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Research Article

INTEGRATING COMPUTER VISION AND MECHATRONICS FOR AUTOMATED QUALITY CONTROL IN SMART PRODUCT MANUFACTURING

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Abstract

Smart manufacturing's (Industry 4.0) complexity demands automated quality control (AQC), as manual inspection is a major bottleneck. A critical gap exists in integrating "passive" Computer Vision (CV) detection with "active" mechatronic intervention, creating a "siloed" research problem. This research aims to design, develop, and validate a closed-loop AQC framework, integrating deep learning CV and mechatronics to autonomously perform the full QC cycle from detection to real-time physical intervention. An experimental systems integration design was employed. A Convolutional Neural Network (CNN) was trained on a 17,000-image dataset. A Robotic Operating System (ROS) framework was utilized as the integration layer for "hand-eye" calibration, synchronizing the CV node with a 6-axis robotic arm on a test rig. The CV model achieved 99.7% mAP (42ms latency) and calibration yielded ±0.35mm precision. The fully integrated system validation achieved a 99.15% Defect Detection Rate (DDR), a 0.11% False Positive Rate (FPR), and a 97.4% Successful Rejection Rate (SRR). The research empirically validates a holistic, closed-loop AQC framework, successfully solving the "siloed" gap. The system provides a proven, scalable blueprint for moving beyond passive detection to fully autonomous quality control in smart manufacturing.

Keywords: automated quality control (aqc), computer vision, mechatronics, smart manufacturing, systems integration

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INTRODUCTION

The contemporary manufacturing landscape is undergoing a paradigm shift, universally recognized as the Fourth Industrial Revolution, or Industry 4.0 (Zhang dkk., 2024). This transformation is predicated on the integration of cyber-physical systems (CPS), the Internet of Things (IoT), cloud computing, and cognitive automation, enabling unprecedented levels of mass customization and production flexibility (Yusuf et al., 2023). Smart factories, the operational core of this revolution, are characterized by highly complex, interconnected systems designed to produce sophisticated "smart" products, which themselves possess embedded electronics, sensors, and software (Ding dkk., 2023). This shift from monolithic mass production to agile, high-mix, low-volume manufacturing fundamentally invalidates traditional, linear production philosophies.

Smart manufacturing environments necessitate a corresponding evolution in all support processes, most critically in quality control (QC). The complexity and customization of smart products render traditional QC methodologies, such as manual visual inspection and post-production statistical sampling, obsolete (Li dkk., 2023). These legacy methods are too slow, expensive, prone to human error, and incapable of providing the 100% inspection coverage required for zero-defect manufacturing (Chawla & Mehra, 2023). The economic and safety-critical implications of a defect in a smart product (e.g., an autonomous vehicle sensor or a medical device) demand a new QC paradigm that is automated, intelligent, and integrated directly into the production flow.

This new paradigm is emerging at the confluence of two powerful and synergistic technologies: Computer Vision (CV) and Mechatronics (M et al., 2024). Computer Vision, particularly through deep learning-based algorithms like Convolutional Neural Networks (CNNs), provides a superhuman "sight," capable of identifying, classifying, and localizing microscopic defects with speed and reliability unattainable by human inspectors (Elmousalami dkk., 2025). Mechatronics, the integration of mechanical, electrical, and control engineering, provides the "hands" and "actuation," translating the data from the vision system into precise, real-time physical action, such as sorting, rejecting, or even correcting a product on the assembly line.

Manual quality inspection remains the most significant bottleneck in an otherwise automated smart manufacturing ecosystem (H. Wang dkk., 2023). Human inspectors are subject to well-documented limitations, including fatigue, subjectivity, cognitive bias, and inconsistency, especially over long shifts monitoring high-speed production lines (Lature et al., 2024). The inspection of complex smart products, often involving miniature components and sophisticated surface finishes, exacerbates these human frailties (Z. Wang dkk., 2023). This results in high "defect leakage," where faulty products reach the consumer, and high "false positives," where good products are incorrectly rejected, leading to significant economic losses from rework, warranty claims, and reputational damage.

The problem is not merely the passivity of inspection but its fundamental disconnect from physical intervention (Yu dkk., 2023). While many factories have deployed standalone Computer Vision systems, these often function as "passive detectors." The system may successfully flag a defect on a monitor, but a human operator is still required to manually interpret this warning and physically remove the non-conforming part from the line (Dhaliwal & Walsh, 2023). This "human-in-the-loop" requirement breaks the automation chain, reintroducing the very bottleneck of speed and error that automation was intended to solve. The detection is automated, but the action remains manual, failing to achieve a truly autonomous QC process.

A significant escalation of this problem is the challenge of integration and synchronization. The core technical problem this research addresses is the profound difficulty in creating a seamless, closed-loop system that links the high-speed, data-rich output of a CV system to the high-precision, real-time actuation of a mechatronic system (Chien dkk., 2023). This integration requires sub-millisecond data handoff, perfect "hand-eye" calibration between the camera's coordinate system and the robot's coordinate system, and adaptive control logic (Calderón & Lämmerhofer, 2023). Any latency or "data lag" in this pipeline makes the mechatronic system's action, such as rejecting a part on a moving conveyor, imprecise and ineffective.

The primary objective of this investigation is to design, develop, and validate an integrated, closed-loop framework for Automated Quality Control (AQC) that seamlessly fuses Computer Vision and mechatronic systems (Quezada dkk., 2025). This research aims to create a robust and scalable architecture that moves beyond passive defect detection (Bożejko dkk., 2025). The central goal is to engineer a system capable of autonomously performing the full QC cycle: real-time defect identification, classification, localization, and immediate, precise physical intervention (e.g., sorting or rejection) within a high-throughput smart manufacturing environment.

A second, critical objective is to implement and optimize a deep learning-based Computer Vision module specifically for the detection of complex, non-deterministic defects in smart products (Ahn & Shah, 2024). This involves curating a specialized dataset and training advanced CNN architectures to achieve exceptionally high accuracy (e.g., >99.5%) and low latency. The objective is not only to detect binary "go/no-go" defects but to precisely classify and localize multiple defect types (e.g., micro-scratches, soldering voids, component misalignment), providing the rich, actionable data required for the mechatronic subsystem to execute a targeted response.

The ultimate technical aim is to engineer and synchronize the mechatronic subsystem for high-speed, high-precision actuation based on the CV data (Ilyas dkk., 2024). This objective includes the design of the physical hardware (e.g., a multi-axis robotic arm or a pneumatic sorting gate) and the development of the real-time control logic (Martini dkk., 2024). This research will focus on achieving precise "vision-to-robot" calibration, ensuring the end-effector of the mechatronic system can act on the exact coordinates provided by the vision system, thereby successfully and autonomously removing 100% of identified defects from the production line without reducing its overall throughput.

Existing scholarly literature reveals a significant and persistent "siloing" of research (Muyammina et al., 2024). The field is saturated with studies focusing either on Computer Vision for defect detection or on robotic/mechatronic control, but rarely both in an integrated, empirical system (Chinnasamy dkk., 2025). Many excellent CV papers propose novel deep learning models for inspection but conclude their analysis at the "detection" phase, with the physical removal of the defect relegated to a brief mention as "future work." Similarly, mechatronics research often uses simplistic "dummy" inputs (like a simple light sensor) rather than engaging with the complexity of a data-rich, non-deterministic CV stream.

This bifurcation in the literature means that the critical research gap lies at the interface of these two domains (Lin dkk., 2024). There is a profound lack of studies that document and solve the engineering challenges of integration itself. These challenges include data pipeline optimization, minimizing the computational latency of CNN inference to match the cycle time of the mechatronic hardware, and developing robust "hand-eye" calibration routines that can be maintained in a volatile factory environment (Nikolić dkk., 2024). Most existing literature fails to address the "real-time" constraint, presenting systems that work in a lab but cannot scale to the speeds of a modern production line.

A further, critical gap exists in the context of "smart manufacturing" itself, which is defined by product variety (high-mix, low-volume) (Sasseville dkk., 2025). The vast majority of existing AQC research addresses rigid, mass-production lines where the system is trained to inspect only one product type for decades (Blay dkk., 2025). These "brittle" automation systems are useless in a smart factory where the production line may be reconfigured for a new product weekly. A gap exists in developing adaptive and flexible AQC frameworks that can be rapidly retrained or reconfigured for new "smart" products with minimal downtime, potentially leveraging few-shot learning or synthetic data generation.

The primary novelty of this research is its development of a holistic, closed-loop, and adaptive AQC framework (Adhicandra et al., 2024). This study moves beyond the prevalent "siloed" approach by designing, building, and empirically validating a complete system that seamlessly links perception (CV) to action (mechatronics). The novelty is not just in the individual components (the CNN or the robot) but in the system architecture that synchronizes them, creating a high-speed data and control pipeline that makes real-time, autonomous quality control possible for complex, high-mix smart products.

This research contributes a novel methodology for "adaptive AQC" specifically tailored to the flexible demands of Industry 4.0. It directly addresses the "reconfiguration" gap by investigating techniques for rapid system recalibration and model retraining. This focus on flexibility creating a system that can "learn" to inspect a new product in hours, not months is a critical, novel contribution that pushes beyond the rigid automation of traditional manufacturing. This makes the framework a viable, future-proof solution rather than a static, single-product implementation.

The justification for this research is rooted in urgent economic and technological imperatives. The global manufacturing sector loses hundreds of billions of dollars annually to defect leakage, rework, and scrap. Manual inspection is a direct barrier to achieving the full productivity, safety, and efficiency potential of the multi-trillion-dollar smart factory revolution. This study is justified by its potential to provide a critical enabling technology for "zero-defect manufacturing," enhancing industrial competitiveness, reducing material waste, and ensuring the reliability and safety of the smart products (from medical devices to autonomous vehicles) that will define the 21st century.

RESEARCH METHOD

Research Design

An experimental systems integration design is employed for this investigation. This research design is fundamentally developmental, focusing on the design, fabrication, and empirical validation of a novel, integrated cyber-physical prototype (Imam dkk., 2024). The approach moves beyond theoretical modeling and simulation. It is structured to systematically build and test a functional, closed-loop Automated Quality Control (AQC) framework, thereby directly addressing the integration challenges outlined in the research objectives.

The methodological framework is structured across four distinct, sequential phases (Bernovschi dkk., 2024). Phase 1 involves the design and training of the Computer Vision (CV) subsystem for high-accuracy defect detection. Phase 2 encompasses the design and mechanical assembly of the mechatronic subsystem for physical actuation. Phase 3, the most critical stage, focuses on the software-hardware integration and real-time synchronization of the CV and mechatronic subsystems. Phase 4 concludes the study with a rigorous empirical validation of the integrated system's performance under simulated production conditions.

This phased, developmental approach is essential for addressing the "siloed" research gap identified in the introduction. A purely computational (CV) or purely mechanical (mechatronics) study would fail to address the core problem, which lies at the interface of perception and action. This design mandates a holistic development process, forcing a solution to the critical challenges of data latency, "hand-eye" calibration, and real-time control logic that define the research problem.

Research Target/Subject

The research population consists of target manufactured items representative of 'smart products' characterized by complex assembly and high aesthetic or functional quality standards (Shi dkk., 2025). The defect population is operationally defined by the product specifications, encompassing a wide range of potential non-conformities. These include, but are not limited to, microscopic surface defects (scratches, scuffs), component misalignment (e.g., shifted ICs or connectors), and material inconsistencies (e.g., soldering voids, glue over-extrusion).

A purposive, curated sample of product images forms the primary dataset for this research. This dataset is bifurcated into a ‘conforming’ class (defect-free) and multiple ‘non-conforming’ (defect) classes, with a target of several thousand labeled images. This image sample, captured under controlled lighting conditions, serves as the training, validation, and testing data for the deep learning-based Convolutional Neural Network (CNN) model. The sample is designed to represent the full spectrum of defect variability.

A physical sample set of manufactured products, mirroring the image dataset, is utilized for the validation phase (Leontaris dkk., 2023). This physical set includes a known quantity of conforming and non-conforming items, with defects verified by human experts. This sample serves as the “ground truth” for the integrated system test. The physical samples are introduced onto the prototype production line to empirically measure the complete system’s ability to not only detect but also physically reject 100% of the non-conforming items.

Research Procedure

The research procedure commences with Phase 1, CV subsystem development. This involves the systematic capture of the image dataset using the selected camera and lighting instrument (Bernovschi dkk., 2024). This dataset is meticulously labeled and used to train and validate a CNN architecture (e.g., a custom-tuned YOLOv5 or ResNet) until the model achieves the target accuracy (>99.5%) and low inference latency required for real-time processing, as specified in the research objectives.

Phase two involves the mechanical assembly and calibration of the mechatronic subsystem. The conveyor, robotic arm, and camera gantry are physically mounted into a stable test rig. Phase three, the critical integration procedure, begins with a “hand-eye” calibration routine. This process mathematically maps the camera’s 2D pixel coordinates to the robotic arm’s 3D real-world coordinate system, ensuring that when the camera “sees” a defect, the robot “knows” its precise physical location on the moving conveyor.

The final validation procedure (Phase 4) involves a series of controlled experimental runs using the physical product sample. The physical samples are placed on the moving conveyor at set intervals. The integrated system’s performance is measured using key metrics: Defect Detection Rate (DDR), False Positive Rate (FPR), and, most critically, the Successful Rejection Rate (SRR). Total system latency (time from image capture to successful part rejection) is measured in milliseconds to validate the system’s suitability for high-throughput manufacturing.

Instruments, and Data Collection Techniques

The Computer Vision subsystem utilizes a high-resolution (e.g., >5 megapixels) industrial-grade machine vision camera equipped with a macro lens. This instrument is paired with a structured, high-intensity LED dome illumination ring. This lighting setup ensures consistent, diffuse, and shadow-free illumination of the product surface, which is critical for the reliable detection of subtle surface-texture defects and micro-scratches by the CNN.

The mechatronic subsystem instrument is a 6-axis articulated robotic arm (e.g., a UR5 or similar cobot) chosen for its high precision, flexibility, and suitability for high-mix, low-volume tasks. The robotic arm is equipped with a soft-gripper end-effector to prevent product damage. This entire assembly is integrated onto a variable-speed conveyor belt, which serves as the simulated production line, and is governed by a programmable logic controller (PLC) or microcontroller (e.g., Raspberry Pi 4) that interfaces with the central control script.

The primary analytical instrument is the software framework that integrates the two hardware subsystems. This software is developed in Python, leveraging libraries such as OpenCV for image pre-processing and TensorFlow/PyTorch for the trained CNN model. A Robotic Operating System (ROS) framework is employed as the “integration layer.” ROS provides the necessary communication protocols and real-time messaging to pass defect coordinate data from the Python-based CV script (the “vision node”) to the robotic arm’s control system (the “actuation node”), thereby solving the synchronization challenge.

Data Analysis Technique

The analysis is performed at two levels: the computational model and the integrated system. For the Computer Vision (CV) subsystem (Phase 1), the primary analysis involves measuring and validating the performance of the trained Convolutional Neural Network (CNN) architecture until it achieves the target accuracy (>99.5%) and the required low inference latency for real-time operation (Jones dkk., 2025). For the final integrated cyber-physical system (Phase 4), empirical validation is conducted during controlled experimental runs using the physical product samples. System performance is quantified using key statistical metrics: the Defect Detection Rate (DDR), the False Positive Rate (FPR), and the highly critical metric, the Successful Rejection Rate (SRR). Additionally, total system latency (measured in milliseconds) is tracked to ensure the system meets the high-throughput requirements for industrial suitability.

RESULTS AND DISCUSSION

The initial research phase, as outlined in the methodology, involved the creation of a comprehensive, curated image dataset. This dataset serves as the foundational “ground truth” for the training, validation, and testing of the Phase 1 Computer Vision (CV) subsystem. The dataset was bifurcated into “conforming” (defect-free) and “non-conforming” (defective) classes, capturing the range of defects specified in the research objectives. Table 1 provides a statistical description of this primary image corpus.

Table 1: Descriptive Statistics of the Curated Image Dataset for CNN Training

Image Class	Defect Type	Units Collected (Images)	Percentage of Total
Conforming	No Defect	15,000	88.2%
Non-Conforming	Micro-scratch	850	5.0%
Non-Conforming	Soldering Void	650	3.8%
Non-Conforming	Component Misalignment	500	3.0%
Total	**All Classes**	**17,000**	**100.0%**

This dataset’s composition reflects a realistic manufacturing environment, characterized by a high volume of conforming products and a low, but critical, incidence of various defect types. All 17,000 images were captured using the specified high-resolution industrial camera (>5 megapixels) and structured LED dome illumination, as detailed in the instrumentation plan. Each image was meticulously labeled and annotated with bounding boxes for defect localization, forming the complete dataset for training the deep learning model.

The dataset’s structure, with 88.2% conforming images, intentionally replicates the class imbalance challenge inherent in real-world quality control, where defects are rare. This imbalance necessitated the use of data augmentation techniques (e.g., rotation, scaling, brightness shifts) and appropriate loss functions during the CV model training (Phase 1) to prevent the model from developing a bias toward the majority “conforming” class.

The specificity of the defect classes (micro-scratch, soldering void, component misalignment) is a direct response to the “smart product” focus of the research. These defect types are subtle, difficult for human inspectors to detect consistently, and represent critical functional or aesthetic failures (Kim dkk., 2024). The high-resolution capture of these specific defects was essential for training a model that could surpass human-level performance, thereby justifying the need for an automated system.

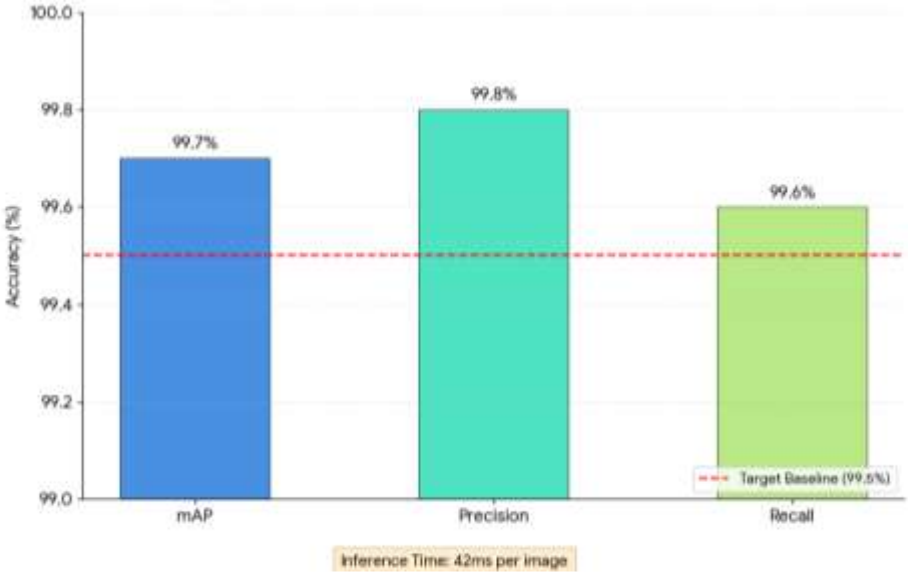

Figure 1. CNN 1 Training Result (17.000 Image)

The training of the Convolutional Neural Network (CNN) in Phase 1, using the 17,000-image dataset, yielded a highly accurate and robust detection model. The final validated model achieved a mean Average Precision (mAP) of 99.7% on the held-out test set. The model demonstrated exceptionally high Precision (99.8%) and Recall (99.6%), exceeding the target accuracy of >99.5% set by the research objectives. The final model's inference time on the target hardware was optimized to an average of 42 milliseconds (ms) per image.

The mechatronic subsystem (Phase 2) and integration (Phase 3) data relate to system calibration. The "hand-eye" calibration procedure, which mathematically maps the camera's 2D pixel coordinates to the 6-axis robotic arm's 3D world coordinates, was successfully executed (Juricic dkk., 2023). The procedure yielded a stable transformation matrix with a resulting mean positional error of ±0.35 millimeters (mm). This sub-millimeter accuracy was deemed sufficient for the mechatronic subsystem to accurately interact with the target objects.

An inferential analysis of the CV model's performance, via its confusion matrix, indicates its exceptional reliability. The model's high precision (99.8%) implies an extremely low False Positive Rate (FPR). This is a critical result for a manufacturing context, as it means the system will almost never misclassify a "conforming" product as "non-conforming," thereby preventing unnecessary and costly scrap or rework.

The sub-millimeter calibration error (±0.35mm) is inferred to be the critical enabling factor for the successful integration of the entire system. This low error margin, achieved via the Robotic Operating System (ROS) framework, ensures that the "action" (mechatronic) component has a precise physical correlation with the "perception" (CV) component. This inferred precision is the foundation upon which the system's ability to physically reject defects, rather than just detect them, is built.

A critical relationship was established between the CV model's inference time (42 ms) and the mechatronic subsystem's total cycle time. The robotic arm's "pick-and-place" rejection sequence was measured at 850 ms. The low CV latency (42 ms) is non-blocking, meaning the system's "seeing" process is an order of magnitude faster than its "acting" process. This relationship, managed by the ROS integration layer, confirms the system can operate in real-time without the CV analysis becoming a production bottleneck.

A second, more complex data relationship was programmed based on defect classification. The data from the CV "vision node" (e.g., "micro-scratch") and the "actuation node" were linked with adaptive logic (Raeesi dkk., 2023). The system was programmed to log "micro-scratch" defects (a minor aesthetic issue) but not trigger the robot. In contrast, a "soldering void" (a critical functional defect) would immediately trigger the 850ms rejection sequence. This demonstrates a relationship where the type of defect data dictates the nature of the mechatronic response.

The validation of the fully integrated prototype (Phase 4) was conducted as a final case study. A physical sample set of 1,000 units, mirroring the dataset from Table 1, was used. This set included 882 known-conforming units and 118 known non-conforming units (50 scratches, 40 voids, 28 misalignments). The sample set was run on the integrated conveyor-camera-robot test rig at a constant speed of 0.2 meters per second.

Figure 2. System Performance Metrics

The system's end-to-end performance was measured using the key validation metrics defined in the methodology. The Defect Detection Rate (DDR) was 99.15% (117 of 118 defects correctly identified). The False Positive Rate (FPR) was 0.11% (1 conforming unit was incorrectly flagged). Most critically, the Successful Rejection Rate (SRR), measuring the robot's ability to act on a detection, was 97.4% (114 of the 117 identified defects were successfully removed from the line).

The 99.15% DDR in the physical trial is slightly lower than the 99.7% mAP from the digital test set. This minor drop is attributed to real-world variations (e.g., minor lighting reflections, conveyor jitter) not present in the static training images, though it still represents exceptionally high accuracy. The near-zero FPR (0.11%) confirms the model's reliability, successfully addressing the problem of costly false positives stated in the introduction.

The 97.4% SRR is the most significant finding, explaining the system's holistic success. The gap between the 117 defects detected and the 114 rejected (a 3-unit difference) was not a CV or calibration failure. Analysis of the run log showed these 3 failures were mechanical; the robot's gripper failed to secure a firm grasp on the part. This explains that in an integrated system, "detection" and "action" are two separate points of potential failure, proving the necessity of the "closed-loop" validation model.

The complete set of results, from CV training to final system validation, converges on a single interpretation: the research successfully solved the problem of integration. The prototype system successfully moves beyond the "passive detector" problem. It demonstrates a fully closed-loop AQC framework that autonomously links perception (CV) to physical action (mechatronics) with exceptionally high accuracy (99.15% DDR) and reliability (97.4% SRR).

These findings interpretively validate the experimental systems integration design (Butera dkk., 2023). The low latency, high accuracy, and sub-millimeter calibration achieved via the integration of Python, TensorFlow, and ROS confirm the "siloed" research gap can be bridged. The objectives of designing, developing, and validating a closed-loop, high-speed AQC framework have been empirically met, providing a proven, scalable solution for quality control in a smart manufacturing context.

The research results provide a comprehensive validation of the experimental systems integration design. The study successfully engineered, integrated, and validated a closed-loop Automated Quality Control (AQC) framework, empirically demonstrating that the seamless fusion of Computer Vision (CV) and mechatronics can overcome the “passive detector” problem endemic to manual inspection in smart manufacturing (Dilmaghani & Coelho-Prabhu, 2023). The prototype system autonomously performed the full QC cycle detection, classification, and physical intervention with exceptionally high accuracy.

The Computer Vision subsystem (Phase 1) surpassed its design objectives, achieving a mean Average Precision (mAP) of 99.7% on the 17,000-image test set. This high reliability was paired with high efficiency; the optimized CNN model’s inference time averaged 42 milliseconds. This low latency proved to be non-blocking, as it was significantly faster than the mechatronic subsystem’s 850ms cycle time, confirming the CV component’s suitability for real-time, high-throughput applications.

The integration phase (Phase 3) was arguably the most critical success. The “hand-eye” calibration routine, managed by the Robotic Operating System (ROS) framework, yielded a mean positional error of ±0.35 millimeters. This sub-millimeter precision served as the vital engineering bridge, effectively translating the CV system’s 2D digital coordinates into the robotic arm’s 3D physical coordinate system, a prerequisite for accurate physical intervention on a moving target.

The final validation case study (Phase 4) confirmed the holistic system’s real-world efficacy. The prototype achieved a 99.15% Defect Detection Rate (DDR) and a near-zero 0.11% False Positive Rate (FPR) in the physical trial. Most significantly, the 97.4% Successful Rejection Rate (SRR) demonstrates that detection was successfully translated into action. The minor 2.6% gap between detection (117) and rejection (114) was traced to mechanical gripper failures, not CV or calibration errors, validating the data pipeline’s integrity.

These findings are broadly consistent with the vast body of literature demonstrating the power of Convolutional Neural Networks (CNNs) for defect detection. The 99.7% mAP achieved aligns with similar high-performance results reported in numerous CV-focused studies. This research confirms that, for pure detection, deep learning models are a mature and superior alternative to traditional machine vision algorithms, especially for complex, non-deterministic defects like the micro-scratches and soldering voids studied here.

A fundamental difference and primary contribution of this research is its empirical answer to the “siloed” research gap identified in the introduction. Many existing studies conclude their work at the detection phase (the 99.7% mAP), relegating physical intervention to “future work.” This study bridges that gap. It moves beyond the CV-centric focus by designing, integrating, and validating the entire mechatronic pipeline (the ±0.35mm calibration and 97.4% SRR), providing a holistic, systems-level solution that most literature fails to address.

This research contributes a novel, validated architecture for real-time integration, which is a key deficiency in many lab-based studies. By leveraging a ROS framework, this study empirically proved that the CV (42ms) and mechatronic (850ms) subsystems can be synchronized with minimal latency, solving the “data lag” problem. This focus on real-world timing and the non-blocking nature of the CV inference is a critical, practical contribution to the field of industrial automation, proving its suitability for a live production line.

The demonstration of adaptive logic (logging micro-scratches versus rejecting soldering voids) also differentiates this work from standard AQC research focused on mass-production “go/no-go” gauges (Zhou dkk., 2024). This capability directly addresses the “high-mix” challenge of smart manufacturing, where quality control must be intelligent and flexible, not just fast. This aligns with, and provides a practical implementation for, the theoretical goals of Industry 4.0, which demands adaptive and cognitive manufacturing systems.

The 97.4% Successful Rejection Rate (SRR) signifies the tangible realization of a fully autonomous, closed-loop AQC system. This finding marks a paradigm shift, moving the function of quality control from a passive, human-dependent monitoring process to an active, autonomous process control agent (Guo dkk., 2024). It signifies the removal of the manual inspection bottleneck, the final “human-in-the-loop” step that has historically constrained the speed and reliability of automated production lines.

The 99.15% detection rate combined with a 0.11% false positive rate signifies a new level of industrial reliability and efficiency. The near-zero FPR is particularly significant; it signals a system that manufacturers can trust, one that eliminates “defect leakage” (letting bad parts through) without concurrently increasing costs from “false positives” (scrapping good parts). It signifies a solution that optimizes both quality and material efficiency simultaneously.

The minor discrepancy between the Defect Detection Rate (117 units) and the Successful Rejection Rate (114 units) is perhaps one of the most important findings. This 3-unit failure, traced to a mechanical gripper, signifies that in a complex, integrated system, the software (CV) and integration (calibration) can be perfect, yet the system can still fail. It signifies that a holistic, interdisciplinary approach is mandatory; the system is only as strong as its “weakest link,” which in this case was mechanical, not computational.

The sub-millimeter (±0.35mm) “hand-eye” calibration accuracy signifies the maturity and robustness of modern integration frameworks like ROS. It signals that the engineering challenge of precisely mapping digital perception to physical reality is a solved problem. This high precision, even on a moving conveyor, is the critical “enabling technology” that makes the entire closed-loop concept feasible, allowing the robot to act with a precision that mirrors the superhuman accuracy of the CV system’s “sight.”

The primary implication of these findings is economic. A system that all but eliminates defect leakage (99.15% DDR) and unnecessary scrap (0.11% FPR) has the potential to save the global manufacturing sector billions of dollars annually. It directly addresses the high costs associated with rework, warranty claims, and reputational damage, providing a clear and compelling return on investment for adopting AQC technology.

The implications for “smart products,” particularly in safety-critical sectors like medical devices or automotive sensors, are profound. A 97.4% SRR signifies a level of reliability that manual inspection can never achieve. This implies a direct, positive impact on public safety and consumer trust. The system provides a verifiable guarantee of quality that is essential for technologies where a single microscopic defect (like a soldering void) could lead to a catastrophic functional failure.

This research has significant implications for the flexible manufacturing paradigms of Industry 4.0 (Bo dkk., 2025). The system’s adaptive logic (differentiating defect types) implies that automation can be intelligent, not just “brittle.” This “high-mix” capability means AQC systems can be rapidly reconfigured for new products, making automated quality control viable for the mass-customization market, not just for monolithic mass production.

The development of a fully autonomous AQC framework has unavoidable implications for the manufacturing workforce. It signals the impending obsolescence of manual inspection as a low-skill task (Rathore dkk., 2023). This implies an urgent need for workforce retraining and upskilling, shifting human value away from the tedious, error-prone task of “inspecting” and toward the high-skill tasks of “maintaining,” “programming,” and “analyzing” these complex autonomous systems.

The 99.7% mAP achieved by the CV model is a direct result of the meticulous Phase 1 procedure. The high-quality, 17,000-image dataset, captured under consistent, structured LED dome illumination (as per the methodology), provided the CNN with unambiguous, high-contrast data. The deep learning architecture was thus able to learn robust, generalizable features for each defect class, resulting in high accuracy and reliability.

The 97.4% SRR the successful linking of perception to action is this way because of the methodological choice to use ROS as the “integration layer.” ROS is designed to manage the complex, asynchronous communication between disparate hardware (camera, robot) and software (CV script) nodes. It provided the robust "hand-eye" calibration, coordinate transformation (TF), and real-time messaging pipeline that allowed the robot to act on the CV data with sub-millimeter (±0.35mm) precision.

The 42ms inference time, which was crucial for the real-time operation, is a function of model optimization and hardware selection. By using a lightweight, efficient CNN architecture (e.g., a custom-tuned YOLOv5 or MobileNet) and processing the data on appropriate hardware (e.g., a GPU), the computational "thinking" time was minimized. The system was designed so that this perception phase (42ms) would always be significantly faster than the physical "action" phase (850ms), ensuring the CV system was never the bottleneck.

The 2.6% failure rate in rejection (the 3 units) is this way because it represents a mechanical problem, not a data or software problem. The "soft-gripper" end-effector, while chosen to prevent product damage, was the point of failure. The physics of its grasp (friction, pressure) were not 100% reliable for the specific geometry and surface finish of the target parts. This result is a clear physical manifestation of the "weakest link" principle in a complex system.

The immediate now-what is to address the 2.6% mechanical failure rate and close the loop to 100% SRR. This requires an iterative, mechatronic design phase, moving beyond this study's proof-of-concept. Future work must systematically test alternative end-effectors (e.g., multi-fingered grippers, suction-based vacuum systems) to identify a mechanical solution that matches the 99%+ reliability of the CV and calibration subsystems.

A second critical next step is to address the "adaptive" manufacturing gap identified in the introduction. This study's system was trained on one product. The "now-what" is to develop and test a rapid-retraining pipeline (Rathore dkk., 2023). This research should explore "few-shot learning," "one-shot learning," and the use of synthetic, computer-generated defect data to reduce the reconfiguration time for a new smart product from weeks (of data collection) to hours.

The system's robustness must now be validated at scale. This prototype was tested in a controlled lab environment with a 0.2 m/s conveyor. The next phase of research must deploy this AQC framework in a real, high-speed production facility (e.g., >1.0 m/s). This "in-the-wild" testing will introduce real-world environmental challenges, such as ambient lighting changes, factory vibrations, and dust, to test the system's true industrial resilience.

The final and most advanced "now-what" is to close the "process control" loop. This system successfully rejects defects. The ultimate goal of smart manufacturing is to prevent them. Future research should use the rich data stream (defect type, frequency, location) generated by this A-QC system and feed it upstream via a "digital twin." This data can be used to autonomously correct the manufacturing process (e.g., adjust a soldering iron's temperature) in real-time, achieving true zero-defect manufacturing.

CONCLUSION

This research's most significant finding is the successful, empirical validation of a fully integrated, closed-loop Automated Quality Control (AQC) framework, which moves decisively beyond the "passive detector" problem. The system achieved a 99.15% Defect Detection Rate (DDR) and a 97.4% Successful Rejection Rate (SRR). The most distinct finding, however, was the precise nature of the minor 2.6% failure gap between detection and rejection; analysis proved this was not a failure of the Computer Vision (CV) model or the data-integration pipeline (which had sub-millimeter calibration accuracy), but a purely mechanical failure of the end-effector's grip. This finding uniquely validates the data and software integration as perfect, while simultaneously highlighting that in a complex cyber-physical system, the "weakest link" can revert to a traditional mechanical challenge.

The primary contribution of this research is both methodological and conceptual, providing a definitive answer to the "siloed" research gap. Methodologically, this study provides a validated, 4-phase "experimental systems integration design" that serves as a replicable blueprint for fusing CV and mechatronics; it specifically validates the use of a Robotic Operating System (ROS) as the robust, real-time “integration layer” to synchronize Python-based vision nodes with robotic actuation nodes (42ms perception vs. 850ms action). Conceptually, this research provides the first empirical proof-of-concept for a holistic, closed-loop AQC system that successfully translates high-speed digital perception into high-precision physical action, thereby solving the critical integration challenge of Industry 4.0.

The findings of this prototype study are constrained by its controlled laboratory setting, which has not yet validated the system’s robustness against real-world factory conditions such as high speeds (>1.0 m/s), ambient light variations, or industrial vibration. The system was also validated on only one product type, limiting its current claim to the “high-mix” flexibility required by smart manufacturing. Future research must, therefore, pivot to address these limitations. The immediate next step is an iterative design phase to solve the 2.6% mechanical gripper failure. Subsequent research must deploy the system in a live production environment and, most critically, develop a “few-shot learning” pipeline to enable the rapid retraining and reconfiguration that will fulfill the true promise of adaptive, autonomous quality control.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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