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Performance Analysis of High-Speed Machine Vision Inspection in Automated Bottling Systems: A Comparative Study of Static vs. Dynamic Performance

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Abstract

Manual quality inspection in high-speed packaging is labor-intensive and prone to error rates of 20-30% due to cognitive fatigue and inconsistent visual search strategies. This study investigates the performance and robustness of an integrated industrial vision system designed to address these shortcomings, consisting of a Cognex IS2000M camera and an Allen Bradley PLC communicating via the Ethernet/IP protocol. The experimental setup utilizes a unique mechanical indexing approach: a servo-driven timing screw maintains a synchronized 8-second interval between consecutive bottles to prevent vision sensory overload during high-frequency cycles. A comparative analysis of 120 samples was conducted to evaluate label and logo verification across static and dynamic states at a conveyor speed of 18.5 cm/sec. Statistical analysis performed in R using Two-Way ANOVA revealed a significant "Motion Penalty" for complex patterns; the mean confidence score for logo inspection dropped from 88.8% in a static state to 72.5% in a dynamic state ($p = 0.0241$). Despite this reduction, the system demonstrated stable inspection performance, with all samples exceeding the selected 50% confidence threshold and no statistically significant performance drift over time ($p = 0.466$). Although static capture produced higher raw confidence scores, dynamic capture maintained acceptable pass/fail inspection performance while reducing processing time from 400 ms to 250 ms per bottle. These results indicate that, under the tested operating conditions, dynamic inspection provides a measurable cycle-time reduction while preserving the required inspection outcome.

Keywords
Machine Vision Inspection, Programmable Logic Controller (PLC), Static vs. Dynamic Performance, Confidence Score Analysis and Servo-Driven Timing Screw

1. Introduction
The modern manufacturing landscape, particularly within the food and beverage sectors, is increasingly defined by high-speed production requirements and stringent quality assurance standards. Central to these operations is the quality control (QC) of packaging, where label and logo verification are critical to brand integrity and consumer safety. Traditionally, industries have relied on human operators for visual inspection; however, this approach is fundamentally limited by human physiology. Manual inspection in high-speed environments is labor-intensive and susceptible to error rates of 20–30% due to cognitive fatigue, and search inconsistency , and the lack of formal training (Smith-Spark et al. 2019; See et al. 2018). As production speeds increase, the "people problem" becomes a bottleneck, leading to significant financial losses and environmental waste from undetected defects (Drury et al. 2021). The integration of machine vision and Programmable Logic Controllers (PLCs) offers a robust solution to these inherent shortcomings. By utilizing industrial-grade sensors like the Cognex IS2000M and centralized controllers like the Allen Bradley PLC, manufacturers can achieve precise, continuous, and high-speed quality control (Maślanka et al. 2025; Akhmetov et al. 2024). Recent research has focused on the complete integration and configuration of these vision systems with external PLCs to improve autonomous product detection (Mikhail and Sealy 2022). Furthermore, integrated inspection systems have been developed to handle in-line feedback and data collection, ensuring that defective objects are identified at specific conveyor positions to prevent downstream delays (Mikhail and Abad 2023). While the technological benefits of such systems are well-documented, a critical operational problem remains regarding the impact of conveyor motion on inspection reliability. Specifically, the trade-off between the high accuracy of static image capture and the superior productivity of dynamic (in-motion) capture requires rigorous experimental justification. Studies have been conducted with uniform bottle spacing to determine best practices for quality control purposes; for instance, Farhangi et al. (2024) utilize distance determination and pattern matching to rate defects in online inspections. This research addresses these gaps by implementing a servo-driven timing screw for controlled release of bottles at a fixed interval, ensuring the vision sensor is not overloaded and providing a direct comparison of static versus dynamic performance metrics.

1.1 Objectives
The primary objective of this research is to evaluate the operational performance and productivity of an integrated machine vision system for high-speed bottling. Specifically, the study aims to implement an orchestrated feeding mechanism using an Allen Bradley PLC and a servo-driven timing screw to maintain a consistent indexing interval. The research seeks to quantify the "Motion Penalty" on label and logo verification scores by comparing static image capture against a dynamic conveyor speed of 18.5 cm/sec. Furthermore, the study intends to validate system robustness against a defined confidence threshold and determine if the reduction in cycle time during dynamic inspection justifies its implementation in a high-speed manufacturing environment.

2. Literature Review
The transition toward automated quality control in the packaging industry is driven by the documented instability of manual inspection. Research by Smith-Spark et al. (2019) and See et al. (2018) highlights that human inspectors are prone to significant error rates, often between 20% and 30%, due to cognitive fatigue and the complex visual search strategies required in high-speed environments. These human issues lead to inconsistent results and high labor costs, prompting a systemic shift toward machine vision systems deployments. The integration of Programmable Logic Controllers (PLCs) and machine vision has emerged as the industrial standard for addressing these shortcomings. Maślanka et al. (2025) and Akhmetov et al. (2024) demonstrate that using a centralized PLC (such as Allen Bradley) to command high-speed cameras (such as Cognex) ensures precise and continuous inspection. Specifically, Mikhail and Sealy (2022) emphasize the importance of communication protocols like Ethernet/IP for real-time feedback. While these studies establish the technical communication framework, they often overlook the "Motion Penalty" associated with dynamic conveyor states. A critical gap in existing literature concerns the mechanical handling with image acquisition pacing and spacing of products. Although Farhangi et al. (2024) emphasizes uniform bottle spacing for defect detection, the specific method used to maintain this spacing is not clearly stated. This research fills that gap by implementing a servo-driven timing screw mechanism, a method supported by Hossain (2016) for liquid fillers, to ensure a time interval. Furthermore, evaluating performance requires a rigorous experimental design to isolate external noise. This study adopts the factorial analysis approach seen in RFID research (Aryal et al. 2010), keeping the Cognex IS2000M at a fixed fixture to isolate the effects of conveyor speed and target complexity. By providing exact

Confidence Scores rather than generic ranges, this work builds upon the measurement tool analysis of Jancarczyk et al. (2024) to justify the industrial shift toward dynamic inspection.

3. Methods

This section details the experimental design, hardware configuration, and the systematic procedure used to evaluate the inspection system's performance. The research was conducted in a controlled laboratory environment using a pilot-scale automated bottling line.

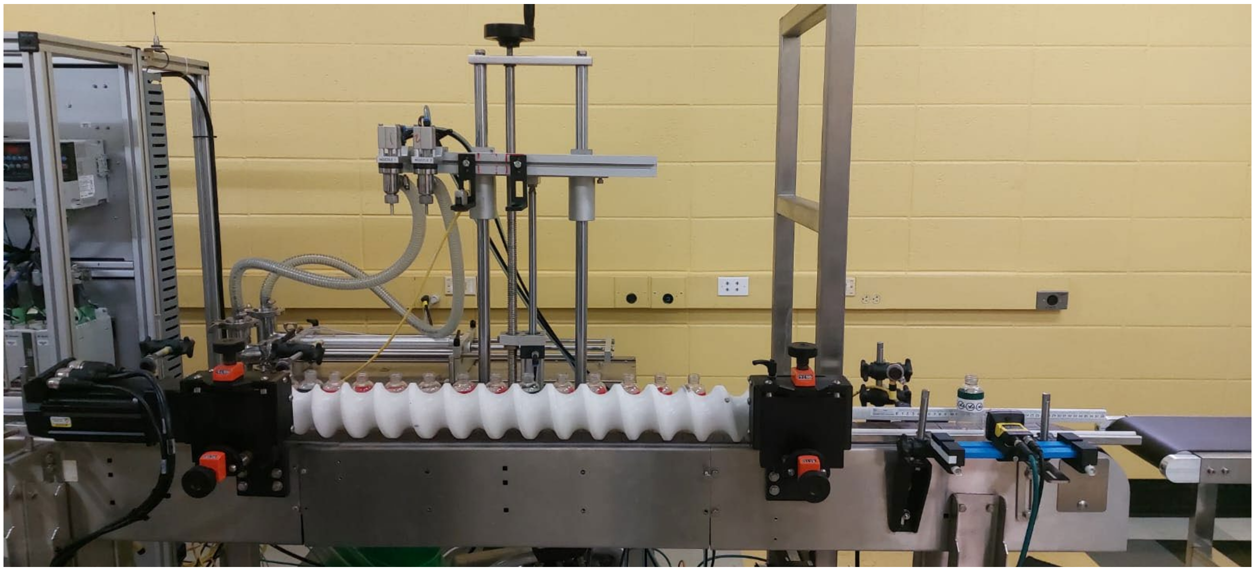

Figure 1. Experimental setup of the automated bottling line used in this study.

As shown in Figure 1, the experimental setup consisted of a conveyor-based bottling line with a mechanical bottle-handling arrangement designed to maintain controlled bottle movement and spacing during testing. This laboratory setup provided the physical platform used to evaluate inspection performance under repeatable operating conditions.

3.1 System Components and Control Architecture

The system is integrated through a centralized control architecture using an Allen Bradley PLC (Logix5000 series) as the primary controller. The vision sensor utilized is a Cognex IS2000M smart camera with a resolution of 640x480 pixels and a high-speed capture capability of up to 75 FPS. Communication between the PLC and the camera is established via the Ethernet/IP protocol, allowing for instantaneous data exchange and trigger synchronization.

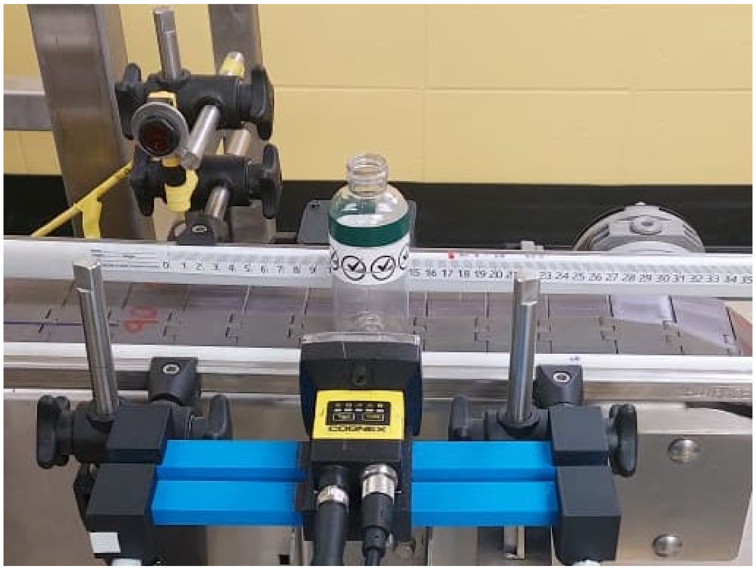

Figure 2. Photo eye and Cognex Camera

Mechanical handling is managed by a servo-driven timing screw (Figure 2), which is critical for maintaining an exact 8-second interval between consecutive empty bottles. This ensures that the vision system is not overloaded and operates within its processing capacity. The conveyor belt speed was maintained at a constant 18.5 cm/sec. Unlike standard industrial setups that rely on external strobe lighting, this research utilizes the camera's internal illumination controlled by industrial Ethernet to evaluate the system’s performance under uniform, fixed-fixture conditions.

3.2 Experimental Procedure

A total of 120 samples were processed to ensure statistical significance. The experimental matrix was designed as a comparative study between two independent variables:
Inspection Complexity: Verification of the "label" and the "logo" (Figure 3).

Figure 3. Bottle Label and Logo

Conveyor State: "Static" capture (belt fully stopped) and "Dynamic" capture (belt moving at 18.5 cm/sec).
The process begins with the timing screw indexing a bottle into the field of view. The PLC triggers the Cognex camera via Ethernet/IP based on the time delay from the photo eye. For static tests, the PLC issues a command to stop the belt before triggering; for dynamic tests, the trigger is issued while the belt maintains speed. The InSight software processes

the captured image and returns a Confidence Score (0–100%) to the PLC. A fail-safe threshold was set at 50% to determine a successful detection.

4. Data Collection

The data collection phase was designed to capture high-resolution performance metrics while maintaining strict control over environmental and mechanical variables. To ensure statistical power and reliability, a systematic sampling plan was executed over a continuous operational run.

4.1 Sampling Strategy

A total of 120 unique inspection events were recorded. The dataset was balanced across four primary experimental cells: 30 samples for static-label, 30 for static-logo, 30 for dynamic-label, and 30 for dynamic-logo. Empty bottles were utilized to isolate the performance of the vision algorithms on the primary packaging surface without the interference of liquid refraction or fill-level variance.

4.2 The Inspection Cycle

The collection process followed a strict temporal sequence managed by the Allen Bradley PLC. Each bottle was indexed by the servo-driven timing screw, ensuring a fixed arrival time at the inspection station every 8 seconds.

- Trigger Mechanism: The PLC utilized proximity sensor and time delay-based logic to issue a trigger command to the Cognex IS2000M via Ethernet/IP.
- Image Capture: For each event, the camera captured a 640x480 pixel image using internal illumination. The InSight software then applied pattern-matching tool to calculate a Confidence Score (0–100%) for the specific target (label or logo).
- Thresholding: A rigid pass/fail threshold was set at 50% based on repetitive verification. Any score below this value was logged as a failure, though the primary data focus remained on the raw numerical score to evaluate the degree of "Motion Penalty."

4.3 Latency and Time Measurements

In addition to confidence scores, the camera internal clock was used to measure pattern recognition processing time and total cycle time.

- Static Collection: Data included the time required for conveyor deceleration and full-stop stabilization (averaging 400ms).
- Dynamic Collection: Data recorded the "on-the-fly" processing time at a constant belt speed of 18.5 cm/sec (averaging 250ms).

5. Results and Discussion

The experimental results demonstrate a clear trade-off between inspection confidence and system throughput. While the automated vision system achieved a 100% success rate relative to the 50% threshold, the data reveals a significant interaction between mechanical motion and target complexity.

5.1 Confidence Score Analysis

Figure 4 presents the distribution of Cognex confidence scores for label and logo inspection under static and dynamic conveyor conditions. The boxplot shows that both inspection categories experienced lower confidence scores during dynamic inspection.

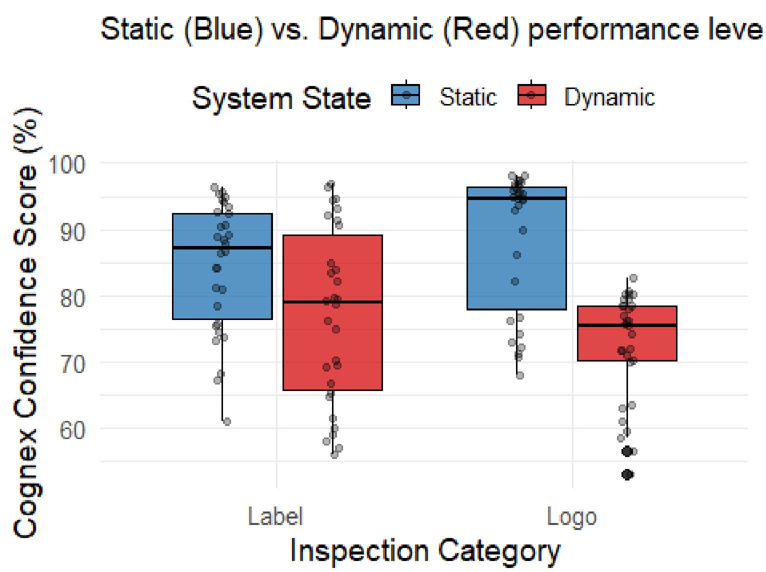

Figure 4. Categorical Confidence Scores

Table 1 summarizes the mean confidence scores obtained from the 120 inspection samples. The motion penalty was more evident in logo verification, where the mean confidence score decreased from 88.8% in the static condition to 72.5% in the dynamic condition. label verification showed a smaller decrease from 84.5% to 77.0%.

Table 1. Mean Confidence Scores by Inspection Type and Conveyor State

Inspection Type	Static Mean (%)	Dynamic Mean (%)	Motion Penalty (Δ)
Logo	88.8	72.5	-16.3%
Label	84.5	77.0	-7.5%

5.2 Statistical Interaction Analysis

The primary finding of this study is the significant interaction between inspection complexity and conveyor state. Figure 5 shows the motion penalty identified through the Two-Way ANOVA. The interaction effect was statistically significant ($p = 0.0241$), indicating that conveyor motion affected the inspection categories differently.

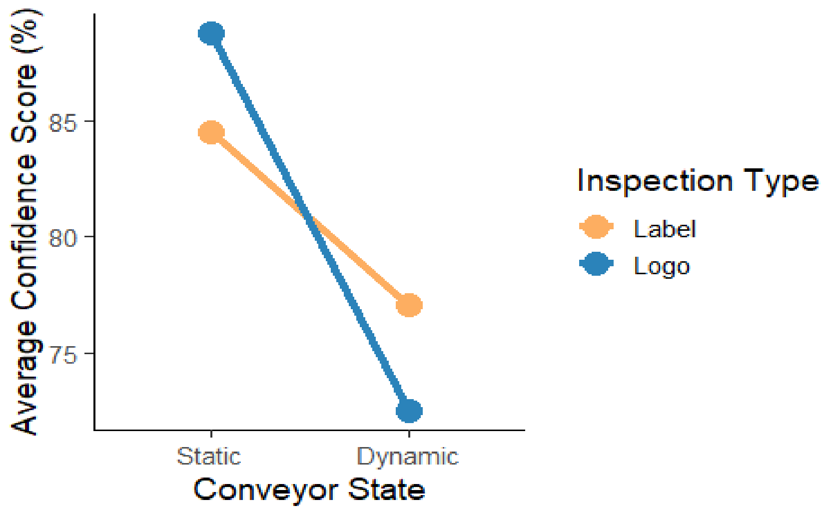

Figure 5. Interaction Plot of Mean Confidence scores

Figure 5 illustrates the motion penalty identified through the Two-Way ANOVA ($p = 0.0241$). While both categories experienced a decrease in confidence when transitioning to a dynamic state, the logo verification (blue line) showed a steeper degradation, dropping 16.3% compared to the 7.5% drop observed in label verification (orange line). This visual divergence confirms that geometric pattern matching is more sensitive to motion blur at 18.5 cm/sec than region verification.

5.3 Temporal Stability and System Robustness

A critical requirement for automated inspection is maintaining stable performance over time. To evaluate this, a linear trend analysis was conducted on the confidence scores across a 15-bottle sequence per run (Figure 6).

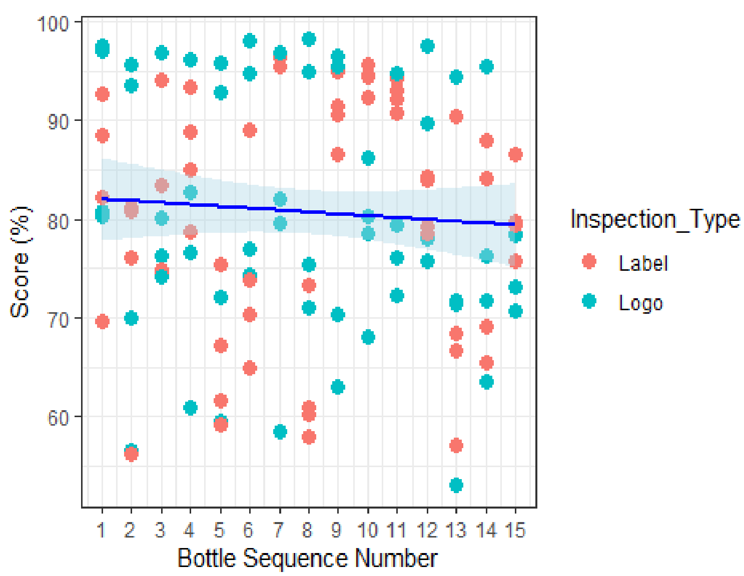

Figure 6. Temporal Stability

The linear model produced an intercept of 82.21 and a slope of -0.18. The p-value of 0.466 indicates that there was no statistically significant performance drift during the operational run. This result supports the stability of the machine vision system during the tested inspection sequence.

6. Conclusion

This study evaluated the performance of an integrated Cognex IS2000M vision system and Allen Bradley PLC for automated bottle label and logo inspection under static and dynamic conveyor conditions. The results showed that dynamic inspection produced a measurable motion penalty, with logo verification decreasing by 16.3% and label verification decreasing by 7.5%. The Two-Way ANOVA confirmed a statistically significant interaction between inspection type and conveyor state ($p = 0.0241$), indicating that complex logo features were more sensitive to conveyor motion. Despite this reduction in confidence, all 120 samples remained above the 50% pass/fail threshold. The temporal stability analysis also showed no statistically significant performance drift across the inspection sequence ($p = 0.466$). In addition, dynamic inspection reduced processing time from 400 ms to 250 ms per bottle under the tested operating conditions. These findings indicate that PLC-controlled dynamic inspection with servo-driven timing screw indexing provided a measurable processing-time advantage while maintaining acceptable pass/fail inspection performance in the laboratory-scale setup. Future work should examine additional conveyor speeds, variable bottle spacing, different lighting conditions, filled bottles with varying liquid levels, longer production runs, and integration with downstream rejection systems.

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Biographies

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