

# Development of an Online Detection System for Surface Defects of Injection Molded Products Based on Machine Vision

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**Abstract:** The injection molding process underpins modern mass manufacturing, yet surface defects like sink marks and flash cause quality issues, material waste and production delays. Traditional manual inspection is labor-intensive, costly and inconsistent, unfit for automated lines. This paper presents an online machine vision detection system for such defects, integrating high-resolution cameras and LED lighting to capture in-line images. Its pipeline includes preprocessing, hybrid feature extraction with traditional analysis and a CNN model, and real-time analysis via PLC for defect flagging and ejection. Trials on polymer components show 99.2% recognition accuracy, 0.5% false positive rate and 180 parts/min processing speed, meeting cycle demands and boosting smart manufacturing quality control with lower operational costs.

**Keywords:** Machine vision; Injection molding; Surface defect detection; Online inspection; Convolutional neural network; Quality control

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## 1. Introduction

Injection molding stands as one of the most prevalent and versatile manufacturing processes globally, responsible for producing millions of plastic components daily across industries ranging from automotive and electronics to medical devices and consumer goods <sup>[1]</sup>. The process's efficiency, repeatability, and ability to fabricate complex shapes with excellent surface finish are its key advantages, making it the go-to choice for mass production where consistency and cost-effectiveness are paramount <sup>[2]</sup>. Despite rapid technological advancements in high-precision molding machines, advanced polymer material science, and mold design optimization, the occurrence of surface defects remains an inherent and stubborn challenge in production <sup>[3]</sup>. These defects, including but not limited to sink marks resulting from uneven cooling and material shrinkage, flow lines from material viscosity variations and improper injection speed, short shots from insufficient material injection or mold cavity blockage, and flash from mold wear, imprecise clamping force or parting surface damage, can severely impact the aesthetic appeal, structural integrity, and functional performance of the final product. In high-precision industries such as aerospace, medical implant manufacturing and

high-end electronic component production, even minor surface imperfections that fall below strict quality tolerances can lead to full part rejection, causing substantial financial loss, excessive material waste and potential supply chain disruptions that ripple across entire production networks <sup>[4]</sup>.

The conventional paradigm for quality assurance in this domain has heavily relied on human visual inspection, a method that has remained largely unchanged for decades in many manufacturing facilities <sup>[5]</sup>. Skilled operators stationed along the production line or at the end of it manually examine products, often based on predefined physical samples, printed quality standards or subjective visual judgment. This method, while simple to implement and requiring minimal initial capital investment, is fraught with significant and unavoidable limitations <sup>[6]</sup>. Human inspectors are inherently susceptible to mental and physical fatigue, leading to decreasing attention spans and inconsistent judgment over long working shifts, especially in high-speed production environments with constant repetitive tasks. Subjectivity further introduces substantial variability in inspection results, as defect criteria and pass/fail thresholds may be interpreted differently among individual operators due to varying experience levels, training backgrounds and even emotional states <sup>[7]</sup>. Furthermore, the increasing speed of modern high-throughput injection molding machines, capable of producing dozens of parts per minute, far surpasses the inherent limits of human visual processing and reaction speed, creating a critical quality control bottleneck that risks defective parts entering subsequent production stages <sup>[8]</sup>. The ongoing cost of training, upskilling and retaining skilled inspectors, coupled with the high turnover rate in manufacturing roles, also adds a significant and recurring financial burden to enterprises. These interconnected challenges have spurred an urgent industry-wide search for automated, objective, and high-speed inspection solutions that can keep pace with modern production demands <sup>[9]</sup>.

Machine vision technology has emerged as a transformative force in industrial automation and quality control over the past two decades, revolutionizing how manufacturers monitor and ensure product quality across diverse sectors <sup>[10]</sup>. By utilizing high-resolution digital cameras, customized lighting systems, and advanced computational algorithms to simulate and even exceed human visual perception capabilities, machine vision systems offer the promise of consistent, tireless, and ultra-rapid inspection with zero subjective bias <sup>[11]</sup>. In the specific context of injection molding, a true online detection system implies seamless integration directly into the existing production line, allowing for real-time or near-real-time non-destructive assessment of every single manufactured part without interrupting or slowing down the production flow <sup>[12]</sup>. Such a system can instantly identify defective parts, trigger automated sorting and ejection mechanisms, and simultaneously collect and store valuable statistical data on defect types, occurrence rates and production trends for subsequent process monitoring, root cause analysis and continuous optimization. While offline vision inspection systems exist in some facilities, they often involve manually or automatically moving parts to a separate inspection station, which adds extra production time, increases process complexity and creates additional opportunities for part damage or mishandling. The development of a robust and reliable online machine vision system for injection molding requires careful and holistic consideration of several interrelated technical factors: the precise selection and optimal configuration of imaging hardware (including cameras, lenses, filters and lighting) to effectively capture clear, high-contrast images that highlight defects while mitigating the challenges of reflective, glossy and varied colored surfaces of plastic products; the design of a sophisticated and adaptive software algorithm capable of accurately distinguishing between acceptable minor surface textures and genuine defects under dynamic production conditions such as slight lighting variations and part positioning deviations; and the seamless communication and integration with existing industrial control systems (such as PLCs and SCADA) for real-time automated decision-making and mechanical actuation.

Recent rapid progress in artificial intelligence, particularly in the field of deep learning, has significantly expanded the capabilities and application scope of machine vision technology, overcoming many of the limitations of traditional image processing methods. Convolutional Neural Networks (CNNs), a class of deep learning models specifically designed for visual data processing that can automatically learn hierarchical and discriminative feature representations directly from raw image data without manual feature engineering, have shown remarkable success in complex image classification and object detection tasks across various industrial and consumer applications. Their application to industrial surface defect detection offers a potent and flexible alternative to traditional rule-based image processing techniques, which often require meticulous manual parameter tuning, struggle with complex or novel defect patterns and lack adaptability to changing production conditions. A hybrid technical approach that leverages the strengths of both classical image processing (for preliminary image preprocessing, noise reduction, contrast enhancement and region segmentation) and deep learning (for high-accuracy final defect classification and localization) has emerged as a leading solution in the field, as it can potentially yield superior robustness, accuracy and generalization performance compared to either method used alone.

The primary objective of this research is to directly address the critical and unmet industry need for a reliable, high-speed and cost-effective automated inspection solution by developing, testing, and validating a fully integrated online machine vision system specifically tailored for detecting a wide range of surface defects in small to medium-sized injection molded plastic products. This paper details the complete end-to-end development journey of the proposed system, from the initial conceptual system architecture design and rigorous hardware selection and testing, to the detailed implementation of the hybrid image processing and deep learning algorithm pipeline, and its comprehensive quantitative and qualitative evaluation in a real-world industrial production setting with actual production data and parts. The subsequent sections of this paper will elaborate on the systematic methodology employed for system construction, hardware integration and algorithm development and testing, present and statistically analyze the detailed experimental results obtained from the industrial trials, discuss the practical implications, performance characteristics and operational limitations of the developed system in real production environments, and finally conclude with key research findings, practical industrial recommendations and promising future research directions for further improving the system's performance and expanding its application scope.

## 2. Experimental methods

The development of the online detection system was a systematic process encompassing hardware design and integration, software algorithm development, and experimental validation. The core requirement was to create a system that could operate reliably in an industrial environment, interfacing directly with a high-speed injection molding production line.

The hardware configuration was designed for stability and consistency. The test platform was a standard injection molding machine producing a common polymer gear component with a diameter of approximately 50mm. This part was chosen for its representative surface geometry and known susceptibility to typical defects like sink marks near the hub and flow lines along the teeth. A structured enclosure was built around the conveyor belt carrying the ejected parts from the molding machine. The heart of the imaging system was two high-resolution monochrome area-scan cameras, each equipped with a fixed focal length lens. The use of monochrome cameras was justified as color information was not critical for the targeted defect types, and they generally

offer higher sensitivity and resolution for a given cost. The cameras were positioned at a 45-degree angle to the conveyor, covering the top and one side of the component as it passed. Lighting is paramount in machine vision. A programmable LED ring light with diffuse illumination was installed coaxial with each camera lens. This configuration was selected after preliminary tests to minimize specular reflections from the glossy plastic surface and to provide uniform, shadow-free illumination that highlighted surface topography variations indicative of defects. The lighting intensity and camera exposure time were finely tuned and fixed for all experiments to ensure consistent image acquisition. The cameras were connected to an industrial-grade computer equipped with a dedicated frame grabber and a high-performance GPU to accelerate image processing, particularly for the deep learning computations. The computer ran the custom inspection software and was linked to the production line's Programmable Logic Controller (PLC). A pneumatic ejection mechanism, also controlled by the PLC, was installed downstream to remove parts classified as defective.

The software algorithm followed a multi-stage pipeline. The first stage was image acquisition and preprocessing. Images captured by the cameras were synchronized with the conveyor speed. Preprocessing operations included Gaussian filtering to reduce sensor noise and a contrast-limited adaptive histogram equalization (CLAHE) technique to enhance local contrast, making subtle defects more discernible without amplifying noise globally. The image was then segmented to isolate the region of interest (ROI), the part itself, from the conveyor background using edge detection and morphological operations.

The second stage involved feature extraction using a dual-path strategy. In the traditional path, texture analysis was performed on the ROI using Gray-Level Co-occurrence Matrix (GLCM) calculations to derive statistical texture features such as contrast, correlation, energy, and homogeneity. Simultaneously, edge-based features were extracted by applying a Canny edge detector and calculating edge density and distribution metrics. In the deep learning path, the preprocessed ROI was fed into a custom CNN model. The CNN architecture was designed to be efficient for near-real-time operation. It consisted of four convolutional layers with ReLU activation and max-pooling for feature extraction, followed by two fully connected layers. The final layer used a softmax activation function to output a probability distribution over two classes: "defect-free" and "defective." The model was trained offline on a separate dataset of over 20,000 annotated images (10,000 defect-free and 10,000 containing various defects like sink marks, flow lines, short shots, and flash) collected from the same production line under identical lighting conditions.

The third stage was decision fusion and control. Features from the traditional path (GLCM and edge features) were concatenated into a feature vector. A separate Support Vector Machine (SVM) classifier was trained on these traditional features. The final classification decision was made by a weighted fusion logic that considered the confidence scores from both the CNN and the SVM. If either classifier indicated a defect with high confidence, the part was flagged. This hybrid approach aimed to leverage the complementary strengths of data-driven deep learning and manually engineered feature-based methods, potentially improving robustness against unusual but non-defective surface patterns. Upon a defect classification, the software sent a digital signal to the PLC. The PLC, tracking the part's position via an encoder on the conveyor, then activated the pneumatic ejector at the precise moment to remove the defective part from the line.

The experimental validation protocol was designed to rigorously assess the system's performance. A batch of 10,000 consecutively produced gear components was used for testing. Before the experiment, all 10,000 parts were meticulously labeled by a panel of three expert human inspectors to establish the ground truth. The inspectors examined each part under controlled lighting and had to reach a consensus on its classification. This labeled set

contained 9,432 parts deemed defect-free and 568 parts with one or more confirmed surface defects. The online vision system was then deployed to inspect this entire batch in real-time as it moved along the conveyor at the standard production speed of 180 parts per minute. The system’s classifications (defect-free/defective) were logged along with timestamps. After the automated inspection, the parts flagged as defective by the system and a random sample of parts passed by the system were re-inspected manually to confirm the accuracy of the automated labels. Key performance metrics calculated included overall accuracy, defect detection rate (recall), false positive rate, false negative rate, and the processing time per part. The stability of the system was also monitored over a continuous 48-hour production run.

### 3. Results

The experimental evaluation of the developed online detection system yielded comprehensive quantitative data on its operational performance. The system successfully processed the entire test batch of 10,000 injection molded gear components at the line speed of 180 parts per minute without any mechanical or software failures, demonstrating its suitability for continuous online operation.

The primary performance metrics are summarized in **Table 1**. The system achieved an overall classification accuracy of 99.2%. Out of the 568 parts with confirmed defects in the ground truth set, the system correctly identified 562, resulting in a defect detection rate (Recall) of 98.9%. This high recall is critical in quality control, as it minimizes the number of defective parts erroneously passed on to customers. The system’s precision, or the correctness of its defect calls, was also high. It generated a total of 610 defect flags during the inspection. Of these, 562 were true defects, leading to a precision of 92.1%. The false positive rate, where a defect-free part was incorrectly classified as defective, was 0.5% (48 false positives out of 9,432 good parts). Conversely, the false negative rate, where a defective part was missed, was 0.1% (6 false negatives out of 568 defective parts). These metrics indicate a system highly tuned to detect anomalies while maintaining a very low rate of mistakenly rejecting good products.

**Table 1.** Overall system performance metrics on test batch (n = 10,000)

Metric	Value
Overall accuracy	99.2%
Defect detection rate (recall)	98.9%
Precision	92.1%
False positive rate	0.5%
False negative rate	0.1%
Total defect flags	610
True defects identified	562
False positives	48
False negatives	6

A more detailed breakdown of the system’s performance against specific defect types is presented in **Table 2**. This analysis reveals that the system exhibited varying sensitivity to different defect classes, which is expected

given their distinct visual characteristics. Sink marks, which create noticeable localized depressions, were detected with the highest precision and recall, both at 99.6% and 99.5% respectively, as their 3D nature creates strong contrast under the chosen lighting. Flow lines, which are subtle surface streaks, were more challenging but still detected effectively, with a recall of 98.2%. The primary cause for missed flow lines was their extremely faint appearance, sometimes below the contrast threshold set in the algorithm. Short shots, resulting in incomplete filling, were detected with 100% recall because they cause a significant and obvious geometric deviation. Flash, or excess material on parting lines, was also detected perfectly (100% recall) due to its protrusive nature. The precision for flash was slightly lower (95.8%) because in a few instances, normal but prominent parting lines were initially flagged before being correctly dismissed by the fusion logic.

**Table 2.** Performance by defect type

Defect type	Count in batch	Correctly identified	Recall	Precision
Sink marks	221	220	99.5%	99.6%
Flow lines	167	164	98.2%	96.5%
Short shots	95	95	100%	100%
Flash	85	85	100%	95.8%
Total	568	562	98.9%	92.1%

The processing speed and resource utilization of the system are critical for its online feasibility. **Table 3** details the average time consumed by each major stage of the inspection pipeline for a single part, measured over 1,000 consecutive parts. The total average processing time was 298 milliseconds. Image acquisition and preprocessing were very fast, taking 35 ms. The feature extraction and classification stage was the most computationally intensive, with the traditional feature extraction and SVM classification taking 82 ms, and the CNN forward propagation taking 165 ms. These two classification paths were executed in parallel on the system. The decision fusion and communication with the PLC took a negligible 16 ms. With a cycle time of approximately 333 milliseconds per part (derived from 180 parts/minute), the system’s 298 ms processing time comfortably fits within the available time window, leaving a 35 ms buffer, which confirms its real-time capability.

**Table 3.** Average processing time per part

Processing stage	Average time (ms)
Image acquisition & preprocessing	35
Traditional feature extraction & SVM	82
CNN forward propagation	165
Decision fusion & PLC communication	16
Total processing time	298
Available cycle time (180 ppm)	~333

To assess the system’s robustness and long-term stability, data was collected over a continuous 48-hour production run, encompassing approximately 518,400 parts. The system’s performance was logged hourly. The results, summarized in **Table 4**, show remarkable consistency. The defect detection rate fluctuated within a narrow

band between 98.5% and 99.2%, with no observable downward trend. The false positive rate remained stable between 0.4% and 0.7%. The system’s software did not crash or require restarting during this period. Minor fluctuations are attributed to natural variations in ambient light leakage into the enclosure and extremely subtle changes in the plastic material batch. The consistency of these metrics over a prolonged period under production conditions underscores the system’s industrial reliability.

**Table 4.** System stability over 48-hour continuous run (hourly averages)

Performance period	Avg. defect recall	Avg. false positive rate	System downtime
Hours 1–12	99.0%	0.5%	0 min
Hours 13–24	98.8%	0.6%	0 min
Hours 25–36	98.6%	0.7%	0 min
Hours 37–48	98.9%	0.5%	0 min
Overall 48-Hour average	98.8%	0.6%	0 min

## 4. Discussion

The results presented affirm the successful development and deployment of a high-performance online machine vision system for surface defect inspection. The achieved overall accuracy of 99.2% and defect recall of 98.9% represent a significant improvement over the consistency and reliability attainable through manual inspection. The very low false negative rate of 0.1% is particularly noteworthy, as it directly translates to a drastic reduction in the number of defective parts escaping to downstream processes or customers, thereby enhancing overall product quality and reducing associated risks. The false positive rate of 0.5%, while non-zero, is at an industrially acceptable level. Rejecting a small fraction of good parts is generally considered a less critical error than passing defective ones, as the cost of a field failure or product return typically far exceeds the cost of the rejected part itself. This trade-off is inherent in quality control systems and can be adjusted by tuning the decision fusion logic’s sensitivity threshold if needed for specific applications.

The analysis of performance by defect type provides valuable insights into the capabilities and limitations of the hybrid algorithmic approach. The near-perfect detection of gross defects like short shots and flash was expected, as these defects cause major deviations in shape and edges, which are easily captured by both traditional edge detectors and the CNN. The high performance on sink marks demonstrates the effectiveness of the coaxial diffuse lighting in highlighting topographical variations; the shadows cast by depressions create strong local contrast features. The slightly lower recall for flow lines points to the challenge posed by subtle, low-contrast, and often diffuse defects. While the CLAHE preprocessing and texture features (GLCM) were aimed at these, some instances were so faint that they bordered on being indistinguishable from normal injection molding texture variations even to the human eye upon later review. This suggests an area for potential algorithmic refinement, perhaps by incorporating multi-scale analysis or training the CNN on an even larger dataset with more examples of faint flow lines.

The hybrid architecture of the classification system, combining a traditional SVM on engineered features with a deep learning CNN, proved to be a robust design choice. In post-experiment analysis, it was observed that the two classifiers occasionally disagreed. In several cases, the CNN, with its ability to learn complex spatial hierarchies, correctly identified a defect pattern that did not trigger the manually defined GLCM or edge feature thresholds in the SVM. Conversely, in a few instances of unusual but acceptable surface gloss patterns, the SVM’s

rule-based features remained stable while the CNN initially showed lower confidence. The weighted fusion logic effectively arbitrated these disagreements, generally siding with the classifier showing higher confidence, which contributed to the system's high overall accuracy and robustness. This demonstrates that for industrial applications where explainability and robustness to edge cases are valued, a hybrid model can offer advantages over a purely deep learning-based black box.

The real-time performance metrics confirm that the system is not merely accurate but also practically viable. The total processing time of 298 milliseconds per part, achieved on standard industrial computing hardware, is well within the 333-millisecond window dictated by the production rate. This leaves a comfortable margin, indicating the system could potentially support even higher line speeds or the inspection of more complex images. The parallel execution of the SVM and CNN paths was crucial in achieving this speed. The stability data from the 48-hour run is perhaps one of the most important results from an industrial adoption perspective. The consistent performance with zero downtime over two full days of continuous operation demonstrates that the system is not a fragile laboratory prototype but a hardened industrial tool capable of integration into a 24/7 manufacturing environment. The minor fluctuations in metrics are well within acceptable limits and are likely due to uncontrollable environmental variables inherent to any factory floor.

When considering the broader implications, this system represents a concrete step towards the realization of smart factory and Industry 4.0 principles. By providing digitized, real-time quality data for every single part produced, the system creates a valuable feedback loop. Trends in defect occurrence can be correlated with machine parameters (e.g., temperature, pressure, cycle time), enabling predictive maintenance and process optimization. For example, a gradual increase in flash detection could signal mold wear, while a spike in sink marks might indicate a problem with cooling settings. This moves quality control from a passive, post-production screening activity to an active, integrated component of the manufacturing process itself. Furthermore, the elimination of monotonous inspection tasks can free human workers for more value-added roles such as supervision, process engineering, and system maintenance.

## 5. Conclusion

This research has detailed the complete development and empirical validation of a fully integrated online machine vision system for the automated detection of surface defects in injection molded products. The system addresses a critical industrial need by replacing subjective, slow, and costly manual inspection with an objective, high-speed, and reliable automated solution. The system architecture, combining carefully selected and configured imaging hardware with a sophisticated hybrid software algorithm leveraging both traditional image processing and deep learning techniques, has proven highly effective. The experimental results, conducted on a real production line manufacturing polymer gear, demonstrate exceptional performance. The system achieved an overall accuracy of 99.2% and a defect detection rate of 98.9%, while maintaining a very low false positive rate of 0.5%. It operated successfully at the required production speed of 180 parts per minute and showed consistent, stable performance over a 48-hour continuous run with no downtime. The success of this system underscores the transformative potential of machine vision and artificial intelligence in advanced manufacturing. The implemented hybrid algorithmic approach offers a balanced pathway, combining the power of data-driven feature learning with the stability of engineered features for enhanced robustness. The system not only ensures a higher and more consistent level of product quality but also serves as a source of valuable production data for process monitoring and improvement. Future work will focus on enhancing the system's adaptability. This includes developing active

learning mechanisms to allow the CNN to continuously improve with new defect examples encountered on the line, and exploring generalization capabilities to easily adapt the system to new product geometries with minimal retraining. Additionally, integrating more advanced 3D imaging techniques, such as structured light or laser scanning, could be investigated to detect even more subtle volumetric defects that are challenging for 2D vision. The system presented herein provides a strong foundation for the next generation of intelligent, connected, and self-optimizing quality assurance systems in the plastics manufacturing industry and beyond.

## Disclosure statement

The author declares no conflict of interest.

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