XAI-IM: Explainable AI Framework for Injection Molding Quality Prediction in Smart Manufacturing

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Abstract

Injection molding is mainly used in manufacturing processes where maintaining consistent product quality remains a difficult challenge. Although **machine learning (ML)** techniques have improved quality assessment, their **black-box nature** limits transparency and reduces confidence in industrial decision-making. To address this limitation, this paper proposes **XAI-IM**, a **domain-specific explainable artificial intelligence (XAI) approach** for injection molding. The proposed approach integrates **machine learning**, **explainability**, **root cause analysis**, **decision support**, and **continuous learning** into a unified architecture. A conceptual use case demonstrates its capabilities to support transparent process optimization and intelligent manufacturing decisions. Future work will validate the proposed approach using **real industrial datasets** and evaluate its applicability in **Industry 4.0-enabled smart manufacturing** environments.

Keywords: Injection Molding, Explainable Artificial Intelligence (XAI), Machine Learning, Quality Prediction, Decision Support, Industry 4.0, Smart Manufacturing

1. Introduction

Injection molding is one of the most widely used manufacturing processes for the production of plastic components for automotive, healthcare, electronics, and consumer products [1]. The quality of molded parts is affected by several process parameters, such as the melt temperature, injection pressure, mold temperature, packing pressure, cooling time, and cycle time. Slight deviations in the above parameters can lead to defects like warpage, shrinkage, sink marks, and flash, which can increase the production costs and lead to wastage of material. Thus, a consistent product quality remains a key goal in modern manufacturing.

Since **Industry 4.0** is being adopted rapidly, manufacturing systems are more and more using machine learning (ML) as a means to monitor production processes and to anticipate product quality [7], [8]. Data-driven models are capable of analyzing complex correlations between process factors and providing accurate quality assessments, which enable the manufacturers to reduce faults and enhance production efficiency. In injection molding, machine learning methods such as Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) have been successfully employed for quality assessments [6]-[8]. These approaches have shown good prediction performance and have become useful instruments for intelligent manufacturing.

In fact, many machine learning algorithms give high accuracy. It works as a **black-box system**, which makes it difficult for industrial engineers to understand how predictions are derived. This lack of transparency reduces the user's trust and blocks the deployment of artificial intelligence in the real world, especially in industry, where judgements about processes must be well explained. To tackle this problem, Explainable Artificial Intelligence (XAI) has been proposed as an efficient method to improve the interpretability of models. Techniques such as **SHAP** (SHapley Additive exPlanations) and **LIME** (Local Interpretable Model-agnostic Explanations) enable us to pinpoint the impact of various parameter factors and understand the model behavior.

The currently available XAI techniques can enhance transparency but are largely aimed at providing explanations **for prediction results, with limited capabilities for root cause investigation, corrective action recommendations, and preservation of manufacturing knowledge for future decision-making**. Engineers need to manually analyze the explanations and identify suitable process improvements, limiting the actual usability of current XAI technologies in industrial production where fast and reliable judgments are needed.

To point out these limitations, this paper proposes the XAI-IM, a domain-specific explainable artificial intelligence technique for quality prediction in injection molding. The proposed approach integrates machine learning, explainability, root cause analysis, decision support, knowledge management, and continuous learning into an integrated architecture. The proposed model not only explains the outputs but also adds explainability into actionable recommendations that assist engineers in optimizing process parameters and improving product quality.

The **main contributions** of this paper are summarized as below:

- **A domain-specific XAI-IM approach** designed for quality prediction in injection molding.
- **An integrated architecture** that combines machine learning, explainability, root cause analysis, decision support, knowledge management, and continuous learning.
- **A conceptual industrial use case** demonstrating the potential application of the proposed approach in smart manufacturing.
- **A future implementation strategy** outlining the validation of the proposed approach using real industrial datasets and Industry 4.0 manufacturing environments.

2. Related Work

The recent studies have shown that machine learning (ML) can potentially improve quality assessment in injection molding [5]. Many algorithms, including Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machine (SVM), and XGBoost, have been widely used to analyze process parameters and estimate product quality [1], [2]. These approaches have been shown to perform well in reducing the manufacturing defects and improving the process efficiency.

To increace model transparency, Explainable Artificial Intelligence (XAI) techniques, spacialy SHAP and LIME, have been adopted to interpret machine learning decisions [4]. These methods help identify

the influence of process variables and improve users' understanding of model behavior. The most existing research focus on model interpretation rather than root cause analysis, decision support, and knowledge management. Consequently, there remains a need for a domain-specific explainable AI solution that converts model explanations into actionable insights for intelligent injection molding applications.

3. Proposed XAI-IM Framework

3.1 Overall Architecture

The proposed XAI-IM is designed to give an explainable and decision-oriented approach for quality evaluation in injection molding. It integrates data acquisition, machine learning, explainability, root cause analysis, decision support, and continuous learning into a unified architecture. The motive is not only to measure product quality but also to guide engineers in understanding the reasons behind model decisions and selecting particular parameter adjustments.

The architecture consists of six interlinked modules as shown in Figure 1. The first module collects process data from the injection molding machine. Typical process variables are **melt temperature, injection pressure, mold temperature, packing pressure, cooling time, and cycle time** [9]. These variables are the operating conditions, which directly affect product quality.

Now, the collected data are used to increase faith. In this work, the missing values are removed, noise is reduced, and process parameters are normalized. Feature engineering is then used to identify the most important variables for model development. The selection of a particular parameter reduces repetition and improves model efficiency.

The processed data are used by the **machine learning module**, where an appropriate learning algorithm estimates product quality [10]. Unlike conventional approaches, the estimated results are forwarded to an **Explainable Artificial Intelligence (XAI)** module instead of being directly presented to engineers. This module applies explanation techniques to determine the contribution of each process parameter to the final decision.

The generated explanations are analyzed by the **decision support module**, which performs **root cause analysis** and recommends suitable process adjustments [7]. The generated recommendations, explanations, and historical decisions are finally stored in a **knowledge repository**. This repository supports continuous learning and enables the system to improve future decision-making based on stored manufacturing knowledge.

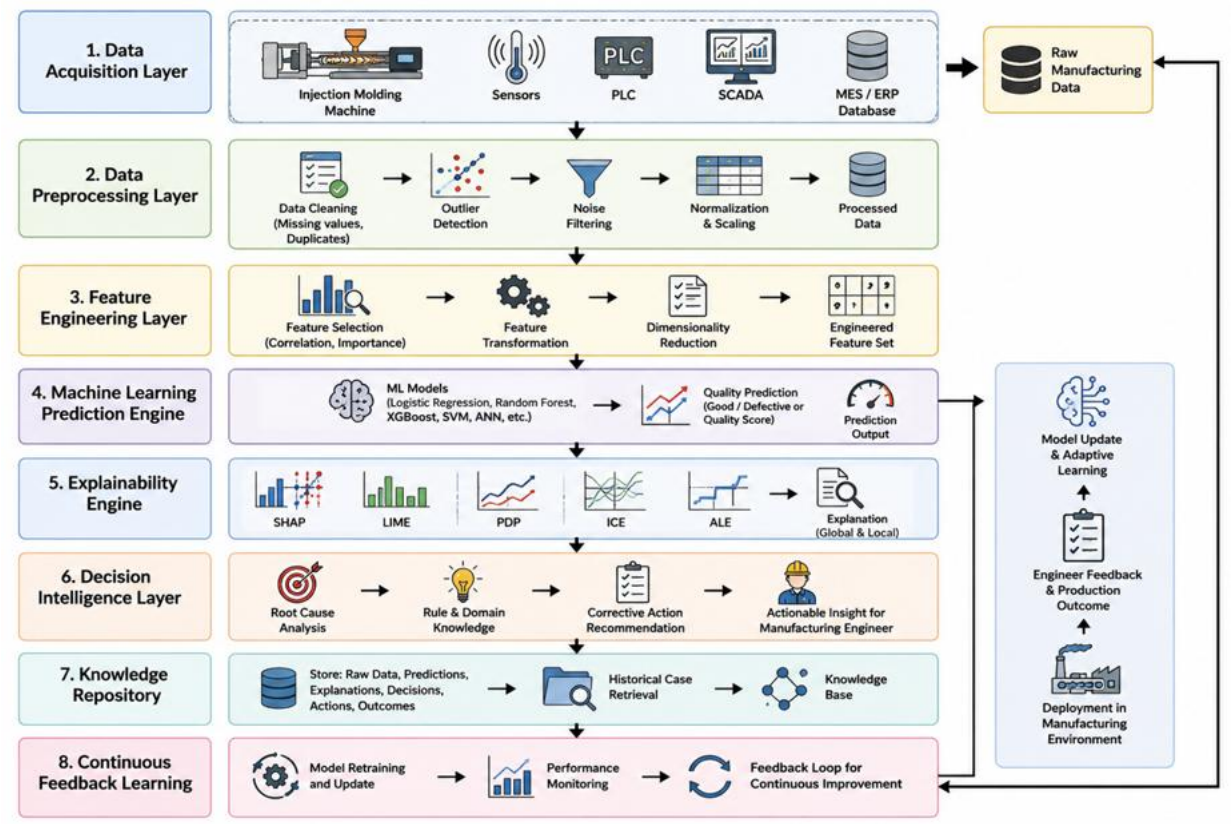


Figure 2. Overall Architecture of the Proposed XAI-IM Framework

3.2 Operational Workflow

The operational workflow starts with the collection of real-time manufacturing data from the injection molding process. After preprocessing and feature engineering, the prepared dataset is used as input for the machine learning model.

Let the input process parameter vector be represented as

$$\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$$

where

- x_1= Melt Temperature
- x_2= Injection Pressure
- x_3= Mould Temperature
- x_4= Packing Pressure
- x_5= Cooling Time
- x_n= Additional process variables

The machine learning model estimates product quality as

$$\hat{Y} = f(\mathbf{X})$$

where

- $\hat{Y}$represents the estimated quality outcome,

- $f(\cdot)$denotes the trained machine learning model.

Instead of using only the estimated output, the XAI module generates an explanation vector

$$\mathbf{E} = g(\hat{Y}, \mathbf{X})$$

where

- $g(\cdot)$represents the explainability function,
- $\mathbf{E}$contains the contribution of each process parameter.

The explanation vector is further processed to identify the dominant process variables responsible for quality variation. Based on these findings, the decision support module generates corrective recommendations.

$$D = h(\mathbf{E})$$

where

- Ddenotes the recommended process adjustment.
- $h(\cdot)$represents the decision-support function.

Finally, all explanations and recommendations are stored within the knowledge repository for future reuse. The repository is updated continuously as

$$K_{t+1} = K_t + \{E, D\}$$

where

- $K_t$denotes the existing manufacturing knowledge,
- K_{t+1}represents the updated knowledge base.

This continuous learning process enables the approach to improve decision consistency and preserve expert knowledge over time.

3.3 Mathematical Formulation

The objective of the proposed approach is to estimate product quality while maximizing interpretability and decision support. Let

$$Q = f(\mathbf{X})$$

where

- Qdenotes the quality score,
- $\mathbf{X}$represents the process parameter vector.

The importance of each process parameter can be represented by

$$I_i = \phi(x_i)$$

where

- $I_i$is the importance score of the i^{th}process parameter,
- $\phi(\cdot)$denotes the explainability function obtained using methods such as **SHAP** or **LIME**.

The overall decision-support function can therefore be expressed as

$$S = \alpha Q + \beta I$$

where

- Sdenotes the final decision-support score,
- Qrepresents the estimated quality,
- Irepresents the cumulative importance of influential process parameters,
- $\alpha$and $\beta$are weighting coefficients satisfying

$$\alpha + \beta = 1.$$

This solution combines model explainability and quality improvement, allowing engineers to consider both the expected outcome and the contribution of influential process parameters during process optimization. The resulting recommendations improve transparency, provide root cause analysis, and support more consistent manufacturing decisions [3]-[5].

4. Industrial Use Case

To express the applicability of the proposed XAI-IM approach, a conceptual use case based on an automotive injection molding process is considered. In the production process, process parameters such as melt temperature, injection pressure, mold temperature, packing pressure, cooling time, and cycle time are continuously collected from the molding machine. These data are processed by the machine learning module to estimate the quality of manufactured components [11].

The expected output is then analyzed using the Explainable Artificial Intelligence (XAI) module, where techniques such as SHAP or LIME identify the process parameters that have their contribution on the developed model's decision. Instead of presenting only an explanation, the proposed approach did the root cause analysis to determine the responsible parameter for quality defects. Based on these insights, the decision support module generates practical recommendations, such as adjusting melt temperature or extending cooling time, to improve manufacturing performance [2].

Finally, the explanations, recommended actions and engineering decisions are stored in a knowledge repository for future reference. This continuous accumulation of manufacturing knowledge can support a more consistent process optimization and improve decisions over time. The conceptual use case tell how the proposed approach combines machine learning, explainability and decision support to enable transparent and intelligent quality management in Industry 4.0 manufacturing environments [8].

5. Future Implementation Strategy

In future work, the proposed XAI-IM will be implemented and cross check using real industrial injection molding datasets. This includes collecting process variables such as melt temperature, injection pressure, mold temperature, packing pressure, cooling time, and cycle time to evaluate the proposed approach under real manufacturing data[3]-[5]. The combination of ML algorithms such as Random Forest, XGBoost, and Support Vector Machine (SVM) with SHAP and LIME would improve the interpretability of the model. The implementation will be evaluated by prediction accuracy, explanation quality, decision support capability, and computational efficiency. The results will be compared with the state-of-the-art explainable AI methods to demonstrate the applicability of the proposed approach in Industry 4.0 manufacturing environments..

6. Conclusion

The current research paper tells XAI-IM, a domain-specific explainable artificial intelligence approach for quality improvement in injection molding. The proposed approach combines machine learning, explainability, root cause analysis, decision support, knowledge management, and continuous learning into a proposed architecture. Unlike conventional explainable AI methods that mainly interpret model outputs, the proposed approach emphasizes actionable recommendations to support engineering decisions and process optimization. The conceptual use case illustrates its potential application in intelligent manufacturing. Future work and industrial validation are expected to describe its effectiveness in improving transparency, decision consistency, and quality management for Industry 4.0-enabled smart manufacturing.

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