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Machine Learning Approaches for Defect Detection in Injection Molding: A Comprehensive Review of Methods, Challenges, and Industrial Integration

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1. Abstract:

Injection molding has become indispensable in the mass production of thermoplastic components, serving key roles across automotive, electronics, and consumer goods industries. However, guaranteeing consistent part quality remains a significant challenge due to the intricate and variable nature of process parameters. Recent advancements in machine learning (ML) and artificial intelligence (AI) have revolutionized defect detection in injection molding, enabling more adaptive, predictive, and interpretable quality assurance systems. This review paper synthesizes the latest research on ML-based defect detection, with a focus on supervised learning algorithms, statistical distance-based modeling, and deep generative modeling techniques. We analyze findings from studies employing classifiers such as Support Vector Machines, Random Forests, Light GBM, and neural networks, as well as unsupervised approaches like Mahalanobis Distance and variation Auto Encoders. Special attention is given to model interpretability, with methods such as SHAP (Shapley Additive Explanations) enhancing transparency and actionable insights for process engineers. Results from recent benchmarking efforts using real-world datasets, such as the Korea AI Manufacturing Platform, demonstrate that model performance is highly dependent on specific part types, data distributions, and the presence of class imbalance. Hybrid models and transfer learning approaches are shown to further boost predictive accuracy and generalizability. Despite these advances, challenges persist in dataset standardization, real-time deployment, and robust model adaptation across diverse manufacturing contexts. This review provides practical recommendations for selecting and deploying ML models in Industry 4.0-enabled injection molding, supporting the ongoing digital transformation of quality control in smart manufacturing.

Keywords: Injection Molding, Defect Detection, Machine Learning, Supervised Learning, Variational Auto Encoder, Mahalanobis Distance, Smart Manufacturing, Quality Control, SHAP, F1-Score, Anomaly Detection, Predictive Maintenance, Industry 4.0, Sensor Data, Deep Learning

2. INTRODUCTION

Injection molding stands as a cornerstone of modern manufacturing, enabling the mass production of complex thermoplastic parts that drive innovation and economic growth across industries. From automotive interiors and under-the-hood components to high-precision electronics housings, packaging, and medical devices, injection molding offers the unparalleled ability to produce millions of near-identical parts at high speed, low cost, and with remarkable dimensional precision. The ubiquity of thermoplastics, their favorable strength-to-weight ratios, and their adaptability to intricate geometries have rendered injection molding indispensable in the quest for functional, aesthetically pleasing, and economically viable products. The ever-increasing quality demands of end-users, coupled with fierce market competition and regulatory requirements, have elevated the role of process monitoring and quality assurance in injection molding plants world wide. Despite its many advantages, injection molding remains a highly complex, nonlinear, and dynamic process. Part quality is governed by a multitude of interdependent process variables—including but not limited to injection pressure, barrel and mold temperature, screw rotation speed, holding and cooling times, material viscosity, and even ambient shop-floor conditions. Even subtle deviations in these parameters can induce a wide array of defects: short shots, war page, sink marks, voids, burn marks, weld lines, or flash, among others. These defects not only compromise the mechanical integrity and dimensional accuracy of the final product but may also render large production batches unusable, resulting in substantial economic losses, increased scrap rates, and heightened environmental impacts. Moreover, the growing trend towards light weighting, miniaturization, and the integration of recycled materials has further increased the sensitivity of the process to parameter variations and introduced new, less predictable failure modes.

Historically, the primary means of ensuring part quality have involved post-production inspection, rule-based process adjustments, and statistical process control (SPC) methods. While these strategies have served industry for decades, they are fundamentally limited by their reactive nature and reliance on human intuition and experience. Traditional inspections—often conducted visually or via off-line metrology—are time-consuming and prone to subjective errors. Rule-based systems, based on expert knowledge or simple statistical thresholds, struggle to capture the full range of nonlinear relationships and latent patterns that underlie process-parameter interactions. SPC techniques, though effective in stable, low-mix environments, are less suited to the high-mix, high-variability production landscapes characteristic of Industry 4.0. More critically, these legacy approaches are fundamentally backward-looking: they identify defects only after they have occurred, leaving manufacturers few options but to rework or scrap faulty parts.

The rise of Industry 4.0—heralding the integration of cyber-physical systems, Industrial Internet of Things (IIoT), advanced robotics, and cloud computing—has dramatically reshaped the manufacturing paradigm. Modern injection molding machines are now routinely equipped with an array of sensors capable of capturing granular process data in real time: temperature profiles, pressure curves, screw position, fill time, cavity pressure, cooling rates, and more. The proliferation of such high-dimensional, high-frequency sensor data has created both an opportunity and a challenge. On one hand, it opens new frontiers for data-driven quality assurance, moving the needle from reactive defect detection to proactive and even predictive process control. On the other hand, it necessitates analytical tools capable of extracting meaningful insights from complex, often noisy, and highly imbalanced datasets. In this context, machine learning (ML) and its broader umbrella, artificial intelligence (AI), have emerged as transformative enablers of intelligent quality control. Unlike traditional algorithms, which require explicit rule formulation, machine learning models learn to uncover hidden relationships within historical and real-time data through a process of training and validation. Supervised learning approaches—such as Support Vector Machines (SVMs), Random Forests (RF), Light Gradient Boosting Machines (Light GBM), and Artificial Neural Networks (ANNs)—are particularly adept at capturing complex, nonlinear interactions among process variables, provided sufficient labeled training data is available. These models have been used to classify parts as pass/fail, predict defect probabilities, and even suggest process adjustments in real time.

However, the application of supervised models in industrial injection molding faces several real-world challenges. The most prominent among these is the class imbalance problem: defective parts typically represent a small fraction of total production, making it difficult for standard classifiers to learn discriminative patterns for the minority class. This often results in high false-negative rates, where defective parts are incorrectly labeled as acceptable, thus defeating the primary goal of quality control. To address this, advanced evaluation metrics such as the F1-score—which balances precision and recall—are favored over simple accuracy metrics. Moreover, real production environments frequently encounter scenarios where labeled data is scarce, outdated, or costly to obtain, such as during new product introduction or material changeovers. Here, unsupervised and semi-supervised models offer distinct advantages. Statistical distance-based methods, such as the Mahalanob is Distance, flag anomalies by identifying points in the feature space that deviate significantly from the "normal" distribution of process cycles. These methods require little or no labeled data and are robust to changes in process drift or part design. Generative models, like Variational Auto Encoders (VAEs), learn the underlying probability distribution of the process data and use reconstruction error to identify potential defects or abnormal process cycles. By focusing on the structure of the data itself, generative models can often detect novel or emerging failure modes that elude traditional classifiers. A crucial dimension in the industrial adoption of ML-based defect detection systems is model interpretability. Manufacturing engineers and process operators need not only accurate predictions but also actionable insights into why a part has been flagged as defective. Black-box models, while potentially powerful, suffer from limited transparency and trust in high-stakes production settings. Recent advances in explainable AI, such as SHAP (SHapley Additive explanations), allow for the quantification of each input variable's contribution to the prediction, enabling process engineers to link specific defects to controllable process parameters. This paves the way for closed-loop quality control and self-tuning manufacturing lines—key tenets of the smart factory vision. Despite the proliferation of research on ML applications in injection molding, several critical gaps persist. Many studies focus narrowly on a single algorithm or a limited dataset, hampering broader generalize ability. Direct comparisons across supervised, unsupervised, and generative approaches—using standardized, real-world datasets—are rare. Issues of data quality, noise, sensor drift, and feature selection remain nontrivial, especially when scaling models across different machines, molds, or materials. Furthermore, the challenge of robust, real-time deployment—integrating ML models with shop-floor automation, manufacturing execution systems (MES), and cloud-based analytics—remains a significant barrier for many manufacturers. This review paper seeks to provide a comprehensive synthesis and benchmarking of current machine learning paradigms as applied to defect detection in thermoplastic injection molding. Building upon recent empirical studies and practical deployments, we explore the strengths, limitations, and practical considerations of supervised classifiers, statistical distance-based anomaly detection, and deep generative models. We place particular emphasis on model evaluation under imbalanced conditions, the role of feature importance analysis (including SHAP), and strategies for model selection and threshold optimization in diverse manufacturing contexts. By consolidating insights from the latest literature and real-world benchmarking, this review aims to offer practical guidance for manufacturers seeking to transition from reactive to predictive quality control, ultimately enabling more resilient, efficient, and data-driven injection molding operations in the era of Industry 4.0.

LITERATURE REVIEW

The integration of machine learning (ML) and artificial intelligence (AI) into injection molding processes has witnessed a surge in attention over the past ten years, particularly with the advancement of Industry 4.0 and the evolution of smart manufacturing paradigms. Early foundational work by Párizs et al. [1] introduced a robust ML-based solution, employing gradient boosting and support vector machines (SVMs) to accurately forecast product quality within injection molding. Their use of real-time sensor analytics, in combination with SHAP-driven interpretability, marked a significant leap toward intelligent, explainable quality control frameworks. Complementing this, Selvaraj et al. [2] offered an extensive survey of ML methodologies tailored to injection molding, covering supervised, unsupervised, and reinforcement learning, and emphasizing the critical role of choosing suitable models according to process complexity and available data.

A notable contribution by Lin and Chen [3] involved the creation of a holistic decision support platform, leveraging a blend of computational intelligence, fuzzy logic, and ensemble learning techniques like LightGBM and XGBoost. This approach facilitated near-zero defect rates by balancing production throughput against quality requirements. Focusing on the prediction of specific defect types, MollaeiArdestani et al. [4] used random forest algorithms to anticipate blush defects and capitalized on SHAP values to provide actionable guidance for process optimization. Expanding into multimodal data, Kim et al. [5] harnessed both imagery and sensor signals via a hybrid CNN-RNN architecture, attaining over 97% accuracy in detecting defects such as warpage and short shots—demonstrating the advantages of merging multiple data streams for superior process insight.

Furthering the scope, Jung et al. [6] incorporated sustainability considerations into ML-powered quality assessments, revealing that SVMs can not only classify defects but also support energy efficiency objectives. In pursuit of practical deployment, Obregon et al. [7] engineered a rule-based ensemble leveraging decision trees and SHAP for transparent sink mark identification, addressing the interpretability needs of operational engineers. On the industrial adoption front, Ogorodnyk et al. [8] applied SVMs and artificial neural networks (ANNs) to datasets from European facilities, achieving strong predictive performance and embedding these tools in live monitoring dashboards. Silva et al. [9] demonstrated the scalability and resilience of ANN-based, digital twin-enabled prediction systems, establishing their applicability in high-precision manufacturing settings. In another advance, El Ghadoui et al. [10] utilized deep neural networks (DNNs) enhanced by Bayesian optimization for hyper parameter search in defect detection tasks, providing an edge-capable system that incorporated uncertainty estimation for transparency and practical deployment.

Addressing the crucial area of parameter optimization, Tayalati et al. [11] relied on support vector regression (SVR) to estimate cooling times, which minimized the reliance on manual trial-and-error during process setup. Hu et al. [12] made notable strides in fault recognition by applying an augmented VGG16 architecture, augmented with attention layers, to image-based datasets—achieving an impressive 98.4% classification accuracy. For predictive maintenance, Rousopoulou et al. [13] leveraged random forest algorithms and rule-based logic to anticipate machine failures, drawing correlations between equipment degradation and subsequent product quality issues. Among the pioneering applications of ML in this sector, Nagorny et al. [14] performed comparative evaluations of ANNs and partial least squares models on real-time process data, thereby laying the groundwork for today's intelligent quality systems.

Transfer learning has emerged as a pivotal approach in this domain. For instance, Chang et al. [15] illustrated how pre-trained models could be customized to new machinery using quality indices, achieving robust cross-machine defect prediction with 91.7% accuracy. Similarly, Liu et al. [16] adopted CNN architectures such as ResNet50, employing transfer learning to enhance defect detection performance on limited data, surpassing the outcomes of models trained from scratch. Im et al. [17] implemented a data-centric workflow, utilizing interactive data labeling, human validation, and active learning strategies to elevate surface defect recognition rates above 96%. Facing challenges posed by the use of recycled materials, Chen and Huang [18] adopted DNNs and sensor fusion, and their transfer learning model maintained high accuracy (92.4%) despite material inconsistencies. To support ongoing adaptation, Maarif et al. [19] introduced a structural learning with forgetting (SLF) paradigm for ANN training, enabling continuous adaptation to process drift without requiring full retraining. Ribeiro [20] stands among the first to apply SVM for monitoring dimensional stability and short-shot issues, highlighting ML's early potential in process monitoring. Meanwhile, Khosravani and Nasiri [21] reviewed the effectiveness of case-based reasoning (CBR) for injection molding, stressing its practicality in small-batch production scenarios where comprehensive ML training is not feasible. Abd Elnaby et al. [22] showcased the synergy of Six Sigma's DMAIC process and ML models such as SVM and random forest, leading to a substantial 34% drop in defect rates on automotive assembly lines.

The latest research trends highlight the integration of deep learning with established quality control methodologies. Tayalati et al. [23] combined autoencoders with statistical process control (SPC) charts, utilizing reconstruction errors as an index for anomaly detection—thereby reducing false alarms and improving traceability of defects. Ketonen [24] implemented a probabilistic variational autoencoder (VAE) to pinpoint anomalies in cycle-level injection molding data, with the model leveraging KL-divergence and reconstruction errors to offer trustworthy predictions under uncertainty. The approach by Chen et al. [25] involved embedding in-mold sensors with ANN-driven online defect detection to facilitate real-time identification of issues such as warpage and voids throughout the molding process. Zhou et al. [26] advanced the field of short-shot defect detection by deploying transfer learning-based CNNs, which proved highly adaptable across various molds and materials. Wang et al. [27] addressed the detection of mechanical component faults by developing a CNN-based solution for diagnosing non-return valve issues through sensor and vibration data analysis, enabling proactive predictive maintenance with 93.7% accuracy. Advancements in model transparency were also significant. Tayalati et al. [28] demonstrated the use of gradient boosting in combination with SHAP and ANOVA analyses to illuminate the causal relationships behind defects, such as how the confluence of elevated mold temperatures and reduced cooling times fostered warpage. Koo et al. [29] designed a two-stage ensemble method combining bagging and boosting strategies for predicting weight defects; their adaptive thresholding improved robustness and allowed seamless integration into smart factory manufacturing execution systems. In related polymer processing applications, Gope et al. [30] deployed LSTM and CNN models for real-time detection of abnormal process parameters in polypropylene melt spinning, succeeding in both process optimization and defect categorization, such as identifying nozzle blockages and pressure anomalies. This work underscores the potential for translating ML-based defect detection approaches across polymer manufacturing disciplines. Collectively, the surveyed literature reflects a profound transformation in the role of machine learning within injection molding—from basic classifiers and regressors to sophisticated transfer learning, explainable AI, hybrid deep learning-statistical systems, and fully integrated real-time solutions. There is a marked shift toward interpretability, scalability, and the ability to generalize models across different machines and defect categories, aligning closely with Industry 4.0 objectives. Nonetheless, persistent challenges remain—such as the need for standardized datasets, robust generalization across diverse defect scenarios, and seamless integration of ML tools with existing manufacturing systems. Despite these hurdles, the fusion of machine learning, sensor fusion, and manufacturing expertise is steadily advancing the frontier of intelligent quality assurance in thermoplastic injection molding.

3. ANALYSIS OF REVIEW

The integration of machine learning (ML) and artificial intelligence (AI) into injection molding quality assurance represents a pivotal transformation in industrial manufacturing. Over the past decade, as manufacturing has embraced Industry 4.0, the landscape of defect detection has rapidly evolved from traditional, reactive inspection to proactive, data-driven, and intelligent prediction frameworks. The literature reflects this evolution, with a clear trajectory from simple classification models toward hybrid, interpretable, and scalable AI solutions that align with smart manufacturing's objectives.

Key Trends and Methodological Evolution

The earliest applications of ML in injection molding largely focused on **supervised learning**, utilizing algorithms such as Support Vector Machines (SVM), Random Forests, and shallow neural networks to classify part quality based on labeled sensor data. These models delivered tangible improvements in defect detection compared to rule-based or statistical process control (SPC) methods. However, they were often limited by the requirement for extensive labeled datasets and susceptibility to class imbalance—a persistent issue in industrial settings where defective parts are rare relative to non-defective parts.

Ensemble models and **gradient boosting** approaches, as highlighted in the work of Párizs et al. [1], offered increased predictive power by combining the strengths of multiple algorithms and handling complex, nonlinear relationships among process variables. Notably, the integration of SHAP-based interpretability allowed for transparent decision-making, enabling process engineers to understand which parameters most influenced defect outcomes. This increased trust in ML-driven recommendations, a critical requirement for industrial adoption.

The literature then shifted towards **multimodal and hybrid approaches**, reflecting an increased interest in leveraging diverse data streams—such as fusing image data from cameras with traditional process sensor signals. CNN-RNN architectures, as employed by Kim et al. [5], demonstrated that combining visual and numerical data could substantially improve the detection of subtle defects like warpage and short shots, especially in high-mix manufacturing environments.

A second major trend has been the **emphasis on unsupervised and generative modeling**. Unsupervised models, such as those employing Mahalanobis Distance, and deep generative models like Variational AutoEncoders (VAEs), were developed to overcome the challenge of limited labeled data and to detect previously unseen (novel) defect types. These approaches are particularly well-suited for dynamic production environments, allowing for real-time monitoring and anomaly detection without the need for exhaustive manual labeling. Ketonen's [24] probabilistic VAE work exemplifies this paradigm, enabling robust detection of abnormal process cycles with quantifiable uncertainty, which is crucial for risk management on the shop floor.

Model Interpretability and Practical Deployment

One of the most consistent themes across the reviewed literature is the growing **demand for model interpretability**. In high-stakes industrial applications, the adoption of black-box AI is often met with skepticism unless clear, actionable insights can be derived from the model's outputs. Methods such as SHAP (Shapley Additive explanations) and other feature importance analyses have become standard, allowing engineers not only to detect defects but to understand their root causes. This interpretability facilitates a feedback loop where insights from ML models can drive continuous process improvement, reduce trial-and-error, and optimize parameter settings.

Real-world deployment is also a recurring focus, with several studies emphasizing the need for **edge-capable**, low-latency systems that can operate within the constraints of industrial hardware and communication networks. The transition from laboratory prototypes to **real-time manufacturing execution systems (MES)** requires robust, scalable, and maintainable solutions. Works such as Ogorodnyk et al. [8] and Silva et al. [9] demonstrate successful integration of ML models into live dashboards and digital twins, providing operators with timely quality predictions and actionable alerts.

Emergence of Transfer Learning and Adaptive Systems

Another significant development in the literature is the **emergence of transfer learning and adaptive algorithms**. As production lines become more flexible, with frequent product changes and material substitutions (e.g., use of recycled plastics), there is a need for models that generalize across machines, molds, and materials. Transfer learning allows pretrained models to be adapted to new settings with minimal retraining, as illustrated by Chang et al. [15] and Liu et al. [16]. Active learning and human-in-the-loop systems, such as those discussed by Im et al. [17], further enhance adaptability by leveraging expert feedback to continuously improve model performance.

Continuous learning frameworks, such as structural learning with forgetting (SLF), allow models to keep pace with gradual process drifts and maintain accuracy without the need for frequent full retraining—a crucial capability in dynamic manufacturing environments.

Challenges and Limitations

Despite significant progress, several **persistent challenges** are evident throughout the literature:

- **Data Quality and Standardization:** The lack of standardized, openly available datasets hampers direct benchmarking and generalization of results. Differences in sensor setups, data formats, and defect labeling make cross-study comparisons difficult.
- **Class Imbalance:** The overwhelming majority of manufactured parts are defect-free, making it challenging to train models that are sensitive enough to catch rare, critical defects without overwhelming operators with false positives.
- **Scalability and Maintenance:** Deploying and maintaining ML models in a production environment is non-trivial. Issues such as sensor drift, data noise, and changing production conditions can quickly degrade model performance if not addressed.
- **Integration with Legacy Systems:** Many factories still operate with a patchwork of old and new equipment, making integration of AI-based solutions with existing MES and SPC systems a technical and organizational challenge.
- **Interpretability vs. Complexity:** More complex models (e.g., deep neural networks, VAEs) often offer better predictive

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accuracy but can be less interpretable. Balancing accuracy with transparency remains a key concern.

Future Opportunities and Research Directions

Looking ahead, the literature suggests several promising avenues for continued research and industrial innovation:

- **Hybrid Models:** The fusion of supervised, unsupervised, and deep generative models, as well as combining traditional statistical approaches with machine learning, offers a path toward robust, versatile quality control systems capable of handling both known and novel defects.
- **Explainable AI (XAI):** The integration of explainable AI techniques into all stages of the process—from feature engineering to real-time inference—will further boost trust and adoption in industrial settings.
- **Real-time and Edge AI:** Continued development of lightweight, energy-efficient AI models suitable for deployment on edge devices will enhance real-time defect detection and reduce latency.
- **Cross-Domain Applications:** The lessons learned from injection molding defect detection are increasingly being transferred to related fields, such as extrusion, blow molding, and additive manufacturing, promoting a broader shift toward intelligent quality assurance across the polymer processing industry.
- **Open Data and Collaborative Benchmarks:** There is a pressing need for more open, standardized datasets and collaborative benchmarking initiatives, which would facilitate reproducibility and accelerate the development of best practices.
- **Human-in-the-Loop and Adaptive Systems:** The combination of automated ML and human expertise can create more resilient systems that quickly adapt to unforeseen process changes, new materials, or shifts in product design.

Table 1: Machine Learning Methods Used in Injection Molding Defect Detection

Study / Author	**ML Method(s) Employed**	**Data Type(s)**	**Notable Features / Additions**	**Reported Accuracy**
Párizs et al. [1]	Gradient Boosting, SVM, SHAP	Sensor, Process Data	Real-time feedback, Model interpretability	High (noted)
Lin and Chen [3]	LightGBM, XGBoost, Fuzzy Logic	Sensor Data	Hybrid decision support, Zero-defect focus	Near-zero defects
Kim et al. [5]	CNN-RNN (Data Fusion)	Image + Sensor Data	Multimodal data fusion	>97%
MollaeiArdestaniet al.[4]	Random Forest, SHAP	Sensor Data	SHAP for parameter tuning	Noted improvement
Jung et al. [6]	SVM	Sensor Data	Sustainability metrics, Energy optimization	Noted
Ketonen [24]	Probabilistic VAE, KL-divergence	Sensor Data	Uncertainty quantification	Robust detection

Table 2: Interpretability and Deployment Strategies

Study / Author	**Interpretability Approach**	**Deployment / Integration**	**Key Impact**
Párizs et al. [1]	SHAP explanations	Real-time sensor feedback	Model transparency, Trust
MollaeiArdestani et al. [4]	SHAP analysis	Process parameter adjustment	Actionable insights
Obregon et al. [7]	Rule-based ensemble, SHAP	Shop-floor engineering integration	Practicality for engineers
Ogorodnyk et al. [8]	SVM/ANN with live dashboard	European plant MES integration	Real-time operator feedback
Silva et al. [9]	Digital Twin, ANN	Precision manufacturing, Digital Twin	Scalability, Robustness
El Ghadoui et al. [10]	DNN, Bayesian optimization	Edge deployment, Uncertainty quant.	Transparency, Industrial adoption

Table 3: Challenges Addressed by Recent Works

Study / Author	**Challenge Addressed**	**Solution Proposed**	**Outcome**
Chang et al. [15]	Model transferability	Pre-trained models with quality indices	91.7% cross-machine accuracy
Liu et al. [16]	Small datasets, transfer learning	ResNet50, transfer learning	Outperformed models trained from scratch
Im et al. [17]	Continuous learning, labeling cost	Human-in-loop, active learning	>96% surface defect accuracy
Maarif et al. [19]	Process drift, continuous adaptation	Structural learning with forgetting (SLF)	Adaptability without full retraining
Zhou et al. [26]	Adaptability across molds/materials	Transfer learning-based CNN with sensor data	Versatility, high accuracy

Table 4: Remaining Gaps and Future Research Opportunities

Area / Gap	Limitation Identified	Future Research Direction
Dataset Standardization	Lack of open, comparable datasets	Collaborative, open-access benchmarks
Class Imbalance	Defective samples underrepresented	Advanced sampling, cost-sensitive algorithms
Real-time Integration	Complexity in MES/legacy system integration	API-based, modular ML solutions for industrial settings
Model Interpretability	Tradeoff with accuracy for deep models	Explainable AI (XAI), interactive dashboards
Generalization	Models often machine/part-specific	Domain adaptation, federated learning
Human-in-the-loop	Limited exploitation of operator expertise	Adaptive, interactive, operator-in-the-loop ML frameworks

This analysis and tabular synthesis demonstrate the impressive progress and persistent challenges in deploying ML-based defect detection within injection molding. As the field continues to advance, the convergence of explainable AI, transfer learning, real-time integration, and collaborative benchmarking will play pivotal roles in realizing the vision of truly intelligent, adaptive, and trustworthy manufacturing systems.

CONCLUSION

The rapid evolution of machine learning (ML) and artificial intelligence (AI) has revolutionized defect detection in thermoplastic injection molding, propelling the industry towards smarter, more adaptive, and predictive quality assurance systems. Through a decade of research and industrial experimentation, the literature highlights a distinct shift from traditional rule-based inspections to sophisticated data-driven approaches—ranging from supervised learning and ensemble models to deep generative methods and hybrid frameworks. These advancements have demonstrated substantial improvements in defect classification accuracy, adaptability to diverse part types, and the ability to extract actionable insights from complex sensor data. Crucially, the integration of interpretability tools like SHAP, as well as human-in-the-loop and transfer learning strategies, has bridged the gap between black-box models and practical shop-floor adoption. Studies reveal that while supervised models excel when ample labeled data is available, unsupervised and generative models offer significant advantages in dynamic, data-scarce, or imbalanced production environments. Despite these achievements, persistent challenges remain—most notably in the areas of dataset standardization, scalability, integration with legacy systems, and balancing predictive performance with interpretability. Looking forward, future research and industrial deployment should prioritize the development of hybrid, explainable, and adaptive AI systems that can generalize across machines, materials, and product lines. Emphasis on open benchmarking, collaborative data sharing, and real-time edge deployment will further accelerate progress and democratize access to intelligent quality control solutions. Ultimately, the convergence of advanced ML algorithms, sensor fusion, and domain expertise heralds a new era of resilient, efficient, and high-quality manufacturing, paving the way for the widespread realization of Industry 4.0 in injection molding and beyond.

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