluated the mechanical properties of PLA-based FDM specimens fabricated under different printing conditions. The study reported that infill density and layer height strongly influence tensile and flexural properties. Higher infill densities generally resulted in improved mechanical performance but increased material consumption and printing time.

Singh et al. proposed statistical and optimization techniques to determine optimal FDM printing conditions. Their research highlighted the limitations of traditional experimental approaches due to the increasing complexity of process parameters and interactions among them. The authors suggested the integration of intelligent prediction systems to reduce experimental burden.

With the advancement of Artificial Intelligence, machine learning techniques have emerged as effective tools for predicting manufacturing outcomes. Zhang et al. developed machine learning models for predicting mechanical properties of additively manufactured components using experimental datasets. Their results demonstrated that ensemble learning algorithms outperform conventional regression approaches in capturing nonlinear relationships between process parameters and material behavior.

Wang et al. employed Random Forest and Gradient Boosting algorithms to estimate tensile strength and dimensional accuracy of 3D-printed products. The study achieved promising prediction accuracy and showed that machine learning can significantly reduce the number of physical experiments required for process optimization.

More recently, researchers have explored advanced ensemble learning techniques such as XGBoost, Extra Trees, and CatBoost for manufacturing applications. These algorithms provide enhanced predictive performance by effectively handling nonlinear feature interactions and complex datasets. Comparative studies indicate that ensemble-based models generally achieve higher accuracy and better generalization than traditional statistical methods.

Although numerous studies have investigated process parameter optimization and mechanical property prediction, limited research has focused on simultaneously predicting multiple mechanical properties, including Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness, using a unified machine learning framework. Furthermore, the application of advanced feature engineering and multi-output regression techniques in FDM process optimization remains relatively unexplored.

Therefore, this research proposes a comprehensive Machine Learning-based prediction framework that utilizes process parameters such as material type, nozzle temperature, infill density, layer height, and printing pattern to accurately estimate multiple mechanical properties of FDM-printed components. The proposed approach aims to improve prediction accuracy, reduce experimental costs, and support intelligent decision-making in additive manufacturing environments.

III. Existing System

The existing approaches for determining the mechanical properties of Fused Deposition Modeling (FDM) manufactured components primarily rely on conventional experimental testing and statistical optimization techniques. Researchers typically fabricate multiple specimens by varying process parameters such as nozzle temperature, layer height, infill density, raster pattern, and material type, followed by destructive mechanical testing to evaluate properties including Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. Although these methods provide accurate measurements, they require significant time, labor, material consumption, and testing costs. Traditional optimization techniques such as Design of Experiments (DOE), Taguchi Method, and Response Surface Methodology (RSM) are commonly employed to identify optimal process parameters; however, their effectiveness decreases when dealing with complex nonlinear relationships among multiple input variables and output responses. Furthermore, existing systems often focus on predicting a single mechanical property rather than multiple properties simultaneously, limiting their applicability in real-world manufacturing environments. The absence of intelligent prediction mechanisms necessitates repeated experimentation whenever process parameters are modified, resulting in reduced productivity and increased manufacturing expenses. Therefore, there is a need for an advanced data-driven approach capable of accurately predicting multiple mechanical properties while minimizing experimental efforts and supporting efficient process optimization.

IV. Proposed System

The proposed system presents a Machine Learning-based framework for predicting the mechanical properties of Fused Deposition Modeling (FDM) manufactured components through optimization of critical process parameters. Unlike conventional approaches that rely on extensive experimental testing, the proposed methodology utilizes data-driven predictive models to estimate multiple mechanical properties accurately and efficiently. The system considers key process parameters such as Material Type, Nozzle Temperature, Printing Pattern, Infill Density, and Layer Height as input features. These parameters significantly influence the structural integrity and performance of 3D-printed components.

Initially, experimental data collected from FDM-printed specimens are subjected to data preprocessing techniques, including data cleaning, missing value handling, categorical encoding, and feature scaling. Additional feature engineering techniques are employed to generate interaction features such as Temperature–Density, Temperature–Layer Height, and Density–Layer Height combinations, enhancing the predictive capability of the models. The processed dataset is then divided into training and testing subsets for model development and evaluation.

Several advanced machine learning algorithms, including Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, Extra Trees Regressor, and CatBoost Regressor, are implemented for multi-output regression. These models are trained to simultaneously predict multiple mechanical properties, namely Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. Model performance is evaluated using statistical metrics such as R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The model achieving the highest prediction accuracy is selected as the optimal prediction model.

A Flask-based web application is developed to provide a user-friendly interface where users can input process parameters and instantly obtain predicted mechanical properties. The system also generates graphical visualizations, including performance comparison charts, feature importance analysis, correlation heatmaps, residual plots, and actual-versus-predicted graphs to support result interpretation and decision-making. By eliminating the need for repetitive physical experiments, the proposed system significantly reduces material consumption, testing costs, and development time while improving process optimization and manufacturing efficiency.

The proposed framework contributes to intelligent manufacturing and Industry 4.0 by integrating machine learning techniques with additive manufacturing process optimization. It enables rapid prediction, improved product quality, and data-driven decision-making for researchers, engineers, and manufacturing industries.

V. System Architecture

The proposed system architecture is designed to predict the mechanical properties of Fused Deposition Modeling (FDM) manufactured components using advanced Machine Learning techniques. The architecture consists of multiple interconnected stages, including data acquisition, data preprocessing, dataset preparation, machine learning model development, model evaluation, deployment, user interaction, and result visualization. Initially, experimental data are collected from FDM 3D printing processes using different combinations of process parameters such as material type, nozzle temperature, printing pattern, infill density, and layer height. Mechanical testing is then performed according to standard testing procedures to measure target properties including Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. These experimentally obtained values form the dataset used for model training and validation.

In the data preprocessing stage, the collected dataset undergoes cleaning and transformation to improve data quality and consistency. Missing values, duplicate records, and invalid entries are removed, while categorical attributes such as material type and printing pattern are converted into numerical representations using Label Encoding techniques. Feature scaling is applied using standardization methods to normalize the input variables and improve model convergence. Additionally, feature engineering techniques are employed to create interaction features such as Temperature–Density, Temperature–Layer Height, and Density–Layer Height combinations, which help capture nonlinear relationships between process parameters and mechanical properties.

After preprocessing, the prepared dataset is divided into training and testing subsets using an appropriate train-test split strategy. The training dataset is used to develop machine learning models, while the testing dataset is reserved for performance evaluation. Multiple regression-based machine learning algorithms are implemented, including Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, Extra Trees Regressor, and CatBoost Regressor. These algorithms are integrated using a Multi-Output Regression framework, enabling simultaneous prediction of multiple mechanical properties from a single set of process parameters. The use of ensemble learning techniques improves predictive capability by effectively handling nonlinear patterns and complex interactions within the dataset.

The trained models are evaluated using performance metrics such as R^2 Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Comparative analysis is performed to identify the best-performing model based on prediction accuracy and error minimization. The model achieving the highest R^2 score and lowest prediction errors is selected as the optimal model for deployment. Visualization techniques such as R^2 comparison charts, feature importance plots, correlation heatmaps, residual error plots, error distribution graphs, and actual-versus-predicted plots are generated to provide deeper insights into model performance and parameter influence.

Once the optimal model is selected, it is serialized and deployed within a Flask-based web application. The deployment stage enables real-time prediction of mechanical properties through a user-friendly graphical interface. Users can input process parameters such as material type, nozzle temperature, printing pattern, infill density, and layer height. The system processes these inputs using the trained machine learning model and instantly predicts the corresponding mechanical properties, including Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. The generated predictions are displayed through the web interface along with graphical visualizations, allowing users to analyze results efficiently.

Finally, the system provides valuable insights for process parameter optimization, quality improvement, and intelligent decision-making in additive manufacturing environments. By reducing the need for repetitive physical experiments, the proposed architecture significantly decreases material consumption, testing costs, and development time while enhancing prediction accuracy and manufacturing efficiency. The integration of machine learning with additive manufacturing supports the development of smart manufacturing systems aligned with Industry 4.0 principles.

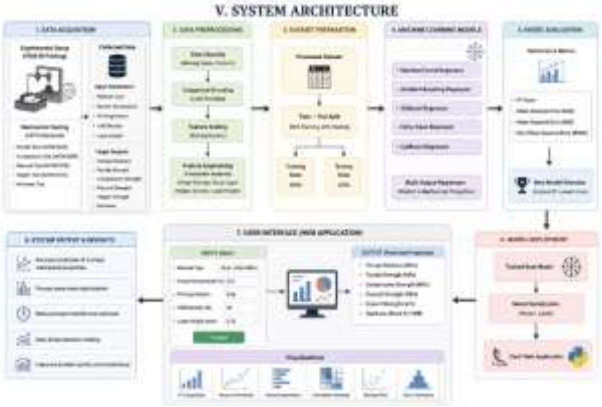
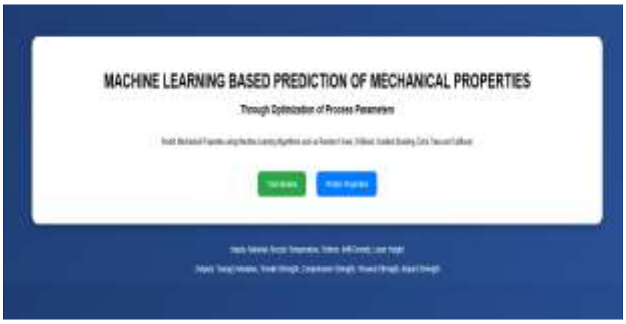


Fig 5.1: System Architecture

VI. IMPLEMENTATION


MACHINE LEARNING BASED PREDICTION OF MECHANICAL PROPERTIES

Through Optimization of Process Parameters

Fig 6.1: Home page

Fig 6.1 Illustrates the Home Page serves as the entry point of the developed Machine Learning-based Mechanical Properties Prediction System. It provides a simple and user-friendly interface through which users can access the model training and prediction functionalities


Machine Learning Based Prediction of Mechanical Properties

Fig 6.2: Models Training Results

Fig 6.2 Illustrates this page displays the performance evaluation results of all implemented machine learning models, including Random Forest, XGBoost, Gradient Boosting, Extra Trees, and CatBoost. The evaluation metrics such as R² Score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are presented for comparison. Graphical visualizations and performance tables assist users in identifying the best-performing model.

Mechanical Properties Prediction

Material: PLA +

Nozzle Temperature: [illegible]

Pattern: RECTILINEAR

Infill Density: 100

Layer Height: [illegible]

Fig 6.3: Prediction Input Page

Fig 6.3 Illustrates the Prediction Input Page allows users to enter FDM process parameters required for mechanical property estimation. Input parameters include Material Type, Nozzle Temperature, Printing Pattern, Infill Density, and Layer Height

Prediction Results

Young's Modulus : 875.0 MPa

Tensile Strength : 33.36 MPa

Compressive Strength : 72.67 MPa

Flexural Strength : 106.52 MPa

Impact Strength : 16.5 J/m

Hardness : 79.0

Fig 6.4: Prediction Results Page

Fig 6.4 Illustrates the Prediction Results Page displays the predicted mechanical properties generated by the selected machine learning model. The output includes Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness.

VII. Results And Discussion

Model Evaluation Graphs

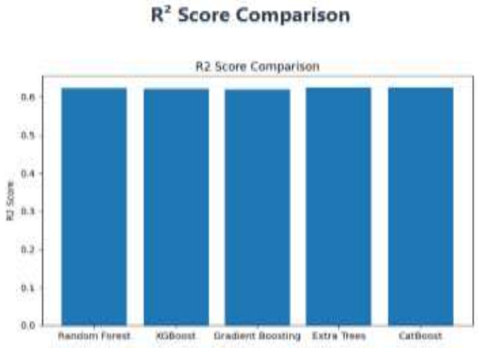


Fig 7.1 : R^2 Score Comparison

Fig 7.1 Illustrates this graph compares the prediction accuracy of all machine learning models using the R² Score metric. A higher R² value indicates better predictive performance and stronger correlation between actual and predicted mechanical properties. The results show that Extra Trees and CatBoost achieved the highest R² values, demonstrating superior capability in modeling the nonlinear relationships between FDM process parameters and mechanical properties.

R² Score Line Chart

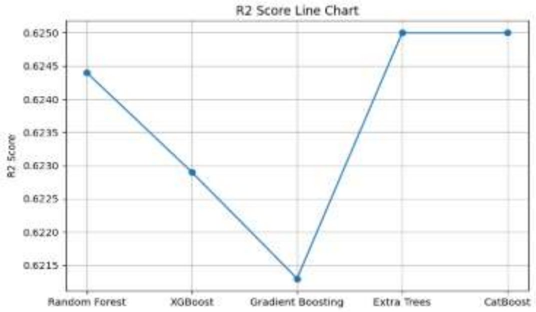


Fig 7.2 : R² Score Line Analysis

Fig 7.2 Illustrates the line chart illustrates the variation in R² scores across different machine learning algorithms. The upward trend observed for Extra Trees and CatBoost indicates improved prediction capability compared to Random Forest, XGBoost, and Gradient Boosting models. This visualization helps identify the most effective algorithm for multi-output mechanical property prediction.

MAE Comparison

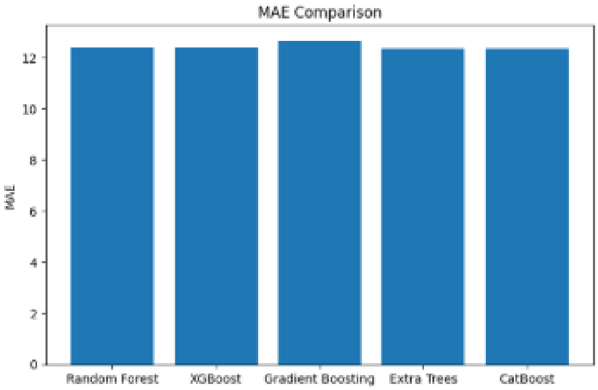


Fig 7.3 : Mean Absolute Error (MAE) Comparison

Fig 7.3 Illustrates the MAE comparison graph presents the average absolute prediction error generated by each machine learning model. Lower MAE values indicate better prediction accuracy. The graph shows that Extra Trees and CatBoost produce the lowest prediction errors, confirming their effectiveness in accurately estimating mechanical properties.

MSE Comparison

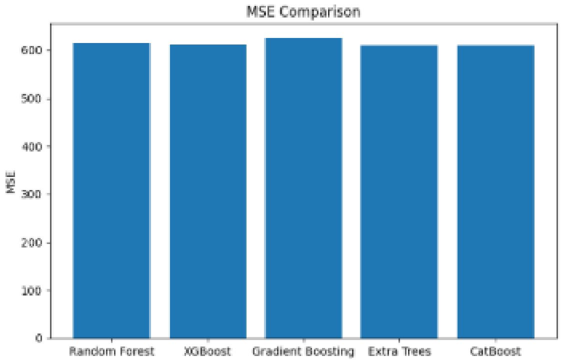


Fig 7.4 : Mean Squared Error (MSE) Comparison

Fig 7.4 Illustrates this graph compares the Mean Squared Error values of the implemented models. MSE penalizes larger prediction errors more heavily than MAE. Lower MSE values indicate more reliable predictions. The results demonstrate that Extra Trees and CatBoost achieve lower error values compared to the remaining algorithms.

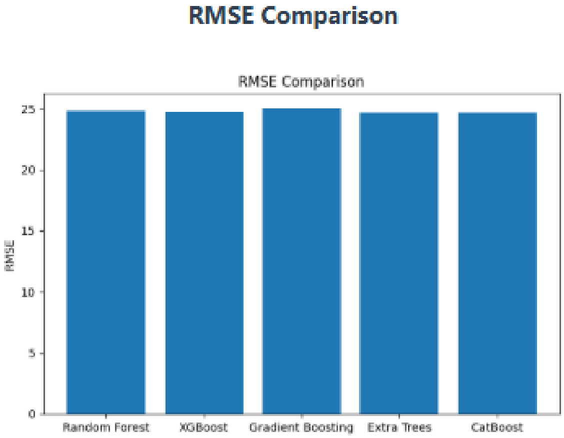


Fig 7.5 : Root Mean Squared Error (RMSE) Comparison

Fig 7.5 Illustrates the RMSE graph provides a measure of the standard deviation of prediction errors. Smaller RMSE values represent better model performance and improved prediction consistency. The comparison confirms that ensemble learning algorithms, particularly Extra Trees and CatBoost, deliver more stable predictions.

Feature Analysis

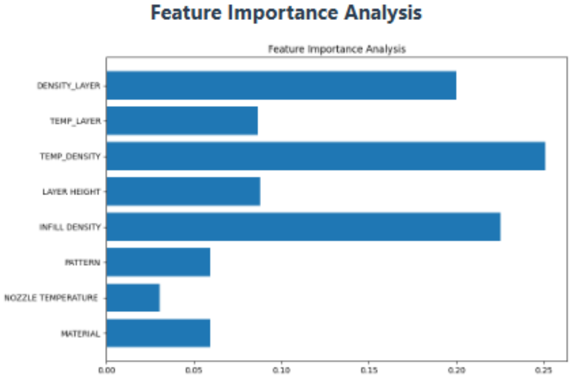


Fig 7.6 : Feature Importance Analysis

Fig 7.6 Illustrates this graph illustrates the relative contribution of each input parameter toward predicting mechanical properties. Interaction features such as Temperature–Density, Density–Layer Height, and Infill Density exhibit the highest importance scores, indicating their significant influence on the mechanical behavior of FDM printed components.

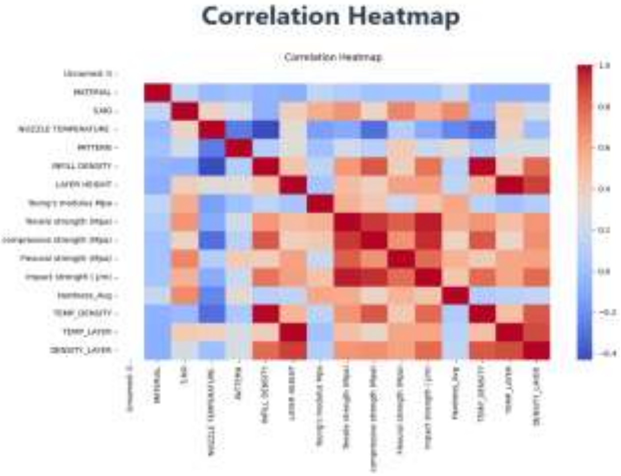


Fig 7.7 : Correlation Heatmap of Process Parameters and Mechanical Properties

Fig 7.7 Illustrates the correlation heatmap visualizes the relationships among process parameters and mechanical properties. Positive correlations are represented by warmer colors, while negative correlations appear in cooler colors. The heatmap reveals strong associations between engineered features and output properties, validating the effectiveness of feature engineering in improving model performance.

Error Analysis

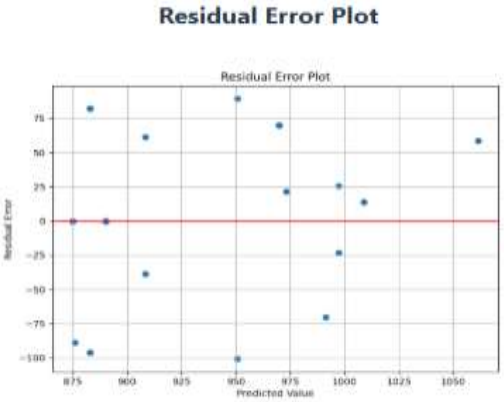


Fig 7.8 : Residual Error Plot

Fig 7.8 Illustrates the residual error plot shows the difference between actual and predicted values. Ideally, residuals should be randomly distributed around zero without any systematic pattern. The graph demonstrates that most prediction errors are centered near zero, indicating good model generalization and minimal prediction bias.

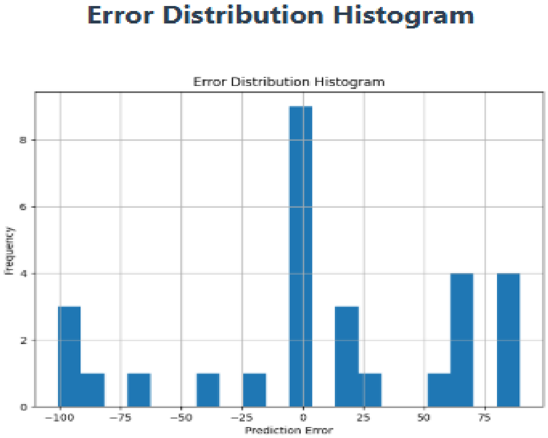


Fig 7.9 : Prediction Error Distribution Histogram

Fig 7.9 Illustrates this histogram illustrates the distribution of prediction errors generated by the selected machine learning model. The concentration of errors around zero suggests that the model produces accurate predictions with limited deviation from actual experimental values.

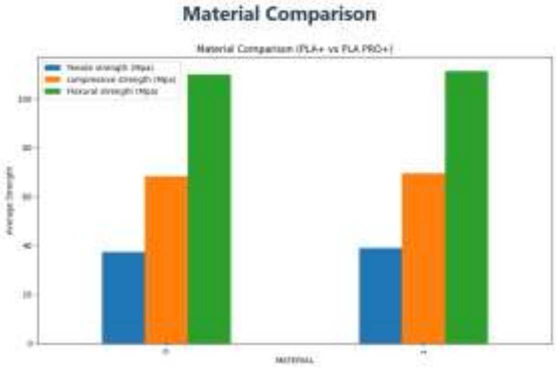


Fig 7.10 : Comparative Analysis of PLA+ and PLA PRO+ Materials

Fig 7.10 Illustrates this graph compares the average mechanical properties obtained from PLA+ and PLA PRO+ materials. The analysis highlights differences in tensile strength, compressive strength, and flexural strength between the two materials, providing valuable insights for material selection in additive manufacturing applications.

Prediction Analysis

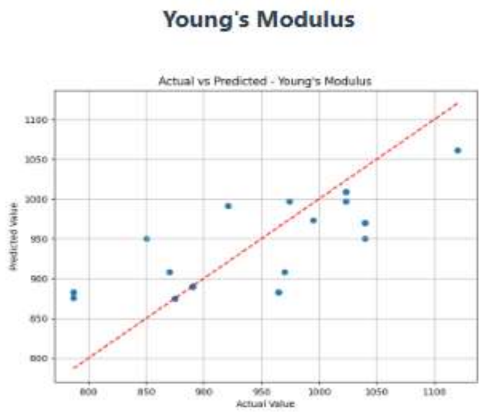


Fig 7.11 : Actual vs Predicted Values for Young's Modulus

Fig 7.11 Illustrates this scatter plot compares experimentally measured Young's Modulus values with machine learning predictions. Data points located close to the diagonal reference line indicate accurate predictions. The graph demonstrates strong agreement between actual and predicted values, validating the model's ability to estimate material stiffness.

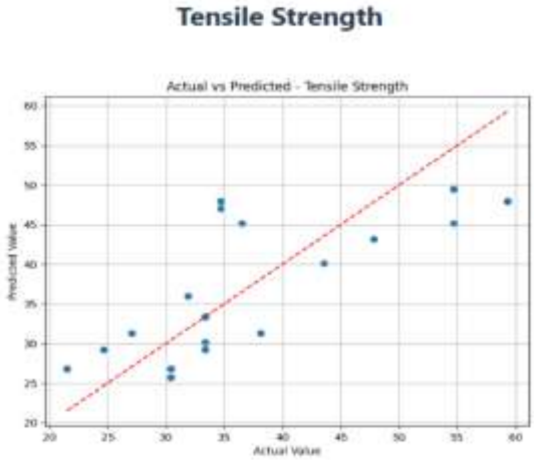


Fig 7.12 : Actual vs Predicted Values for Tensile Strength

Fig 7.12 Illustrates the graph presents the relationship between actual and predicted tensile strength values. Most observations lie near the reference line, indicating that the developed model successfully captures the tensile behavior of FDM printed components under varying process conditions.

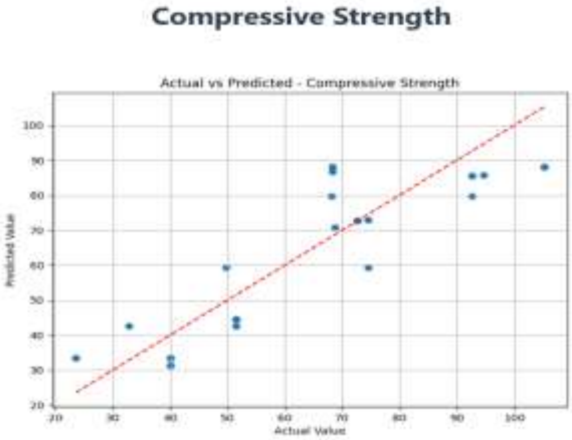


Fig 7.13 : Actual vs Predicted Values for Compressive Strength

Fig 7.13 Illustrates this figure evaluates the prediction accuracy of compressive strength. The close alignment of data points with the ideal prediction line confirms that the model effectively predicts compressive performance using process parameter information.

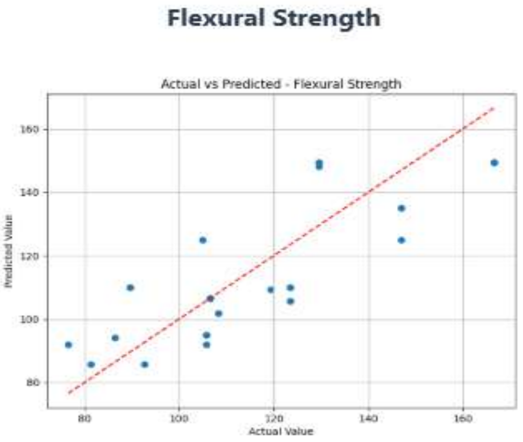


Fig 7.14 : Actual vs Predicted Values for Flexural Strength

Fig 7.14 Illustrates the flexural strength prediction graph demonstrates the model's capability to estimate bending performance. The majority of observations are distributed near the diagonal line, indicating good prediction accuracy and strong model reliability.

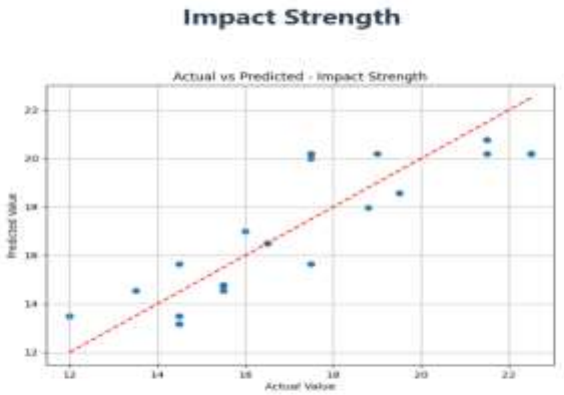


Fig 7.15 : Actual vs Predicted Values for Impact Strength

Fig 7.15 Illustrates this scatter plot compares actual and predicted impact strength values. The distribution of points near the ideal prediction line confirms that the machine learning framework can effectively estimate impact resistance based on FDM process parameters.

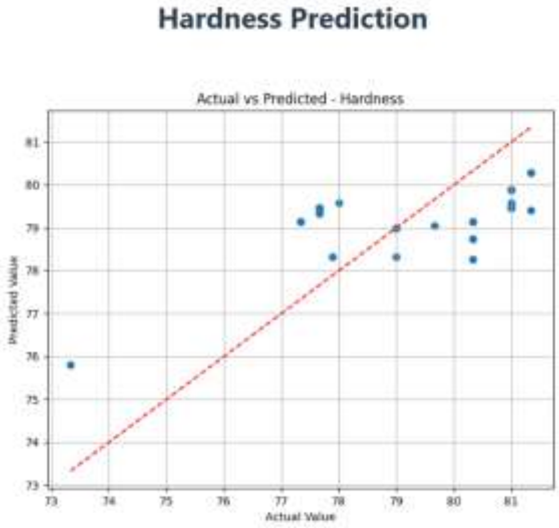


Fig 7.16 : Actual vs Predicted Values for Hardness Prediction

Fig 7.16 Illustrates this graph illustrates the prediction performance for hardness values. The close correspondence between actual and predicted observations indicates that the model accurately captures hardness characteristics and can be used for rapid hardness estimation without physical testing.

VIII. Conclusion

This research presented a Machine Learning Based Prediction of Mechanical Properties Through Optimization of Process Parameters for Fused Deposition Modeling (FDM) based additive manufacturing. The proposed framework utilizes important process parameters such as material type, nozzle temperature, infill density, layer height, and printing pattern to predict critical mechanical properties including Young's Modulus, Tensile Strength, Compressive Strength, Flexural Strength, Impact Strength, and Hardness. Advanced machine learning algorithms including Random Forest, XGBoost, Gradient Boosting, Extra Trees, and CatBoost were implemented and evaluated to identify the most suitable predictive model.

Experimental results demonstrated that ensemble-based machine learning techniques effectively capture the complex nonlinear relationships between process parameters and mechanical properties. The developed system achieved reliable prediction performance with improved accuracy and reduced prediction errors. Various evaluation metrics such as R^2 Score, MAE, MSE, and RMSE confirmed the effectiveness of the proposed approach. Graphical analyses including feature importance, correlation heatmaps, residual plots, error distributions, and actual-versus-predicted comparisons further validated the robustness of the developed prediction framework.

The integration of a Flask-based web application provides a user-friendly platform for model training, performance visualization, and real-time prediction of mechanical properties. The proposed system significantly reduces experimental effort, material wastage, testing time, and production cost while supporting intelligent decision-making in additive manufacturing environments. Therefore, the developed machine learning framework can serve as an effective tool for process optimization and quality improvement in modern smart manufacturing systems.

IX. Future Scope

In future work, larger datasets containing additional process parameters and material combinations can be incorporated to further improve prediction accuracy. Deep learning techniques, hybrid ensemble models, and automated hyperparameter optimization methods may be explored to achieve superior predictive performance. Integration with IoT-enabled manufacturing systems and real-time monitoring platforms can facilitate adaptive process control and intelligent production management. Furthermore, the proposed framework can be extended to other additive manufacturing technologies and advanced composite materials, supporting the development of Industry 4.0 and smart manufacturing applications.

X. References

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