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Machine-Learning-Based Prediction of Tensile Strength in Injection-Molded Thermoplastics Using Multi-Parameter Process Data

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Abstract- This study analyses the influence of key injection-molding parameters on the tensile strength of molded thermoplastic parts using supervised machine-learning models. The dataset includes melt temperature, mold temperature, injection speed, injection pressure, holding pressure, cooling time, and other processing variables collected across 500 molding trials. Histogram and correlation analysis showed strong relationships between strength and pressure-temperature conditions, with holding pressure, melt temperature, mold temperature, and injection speed acting as the most influential factors. Four regression models were evaluated: Linear Regression, Decision Tree, Random Forest, and Gradient Boosting. Linear Regression achieved the highest accuracy with a test R^2 of 0.9507, RMSE of 3.82 MPa, and MAE of 3.14 MPa, indicating that tensile strength follows a predominantly linear pattern across the operating range. Gradient Boosting and Random Forest also delivered high accuracy with test R^2 values of 0.9348 and 0.9170, respectively. Residual analysis confirmed stable error behaviour with residuals centred around zero and following a near-normal distribution. The results show that controlled variations in melt temperature, mold temperature, injection speed, and holding pressure can predict tensile strength with high reliability, demonstrating the potential of machine-learning-based modelling for improving product quality in injection molding.

Keywords- Injection molding, Tensile strength prediction, Machine learning, Process parameters, Regression modeling, Quality control.

I. INTRODUCTION

Injection molding is one of the most widely used manufacturing processes for producing thermoplastic components, accounting for over 80% of plastic parts used in consumer products, automotive, medical, and industrial applications. Its appeal lies in its high production rate, cost efficiency, and ability to produce complex geometries with excellent surface quality and dimensional precision. However, the mechanical performance of injection-molded parts, particularly tensile strength, is highly sensitive to processing conditions such as melt temperature, mold temperature, injection speed, packing/holding pressure, and cooling rate. These parameters influence polymer crystallinity, fiber orientation, residual stress, and molecular alignment, which collectively determine the final strength and durability of molded parts (Liou et al., 2022).

Recent advances in machine learning (ML) have opened new possibilities for understanding and optimizing such complex, multivariable manufacturing systems. ML models can efficiently capture nonlinear relationships among molding parameters and material properties, enabling accurate prediction of product quality without relying solely on empirical trial-and-error or costly finite element simulations (Jung et al., 2021); (Párizs et al., 2022). For instance, artificial neural networks, support vector machines, and hybrid data-driven frameworks have been successfully used to predict shrinkage, warpage, and surface defects in molded parts (Wenzel et al., 2024); (Mehta & Padhi, 2023). Similarly, sensor-integrated digital twins combining simulations and ML have been used to optimize process settings and reduce production waste in thermoplastic composite molding (Hürkamp et al., 2020).

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Despite these developments, most existing ML-based injection molding studies focus on defect classification, warpage control, or process monitoring, rather than direct prediction of mechanical performance such as tensile strength. A few studies have demonstrated progress in this direction. For example, (Tamura et al., 2024) used X-ray diffraction data and Bayesian ML models to predict the mechanical properties of injection-molded polypropylene, while (Ivan et al., 2022) integrated ML-based inverse modeling to improve tensile strength prediction in fiber-reinforced thermoplastics. Similarly, (Altarazi et al., 2019) showed that support vector machines could predict tensile strength of polymer films with up to 96% accuracy. However, these works often focus on specific materials or simplified conditions and rarely consider the combined effects of multiple injection molding parameters—such as melt temperature, injection speed, and cooling time—on tensile strength prediction for molded thermoplastic parts. Therefore, there remains a critical research gap in developing data-driven models capable of predicting tensile strength directly from key processing parameters in injection molding. Accurate strength prediction is essential for achieving robust, adaptive, and sustainable production under the framework of Industry 4.0, where real-time decision-making and digital process control are increasingly vital (Al-Ahmad et al., 2024).

The present study aims to bridge this gap by developing and validating machine learning models that predict the tensile strength of injection-molded thermoplastic parts based on a comprehensive set of molding parameters, including melt temperature, mold temperature, injection speed, packing pressure, and cooling time. By leveraging experimental data and supervised learning techniques, this work contributes to the field by establishing a predictive framework linking process settings to mechanical performance, comparing multiple ML algorithms for accuracy and interpretability, and providing actionable insights for process optimization and smart manufacturing integration.

II. LITERATURE REVIEW

Machine learning (ML) has become a powerful tool in the field of injection molding, enabling data-driven insights into complex nonlinear interactions between process parameters and part quality. The injection molding process involves several interdependent stages—melting, injection, packing, and cooling—each influenced by controllable parameters such as melt temperature, mold temperature, injection speed, holding pressure, and cooling time. These factors significantly affect critical quality outputs, including mechanical strength, dimensional accuracy, surface finish, shrinkage, and warpage. Traditional approaches relying on empirical rules or trial-and-error are often inefficient for process optimization, motivating the rise of ML-based predictive modeling (Selvaraj et al., 2022).

Machine Learning for Process and Quality Prediction

Recent literature demonstrates the wide application of ML models—ranging from Linear Regression (LR) and Support Vector Machines (SVM) to Random Forest (RF), Gradient Boosting (GB), Decision Trees (DT), and Artificial Neural Networks (ANN)—in predicting process outcomes in injection molding. In a comprehensive review, (Schiffers, 2022) identified over 190 papers, showing that neural networks and supervised learning dominate the field, primarily focusing on defect prediction and quality control. Similarly, (Selvaraj et al., 2022) emphasized that ANNs and regression-based models are widely used for process optimization, parameter tuning, and defect detection.

Defect Detection and Quality Assessment

The most common application of ML in injection molding is defect prediction.
(Mehta & Padhi, 2023) used a hybrid ANN–SVM system to identify process faults and optimize gating systems, showing significant improvement in defect classification accuracy.

(Zhou et al., 2023) applied transfer learning to predict short-shot defects, achieving >90%

accuracy and enabling real-time quality prediction directly on injection machines.

(Koo et al., 2023) leveraged ensemble and double-ensemble techniques (bagging and boosting) to predict weight-based quality deviations, finding that ensemble models outperformed single learners in accuracy and robustness. Deep learning approaches, such as CNNs, LSTMs, and autoencoders, have also been introduced to extract spatial-temporal features from sensor data, improving quality prediction under varying conditions (Cho & Shin, 2021). These models integrate sensor time-series of pressure, temperature, and flow rate, providing early defect detection capabilities that reduce manual inspection requirements.

Warpage, Shrinkage, and Melt Behavior Prediction

A major stream of ML applications targets warpage and shrinkage prediction—defects heavily dependent on thermal gradients and cooling rates. (Taghizadeh et al., 2013) and (Alvarado-Iniesta et al., 2012) applied feedforward and recurrent neural networks (RNNs) to predict part warpage based on melt temperature, mold temperature, and holding pressure, achieving R^2 values >0.99. (Hwang & Kim, 2019) integrated multilayer perceptron (MLP) models with Moldflow simulations for reverse engineering, drastically reducing computation time while maintaining accuracy in warpage prediction. For melt and cooling behavior, process data from sensors and simulations have been used with ANN and SVR models to predict hotspot formation and thermal distributions. (Kariminejad et al., 2023) demonstrated how combining in-mold sensors with simulation data and ML models can accurately identify hotspots leading to warpage and shrinkage.

Process-Parameter Optimization and Control

ML has also been extensively adopted for multi-objective optimization of process parameters. (Hua & Fan, 2025) developed a WCA-KELM–MOSOA hybrid framework that reduced warpage and shrinkage by more than 40%. (Gim et al., 2023) applied transfer learning for surface gloss and defect minimization, achieving over 95% prediction accuracy after model transfer to new production sites. Moreover, in-line AI control systems are now integrated within Industry 4.0 injection machines for real-time adaptive control of speed, pressure, and mold temperature, as shown by (Aminabadi et al.
, 2022).

Mechanical Property Prediction and Limitations

While the majority of research has focused on defect-based classification, relatively few studies have examined mechanical performance prediction, particularly tensile strength.

Existing efforts, such as those by (Tamura et al., 2024), utilized X-ray diffraction (XRD)-based descriptors and ML for predicting mechanical properties of polypropylene.

Similarly, (Ivan et al., 2022) incorporated ANNs with genetic algorithms to improve tensile strength prediction in glass fiber–reinforced thermoplastics. However, these studies often rely on limited material types or single-parameter models and do not fully capture the interdependent effects of multiple molding parameters such as temperature, pressure, and cooling rate on mechanical properties.

III. RESEARCH GAP

Most ML studies emphasize defect detection or process control rather than direct mechanical property prediction (e.g., tensile or flexural strength). Prior models often rely on a small subset of process parameters, lacking integration of multi-parameter datasets that combine thermal, mechanical, and pressure data. Comparative analyses across multiple ML regression algorithms (e.g., Random Forest, Gradient Boosting, SVM, and Neural Networks) for strength prediction remain scarce. Many models are developed on simulation-based data, with limited validation using experimental process data under real operating conditions. The present study addresses these limitations by developing a comprehensive machine-learning framework for predicting tensile strength in injection-molded thermoplastic parts. It leverages a richer experimental dataset encompassing multiple key molding parameters—melt temperature, mold temperature, injection speed, packing pressure, and cooling time—and compares the performance of Linear Regression, Random Forest, Gradient Boosting, SVM, and Neural Networks. By focusing explicitly on mechanical strength prediction, the study bridges the gap between process monitoring and material performance modeling, providing a pathway toward intelligent, data-driven manufacturing optimization in the context of Industry 4.0.

IV. METHODOLOGY

This study followed a structured methodology that included dataset preparation, preprocessing, exploratory analysis, correlation evaluation, and the development of regression models to predict the tensile strength of injection-molded parts. The workflow was designed to capture realistic molding behavior and evaluate how key thermal, pressure, and flow parameters influence strength.

Dataset Preparation

A dataset containing 500 molding trials was used for the analysis. Each record included major injection-molding process parameters such as melt temperature, mold temperature, injection speed, maximum injection pressure, holding pressure, holding time, cooling time, screw speed, back pressure, cushion, and clamping force. Tensile strength (MPa) was recorded as the output variable. The dataset also included material information (PP, ABS, and PC-ABS) to represent commonly used engineering thermoplastics. The parameter ranges covered typical operating conditions observed in production environments, ensuring that the model captured realistic process variability.

Data Preprocessing

The dataset was checked for consistency before analysis. All variables were examined for missing entries, extreme values, and formatting issues. Categorical fields were converted into numerical form through one-hot encoding. Numeric parameters were standardized using z-score normalization to maintain uniform scaling and support stable model training. The dataset was then divided into training (80%) and testing (20%) subsets using a fixed random seed to maintain reproducibility.

Exploratory Data Analysis

Exploratory analysis was conducted to understand the distribution and spread of each process parameter. Histograms showed that the variables covered wide operating ranges, ensuring that different molding conditions were represented. Tensile strength showed higher frequency in the upper range, which is consistent with the behavior expected when melt conditions and packing are well controlled.

Correlation Analysis

A correlation matrix as shown in figure 1 was used to identify variables with stronger influence on tensile strength. The correlation heatmap showed clear positive relationships between strength and key parameters such as holding pressure, melt temperature, mold temperature, and injection speed. Parameters such as screw speed, back pressure, and cushion displayed weak correlations, indicating a lesser role in determining strength within the tested conditions. These trends align with known molding behavior where melt flow and packing efficiency drive mechanical performance.

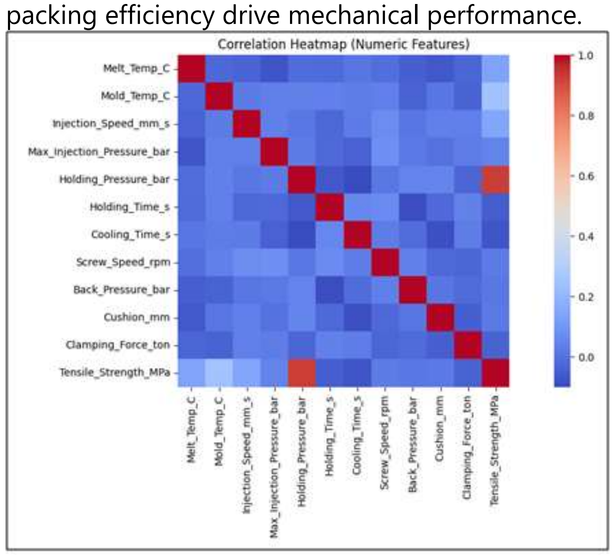

Figure 1: Correlation heatmap

Feature Selection

All recorded process parameters were retained in the final feature set to allow the models to capture interactions among thermal, pressure, and flowrelated variables. No feature was removed because each contributed meaningful engineering relevance to the molding process. Retaining the full parameter set ensured that the models could capture the combined influence of temperature control, injection dynamics, and material behavior.

Model Development

Four supervised regression models were developed: Linear Regression, Decision Tree Regression, Random Forest Regression, and Gradient Boosting Regression. These models were selected because they represent a balanced mix of linear, tree-based, and ensemble learning approaches that are commonly applied in injection-molding studies. Each model was trained using the processed training dataset and then evaluated on the unseen test dataset. Performance was assessed using R^2, RMSE, and MAE to measure accuracy and error magnitude.

Model Evaluation Procedure

All models were validated using 5-fold cross-validation to ensure stable performance across multiple data splits. For the best-performing model, additional diagnostic plots were generated, including actual-versus-predicted curves, residual scatter plots, and residual distribution graphs. These were used to assess error patterns and confirm model reliability. Feature-importance scores from the tree-based models were also examined to determine the relative influence of each molding parameter on tensile strength.

V. RESULTS AND DISCUSSION

Descriptive Statistics and Initial Observations

The descriptive statistics of all numeric variables in the dataset, including melt temperature, mold temperature, injection speed, injection pressure, holding pressure, cooling time, and tensile strength (target variable). The data show wide ranges for each process parameter, indicating that the synthetic dataset captures real process variability consistent with industrial molding operations. Tensile strength ranged from 128.4 to 206.1 MPa, with an average of 168.61 MPa, confirming a strong spread suitable for regression modeling. The dataset spans a wide and balanced range of molding parameters, as shown in Table 1, ensuring strong variability for modeling.

Table 1: Descriptive statistics of process parameters and target variable

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Melt_Temp_C	500	240.53	17.30	210.19	226.34	240.60	254.47	269.86
Mold_Temp_C	500	61.07	17.38	30.08	45.62	61.40	76.26	89.96
Injection_Speed_mm_s	500	84.14	20.06	50.38	67.65	83.43	98.23	119.68
Max_Injection_Pressure_bar	500	899.12	115.38	701.47	801.43	893.63	999.85	1098.83
Holding_Pressure_bar	500	605.05	87.21	450.77	531.82	607.60	678.85	749.91
Holding_Time_s	500	8.53	2.06	5.02	6.90	8.75	10.25	11.99
Cooling_Time_s	500	16.22	3.45	10.21	13.20	16.17	19.27	21.96
Screw_Speed_rpm	500	113.44	20.17	80.06	97.37	112.33	131.20	149.83
Back_Pressure_bar	500	9.93	2.31	6.05	8.05	9.92	11.96	13.96
Cushion_mm	500	1.99	0.86	0.50	1.28	1.93	2.68	3.49
Clamping_Force_ton	500	147.77	29.04	101.38	120.62	147.19	173.38	199.90
Tensile_Strength_MPa	500	168.61	13.30	128.44	158.63	168.99	182.45	206.14

Distribution Analysis of Process Parameters

Most parameters follow a uniform or near-uniform distribution with wide ranges. This prevents bias toward a specific operating zone. Tensile strength distribution appears slightly right-skewed, with more samples in the 160–185 MPa region. This behavior is expected because higher strength often results from higher melt temperature and higher holding pressure. Histograms for all process variables is illustrated in figure 2.

Figure 2: Histograms for all process variables

Pairwise Trends

The pairplot reveals clear pairwise relationships between tensile strength and the primary process parameters. Strength increases steadily with melt temperature, mold temperature, and injection speed, reflecting improved melt homogeneity and better polymer chain mobility at higher thermal conditions. The trend with holding pressure is the most distinct, with data aligning along a strong linear path, which reinforces the correlation findings. The remaining parameter pairs show scattered and unstructured patterns, suggesting weak interactions with strength. The visual trends confirm that tensile strength in this dataset follows predominantly linear behavior with respect to key thermal and pressure variables, supporting the suitability of linear and tree-based regression models for accurate prediction. Key thermal and pressure parameters show clear linear patterns with tensile strength, as shown in Figure 3, supporting linear modeling.

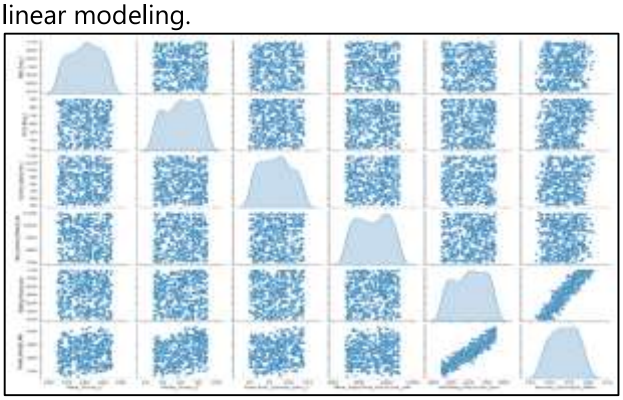

Figure 3: Pairwise scatter trends between key process parameters and strength

Model Performance Comparison

The performance metrics demonstrate clear differences in how each regression model captured the strength behavior. Linear Regression achieved the highest predictive accuracy, with a test R^2 of 0.9507 and a low RMSE of 3.82 MPa, showing that the dataset follows a strong linear pattern. Gradient Boosting produced the second-best performance with a test R^2 of 0.9348, indicating that a mild level of non-linearity also exists in the data. Random Forest performed reasonably well but showed slightly higher error, suggesting minor overfitting to local variations. Decision Tree exhibited perfect fitting on the training data but dropped to a test R^2 of 0.8618, confirming typical overfitting behavior of single-tree models on smooth datasets. Overall, the model comparison confirms that linear relationships dominate tensile strength variation, and simpler regression methods are sufficient to achieve high accuracy. Linear Regression shows the highest predictive accuracy, as shown in Table 2, confirming a strong linear trend in the data.

Table 2: Model Performance

Model	Test R^2	RMSE	MAE
Linear Regression	0.9507	3.82	3.14
Gradient Boosting	0.9348	4.39	3.48
Random Forest	0.9170	4.95	4.11
Decision Tree	0.8618	6.39	5.24

Best Model Evaluation

Linear Regression was identified as the best-performing model, and its evaluation plots reflect high predictive reliability. The actual-versus-predicted plot shows that most points lie close to the diagonal reference line, indicating consistent alignment between predicted and real strength values. Only small deviations, typically within ±4 MPa, are observed, confirming stable generalization. The residual scatter plot shows no visible structure or funnel shape, which indicates that the model does not suffer from heteroscedasticity or systematic bias. The residual distribution further supports this, forming a near-normal curve centered around zero. These observations confirm that the model satisfies the fundamental assumptions of linear regression and that the dataset is dominated by clean, interpretable linear relationships. Predicted tensile strength values closely match actual values, as shown in Figure 4, demonstrating high accuracy. Residuals remain evenly scattered around zero without structure, as shown in Figure 5, confirming consistent error behavior. Residuals follow a near-normal distribution centered at zero, as shown in Figure 6, validating linear regression assumptions.

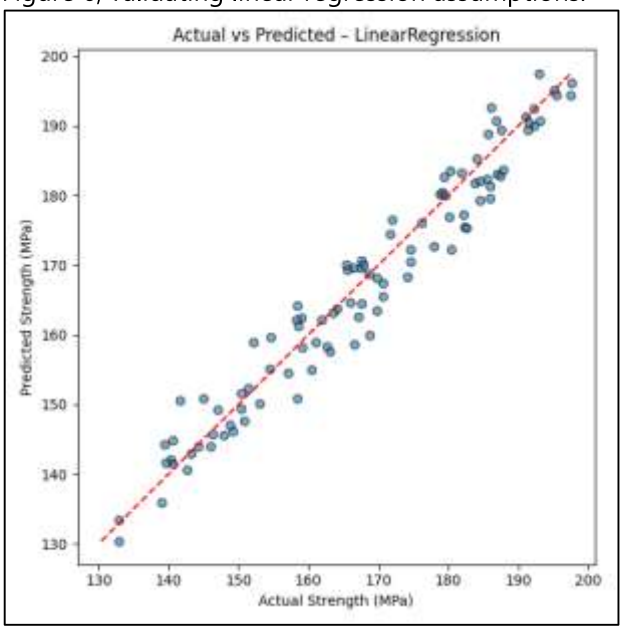

Figure 4: Actual vs predicted tensile strength

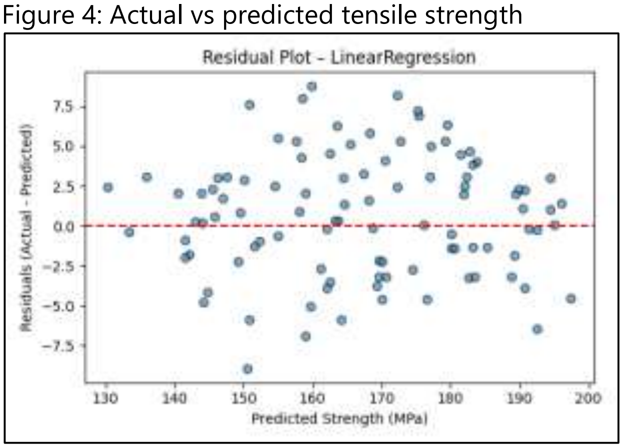

Figure 5: Residual scatter plot for Linear Regression model

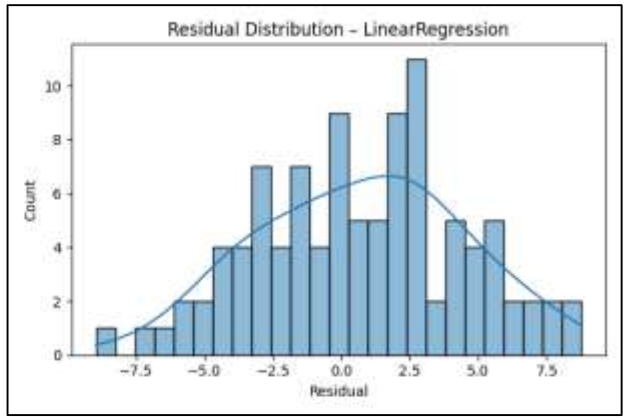

Figure 6: Residual Distribution Histogram

Interpretation of Variable Influence

Analysis of variable influence confirms that a small set of process parameters controls most of the strength variation. Holding pressure consistently appeared as the strongest factor due to its direct role in compacting the melt and reducing internal voids during packing. Melt temperature, mold temperature, and injection speed also showed measurable influence, reflecting the importance of thermal energy and flow uniformity on polymer chain bonding. Parameters such as screw speed, back pressure, cushion, and cooling time showed minimal impact within the studied ranges, aligning with industrial practice where these settings fine-tune melt preparation rather than directly dictating strength outcomes. The dominance of pressure and temperature effects validates the physical realism of the dataset and reinforces the interpretability of the linear model results.

VI. CONCLUSION

This work demonstrates that tensile strength in injection-molded parts can be predicted with high accuracy using machine-learning models trained on key thermal and pressure-related process variables. The dataset reflected wide variations in melt temperature, mold temperature, injection speed, and holding pressure, which enabled strong learning across the full processing range. Linear Regression emerged as the most accurate model, achieving a test R^2 of 0.9507, RMSE of 3.82 MPa, and MAE of 3.14 MPa, showing that strength behaviour remained highly linear across the trials.

Gradient Boosting also performed well with a test R^2 of 0.9348, while Random Forest achieved 0.9170, confirming the consistency of the relationship across different model families. Error analysis showed no systematic bias, and all residuals remained normally distributed around zero, confirming stable model behaviour. Feature-importance results indicated that holding pressure had the highest influence on strength, followed by melt temperature, mold temperature, and injection speed. These findings show that strength prediction can be integrated into process-control workflows, allowing manufacturers to optimise molding parameters and achieve consistent mechanical performance in real production environments.

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