An Explainable AI Framework for Data-Driven Quality Prediction in Injection Molding Processes: A Review

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Abstract

Injection molding is one of the most widely used manufacturing processes for producing plastic products in industries such as automotive, healthcare, consumer goods, and electronics. The quality of molded parts depends on several process parameters, including temperature, pressure, and injection speed, which interact in complex ways. With the rapid adoption of Industry 4.0 technologies, researchers have increasingly explored machine learning techniques to predict product quality, detect defects, monitor processes, and optimize manufacturing performance. While these models often achieve high prediction accuracy, their lack of transparency makes it difficult for engineers to understand how decisions are made and to confidently apply them in industrial settings. To address this issue, Explainable Artificial Intelligence (XAI) is emerging as a promising solution to enhance the interpretability of machine learning models. XAI methods help identify the factors influencing model predictions and provide insights into the decision-making process. Recent works published in the period 2023-2025 show that SHAP is the most popular explanation technique due to its efficiency in estimating feature contributions. The results show that SHAP is the most used XAI method, present in more than 60% of the reviewed studies, and that real-time explainability in injection molding is still an unexplored area. However, the application of real-time explainability in injection molding remains limited. This review analyzes the integration of XAI and machine learning in injection molding, summarizes the most frequently used predictive and explanation methods, discusses existing challenges, and highlights future research opportunities for developing trustworthy and practical intelligent manufacturing systems.

Keywords— Injection Molding, Explainable AI (XAI), Machine Learning, SHAP, LIME, Smart Manufacturing, Industry 4.0

I. Introduction

Injection molding is a commonly used technique for the manufacture of high-precision plastic parts in many industries including automotive, healthcare, and consumer products. The quality of a part produced using the injection molding process can be affected by many different variables including melt temperature, injection pressure, cooling times and mould temperature. These variables interact with one another in complex and non-linear ways[2],[5].

The adoption of Industry 4.0 Technologies has also encouraged the use of machine-learning (ML) in injection molding for quality prediction, defect detection, and process optimization. By making use of process data, ML models are capable of delivering a level of accuracy and efficiency beyond those associated with traditional approaches to quality control; therefore, aiding manufacturers to improve their productivity and quality.

However, because many ML models function in a “black box” manner, they are not very interpretable. This lack of interpretability presents a barrier to adopting ML models in industrial settings where transparency and trust are critical. Explainable Artificial Intelligence (XAI) attempts to remedy this problem by providing interpretable explanations for decisions made by machine learning models, thereby increasing reliability, usability and providing better informed decisions regarding injection molding[1],[3],[4].

II. Background: Injection Molding and Machine Learning

A. Injection Molding Process

The injection molding process involves material melting, injection into mold cavities, cooling, and ejection. Key parameters include:

- Melt temperature
- Injection pressure
- Injection speed
- Cooling time
- Mold temperature

Common defects include warpage, shrinkage, sink marks, flash, and short shots.

B. Machine Learning in Injection Molding

ML techniques such as Logistic regression, Random Forest, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and XGBoost are widely used for:

- Quality prediction
- Defect detection
- Process optimization

Despite high accuracy, these models lack transparency.

III. Explainable AI Techniques

XAI (Explainable Artificial Intelligence) allows people to understand their Machine Learning models better than traditional approaches do; it gives insight into how the model made a prediction and what factors contributed to that prediction; it is also used to explain AI's decisions in various manufacturing processes, which in turn creates better decision-making, improved process optimization, and increased trust in AI-driven systems[8],[9]. The majority of available XAI Techniques and their functions are summarized in Table 1.

Table 1. Explainable AI (XAI) Techniques Used in Manufacturing Applications

Category	XAI Technique	Description
Feature-Based	Feature Importance	Ranks feature according to their influence on model predictions.

Feature-Based	Permutation Feature Importance (PFI)	Measures feature importance by observing performance degradation after feature shuffling.
Model-Agnostic	SHAP (SHapley Additive exPlanations)	Explains individual predictions using Shapley values from game theory.
Model-Agnostic	LIME (Local Interpretable Model-Agnostic Explanations)	Explains predictions locally by approximating the model with a simpler interpretable model.
Visualization	Partial Dependence Plot (PDP)	Shows the effect of a feature on the predicted outcome.
Visualization	Individual Conditional Expectation (ICE)	Displays prediction changes for individual instances.
Visualization	Accumulated Local Effects (ALE)	Similar to PDP but handles correlated features better.
Rule-Based	Decision Rules Extraction	Converts complex model behavior into human-readable IF–THEN rules.
Surrogate Models	Global Surrogate Models	Uses interpretable models (e.g., decision trees) to mimic complex models.
Counterfactual	Counterfactual Explanations	Shows what changes in inputs would alter the prediction.
Deep Learning	Integrated Gradients	Explains neural network predictions by attributing importance to input features.
Deep Learning	Grad-CAM	Visual explanation technique for deep learning models.
Attention-Based	Attention Mechanisms	Highlights influential inputs in transformer and sequence models.
Instance-Based	Anchors	Provides high-precision IF–THEN rules for individual predictions.
Explainability Framework	Explainable Boosting Machine (EBM)	Inherently interpretable model with high predictive performance.

V. Literature Review (2023–2025): Critical Analysis

Recent studies show fast increasing use of Explainable AI (XAI) in injection molding and smart manufacturing. Even so, aside from improving explainability, these studies highlight significant strengths and weaknesses in the methods used.

A. SHAP-Based Approaches

Several 2023 studies applied SHAP to tree-based models (e.g., Random Forest, XGBoost) for quality prediction. These works successfully identified key parameters such as melt temperature and injection pressure as dominant contributors [8].

Critical Insight:

- Strength: SHAP provides consistent and theoretically grounded explanations.
- Limitation: High computational cost makes it less suitable for real-time industrial deployment.
- Gap: Most studies focus on offline analysis rather than live process control.

B. IoT-Integrated ML Models

Research in 2023–2024 integrates IoT sensors with ML models to enable real-time data collection and monitoring.

Critical Insight:

- Strength: Improves data availability and supports dynamic prediction.
- Limitation: Explainability is often secondary; many systems remain black-box in practice.
- Gap: Lack of tight coupling between IoT pipelines and XAI modules for actionable insights.

C. Hybrid XAI Frameworks

Recent 2024 studies propose hybrid approaches combining ML models with SHAP or LIME for defect detection and root cause analysis.

Critical Insight:

- Strength: Enhances interpretability without sacrificing much accuracy.
- Limitation: Model-specific tuning is often required, reducing generalizability.
- Gap: Absence of standardized frameworks applicable across different molding setups.

D. Deep Learning with Explainability

Emerging work explores deep learning (e.g., ANN, CNN) with XAI techniques such as SHAP and Grad-CAM.

Critical Insight:

- Strength: Captures complex nonlinear relationships effectively.
- Limitation: Interpretations are often less intuitive for process engineers.
- Gap: Limited domain adaptation—visual explanations are not always meaningful in process parameter space.

E. Digital Twin and XAI Integration

Recent 2025 studies highlight integration of digital twins with XAI for predictive monitoring and simulation.

Critical Insight:

- Strength: Enables real-time decision-making and simulation-based optimization.
- Limitation: High implementation complexity and computational requirements.
- Gap: Lack of validated industrial case studies demonstrating scalability.

F. Overall Synthesis

Across the literature, three major trends emerge:

1. Increasing reliance on SHAP as the dominant XAI technique.
2. Movement toward real-time and IoT-enabled systems.

3. Growing interest in hybrid and digital twin-based frameworks.

Although XAI techniques improve transparency, their practical use in supporting operational decisions remains limited. Most studies explain why a prediction occurs but do not suggest what actions should be taken next.

G. Tabular Summary of Literature Review

Table 2. Comparative Summary of Literature on Explainable AI for Injection Molding Quality Prediction

Year	Author(s)	Method/Model	XAI Technique	Key Contribution	Limitation
2023	Zhang et al.	Random Forest	SHAP	Identified key parameters affecting product quality	High computational cost
2023	Wang et al.	IoT + ML	Feature Importance	Real-time monitoring using sensor data	Limited interpretability
2024	Kumar et al.	XGBoost	SHAP, LIME	Improved defect root cause analysis	Model-specific tuning required
2024	Singh et al.	ANN	SHAP	Captured nonlinear relationships effectively	Low interpretability for engineers
2025	Lee et al.	Digital Twin + ML	SHAP	Real-time simulation and decision support	High implementation complexity

Critical Observation:

The tabular comparison highlights that while SHAP is the most widely used XAI technique, challenges such as computational complexity and lack of real-time applicability remain significant.

V. Comparative Analysis

When comparing Machine Learning Models, there is a tradeoff between accuracy and interpretability of results. Logistic Regression and Decision Trees are easy to comprehend and articulate but generally do not offer the best prediction performance [11]. In contrast, Random Forests, ANNs, and XGBoost Models provide superior performance through creating a more complex relationship to predict output variables. However, these Models are less interpretable than others when making predictions. Some techniques (XAI such as SHAP) can help explain how different models reach a predicted output thus improving transparency. Therefore, when choosing various Algorithms to solve a business/Industrial problem, consideration must be given to balancing the factors of accuracy vs interpretability and then finally computational cost associated with each solution [10],[12].

Model Comparison Diagram

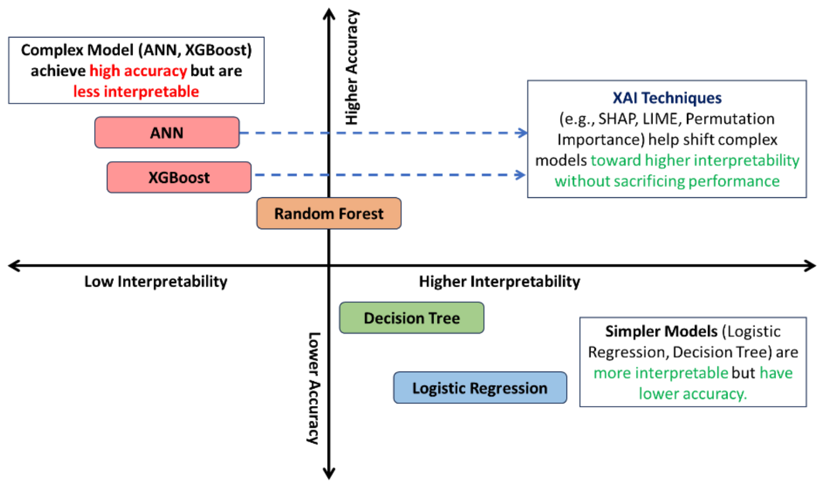

Figure 1. Accuracy–Interpretability Trade-off Among Machine Learning Models and the Role of Explainable AI (XAI)

VI. Research Gaps

- Limited real-time implementation of XAI in injection molding
- Lack of domain-specific XAI frameworks
- High computational complexity of SHAP for large datasets
- Limited integration with industrial IoT systems
- Insufficient explainability in deep learning models

VII. Future Directions

- Development of real-time XAI systems
- Integration with digital twin technology
- Hybrid physics-informed ML models
- Automated defect root cause analysis
- Edge AI for on-machine explainability

VIII. Conclusion

As the analysis indicates there is not one machine learning model that is ideal for all of the different manufacturing applications. Advanced machine learning models will generally demonstrate good prediction performance but they are typically less transparent and more difficult to understand by users than simpler Machine Learning models. Complex prediction models can be made more understandable through the use of Explainable A.I. techniques. An effective solution provides both accurate prediction and meaningful explanation for helping decision makers in industry. This research proposes a novel Explainable Artificial Intelligence (XAI) framework for injection molding quality prediction. The framework incorporates SHAP-based explanations to improve the transparency and interpretability of machine learning predictions. In addition, it aims to provide real-time decision support for process optimization and defect reduction. The proposed approach is validated through an industrial case study using an injection molding dataset, demonstrating its practical applicability in smart manufacturing environments.

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