Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 5 (No. 2), pp. 56-65, 2025
doi: 10.54569/aair.1808940
Published online: Dec 25, 2025

The Impact of Artificial Intelligence-Based Quality Control Systems on Production Efficiency in the Context of Industry 4.0: An Empirical Study

Begüm Acar [1,2,] *, Özkan Şahin [3]

[1] Düzce University, Faculty of Engineering, Department of Computer Engineering, Türkiye
[2] Şafak Makina A.Ş., Software Specialist, Türkiye
[3] Düzce University, Faculty of Business Administration, Department of International Trade and Finance, Türkiye

Abstract

This study presents an integrated quality control architecture designed in line with Industry 4.0 principles for an automotive-focused production line. The architecture unifies micron-level dimensional inspection via air gauges, assembly verification through CNN-based computer vision, and full traceability based on DMC/QR + OCR within a single decision layer. A three-tier software stack (data acquisition, processing/analysis, decision/feedback) operates in real time through a microservices architecture with MES/PLC integration. Decision fusion triggers the right intervention without stopping the line through an "accept–gray zone–segregate" policy; SPC-based online monitoring makes minor drifts visible at an early stage. The implementation increased assembly accuracy and measurement reliability, strengthened traceability by catching duplicate identity assignments in process, reduced the risk of shipping defects, and lowered manual inspection burden. By integrating measurement, visual, and identity data into a single traceability chain, the study proposes a practical and scalable model for transitioning from reactive inspection to proactive/preventive quality assurance.

Keywords: *Industry 4.0; Air gauge; Assembly verification; Artificial intelligence; CNN; SPC; Data Matrix (DMC); Traceability; Microservice architecture.*

1. Introduction

With the acceleration of digital transformation in industry, making production processes more flexible, efficient, traceable, and quality-oriented has become a strategic imperative for firms seeking to enhance their competitiveness. Industry 4.0 provides the overarching conceptual framework for this transformation, envisaging the integrated use of cyber-physical systems, the Internet of Things (IoT), big data analytics, artificial intelligence (AI), machine learning (ML), cloud computing, and autonomous decision-making mechanisms within production environments [1, 2]. One of the most significant outcomes of Industry 4.0 is the establishment of proactive quality control mechanisms aligned with the zero-defect target, enabled by real-time data flow and decision-support systems on production lines [3]. In this way, production speed can be increased, product quality can be assured, defect rates can be minimized, processes can be made retrospectively traceable, and customer satisfaction can be improved on a sustainable basis [4].

In sectors that demand high precision, such as automotive, defense, and aerospace, smart quality control systems integrated into production processes are replacing traditional manual inspection methods and providing more reliable, faster, and objectively measurable solutions [5]. In this context, Industry 4.0 integration efforts carried out within the Application Site have enabled the digital transformation of production lines and have contributed significantly to achieving critical targets such as measurement accuracy, assembly reliability, and full traceability. Assigning each part a unique digital identity at the outset of the production process has enhanced traceability and process control, while part-specific measurement and assembly verification systems have given quality assurance a multi-layered structure. The field study presented in this paper was conducted at Şafak Makina A.Ş., an automotive supplier located in Düzce, Türkiye, which manufactures machined castings, tube and hose assemblies, and other high-precision components for international OEM customers. The analyzed line operates as a high-volume, multi-shift production system under tight dimensional and assembly tolerances, making systematic, AI-enabled quality control a strategic necessity rather than an optional add-on.

However, certain system-level issues can arise during the implementation of this digital infrastructure. For example, duplicate identity assignments—where the same identity number is assigned to more than one part—or structural deficiencies such as missing components during assembly pose risks that directly affect final product quality and production safety [6]. The literature notably lacks a comprehensive application that integrates air-gauge-based measurement systems with CNN-based computer vision and duplicate part-ID synchronization. This study aims to fill that gap and details an AI-enabled integrated quality control architecture developed to overcome such challenges.

*Corresponding author
E-mail address: begumacaar@gmail.com

Received: 22/Oct/2025; Accepted: 8/Dec/2025.

The system integrates both micron-level measurement via air gauges and camera-based assembly verification technologies into the production process, creating a dual-track inspection mechanism. The system not only ensures measurement and assembly accuracy but also enables the real-time detection and segregation of defective parts that must be removed from production. In this way, preventive quality assurance has been established on production lines through a process-oriented and adaptive quality management approach. This study analyzes, considering quantitative data, the system's development, components, and impact on production outputs and evaluates it as a concrete example of Industry 4.0 applications.

To understand how Industry 4.0 reshapes quality control practices, it is first necessary to examine the core technological components that underpin this paradigm. The concept of Industry 4.0 was first introduced in Germany at the 2011 Hannover Fair and was developed to describe the digitalization of the manufacturing sector. Unlike classic automation systems, this approach aims to embed intelligence, adaptability, and integrated data analytics into production processes [2]. In this paradigm, the core components of Industry 4.0 are the technological building blocks that render manufacturing environments smart and autonomous. The Internet of Things (IoT) enables machines, sensors, gauges, PLCs, and other devices on the shop floor to communicate with each other and with central systems over the internet, thereby ensuring continuous real-time data flow from the field [8]. Cyber-Physical Systems (CPS) refer to the real-time modeling and management of physical machines through their digital twins, making it possible to digitally monitor, predict, and control the condition and performance of machines on production lines [7]. Big data and cloud computing allow high-volume data obtained from the production process to be stored, analyzed, and integrated with decision-support systems on central servers or cloud infrastructures, forming the basis of data-driven production management [4]. Artificial intelligence and automation, through techniques such as machine learning, deep learning, and statistical modeling, are deployed in quality control, predictive maintenance, production planning, and error prevention, thereby creating systems that can learn and decide beyond the capabilities of classical automation [9]. The integration of these components leads to smart production systems that can self-optimize, adapt to environmental variables, and enable production infrastructures that operate with minimal human dependency.

Within this framework, quality control processes have evolved from a reactive structure to a proactive and even preventive one with Industry 4.0 applications. Whereas in classical methods defect detection was generally carried out at the final inspection stage, in production lines equipped with smart systems defects can be predicted during the process or even before they occur [5]. Proactive defect detection becomes possible because data from sensors, cameras, and gauge systems can be analyzed with AI algorithms to detect anomalies; thus, before a defect's physical outcome emerges, tendencies toward process drift can be identified and appropriate interventions can be made [6]. Real-time production data analysis further strengthens decision-making, as variables such as measurements, temperature, pressure, and vibration are continuously analyzed during production and compared with quality parameters, thereby supporting fast and accurate decisions [10]. At the same time, flexible and autonomous quality systems are enabled, since ML-based systems learn from historical production data and automatically classify incoming data, providing adaptive control by dynamically redefining quality limits [11]. Traceability and production safety are also enhanced: tracking each part throughout the production process with a unique identity number, verifying assembly accuracy, and detecting duplications become critical mechanisms for ensuring product safety [12].

Industry 4.0-enabled quality control systems thus create high added value, particularly by preventing the shipment of defective products, reducing customer complaints, avoiding resource waste, and lowering maintenance costs. In this context, the system developed at the Application Site constitutes an integrated model that can serve as a benchmark for the sector. Within this integrated architecture, air-gauge systems play a key role in Industry 4.0-oriented quality control because they provide fast, non-contact, micron-level dimensional feedback directly from the production line. Unlike offline CMM measurements, inline air gauges can be continuously connected to CPS and MES infrastructures, stream real-time data into SPC and AI modules, and thereby act as one of the main sensory inputs of the cyber-physical quality loop. When combined with camera-based assembly verification and digital identity management, air-gauge data closes the gap between geometric conformity, assembly correctness, and traceability, supporting both zero-defect ambitions and data-driven continuous improvement.

2. Methodology

2.1. Existing Production Infrastructure and Need for Transformation

The Application Site corresponds to the main plant of Şafak Makina A.Ş., an automotive-focused manufacturer headquartered in Düzce, Türkiye, supplying machined castings, tube and hose assemblies and other precision components to international OEM and Tier-1 customers. As an enterprise producing for the automotive industry, the relevant production facility embarked on a digital transformation to minimize quality risks in high-volume production environments and to increase traceability in production processes. The human-error-prone nature of traditional inspection methods and the inadequacy of manual traceability systems necessitated investment in automated quality control systems that work in integration with Industry 4.0

solutions. This transformation not only reduced operator dependency but also aimed to achieve sustainable improvements in fundamental quality indicators such as measurement accuracy, assembly reliability, and full traceability. The overall layout of the dedicated control line established within this plant is illustrated in **Figure 1**.

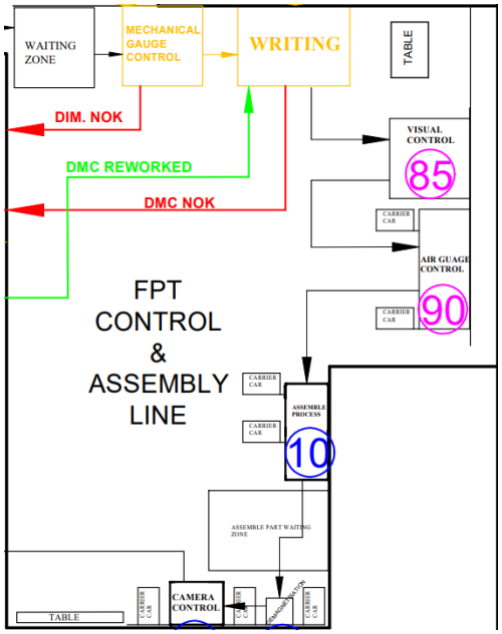

Figure 1. *Control line within the factory.*

The integrated system is built on three core modules: micron-level measurement via air gauges, deep-learning-based computer vision for assembly control, and part-based digital identification (ID assignment) [13].

Within this scope, an integrated quality control system was installed on a dedicated control line. The system consists of three main modules: (i) micron-level dimensional measurement via air gauges, (ii) deep-learning-based computer vision for assembly verification, and (iii) part-based digital identification through Data Matrix Codes (DMCs). Each part is assigned a unique code at the beginning of the line, its critical dimensions are measured non-contact within a ±5 µm tolerance range, and assembly correctness is checked via camera-based inspection. All measurement, assembly and identity data are collected in a central database and used as inputs to AI-based decision mechanisms. The station where micron-level dimensional measurement and camera-based assembly verification are jointly carried out is depicted in **Figure 2**.

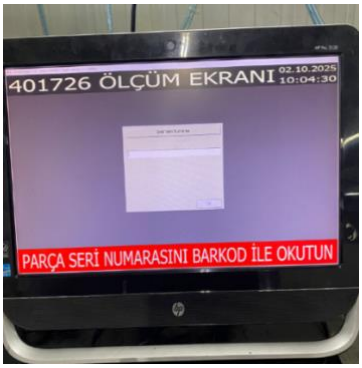

Figure 2. *Station where measurement is performed with an air gauge and the integrated camera system.*

2.2. System Architecture and Data Flow

The integrated system is implemented as a three-tier architecture comprising a data acquisition layer, a processing and analysis layer, and a decision/feedback layer. The data acquisition layer includes industrial cameras, air gauges, laser marking units and IoT sensors communicating over Profinet and OPC-UA. These devices continuously stream images, dimensional measurements and contextual data to a central server. The main components of this three-tier architecture and their data flows are summarized in **Figure 3**.

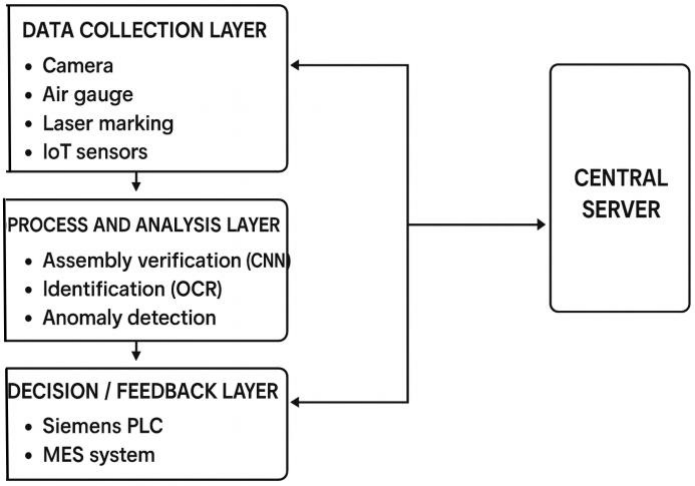

Figure 3. *General architecture*

On the processing and analysis layer, a Python-based AI stack runs multiple services: convolutional neural networks (CNNs) for assembly verification, OCR modules for DMC/QR decoding, anomaly-detection algorithms, and Statistical Process Control (SPC) routines ($\bar{X}$–R, EWMA, CUSUM). The system is organized as a microservices architecture (e.g., vision-svc, gauge-svc, id-svc, anomaly-svc, mes-adapter, plc-gateway, data-svc, orchestrator), allowing independent scaling and fault isolation. All services share a common data model keyed by part identity and timestamps, ensuring that every measurement and decision can be linked to a specific part and MES record.

The decision/feedback layer interacts with Siemens PLCs and the Manufacturing Execution System (MES). Based on the evaluated data, the system can automatically classify parts as conforming or defective, stop the line, segregate parts, or request operator confirmation. Every action is simultaneously recorded in the quality assurance database, creating a complete digital trace for retrospective analysis.

2.3. Algorithms and Learning Paradigm

The system combines supervised and unsupervised learning. For assembly verification, a lightweight single-stage object detection model (YOLOv8n-based CNN) is used to classify assembly states into three categories: OK assembly, missing component, and misoriented/misplaced component. The model is trained on 6,048 labeled images covering more than 6,000 assembly scenarios, with data augmentation (brightness/contrast variation, rotation, translation, blur) to improve robustness. The dataset is split into training, validation and test sets on a scene basis to avoid leakage. The production line where camera-supported assembly control is applied is shown in **Figure 4**, while representative outputs of the visual analysis algorithms used for assembly accuracy verification are presented in **Figure 5**.

Figure 4. *Production line where camera-supported assembly control is applied.*

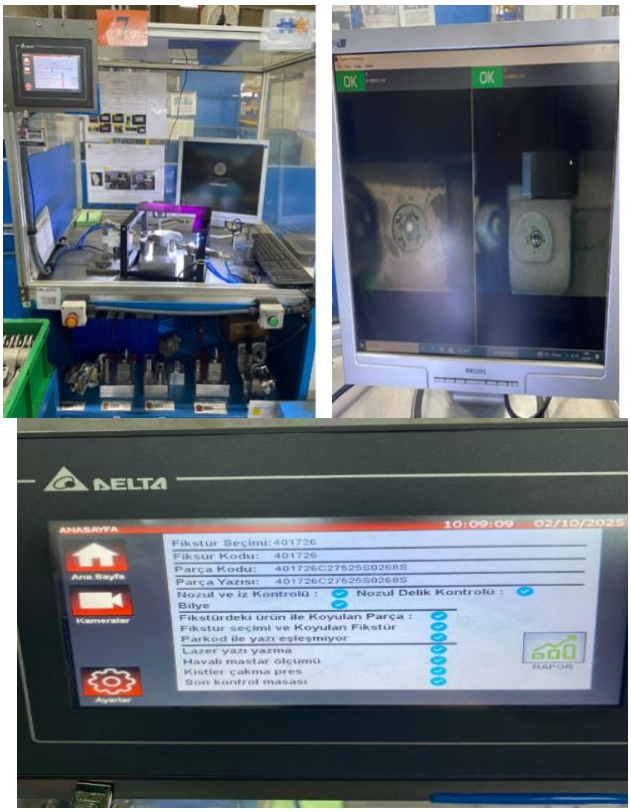

Figure 5. *Outputs of visual analysis algorithms used in assembly accuracy verification*.

For code reading and traceability, OCR-supported modules decode DMC/QR codes and match them with MES records. Pre-processing (cleaning, deskewing, contrast enhancement) is applied for low-quality or low-contrast codes, and an OCR-based fallback is used when standard decoding fails.

To detect rare and previously unseen phenomena such as illumination drift, lens contamination or unusual process conditions, an autoencoder plus one-class SVM configuration is employed. The autoencoder learns the representation of normal operation data; samples with high reconstruction error are passed to the one-class SVM (RBF kernel, $\nu = 0.05$, γ selected via grid search on a validation set) to flag anomalies. Models are trained on historical production data and simulated fault scenarios, and their generalization ability is checked via cross-validation.

Outputs from CNN, SPC, anomaly detection and ID verification are fused in a time-aligned decision logic. A three-zone policy is applied: (i) automatic accept at high confidence with no rule violation, (ii) operator approval (gray zone) at intermediate confidence, and (iii) automatic segregation in cases of low confidence, SPC violations or identity conflicts. Thresholds and policies are periodically recalibrated based on performance indicators and false-reject behavior; numerical results are reported in the Findings section.

2.4. Traceability and Duplicate Identity Handling

Traceability is ensured by assigning a unique DMC/QR identity to each part at the beginning of the line and using this code as the primary key across all system layers. Every dimensional measurement, assembly decision and inspection result is stored together with this identifier and an MES record number. This enables part-level reconstruction of production history within seconds. The real-world implementation of the part-recognition and DMC-based ID assignment station used for this purpose is presented in **Figure 6**.

Figure 6. *Part recognition and DMC-based ID assignment station (real image from the factory environment).*

To address the risk of duplicate identity assignment—where the same ID is accidentally given to more than one part—AI-based consistency checks are integrated into the database and line logic. ID streams are continuously monitored to detect duplicates in real time, while camera systems re-identify parts at multiple checkpoints on the line and verify that their codes match MES and local records. Parts with inconsistent identities are automatically segregated, and associated records are updated through predefined workflows.

Performance indicators such as the number and stage of detected duplicate-ID cases, median detection time and false-positive ratio are monitored over defined observation windows; their quantitative values and before/after comparisons are presented in the Findings section.

AI-based inconsistency-checking algorithms have been integrated to prevent such issues. These algorithms continuously monitor IDs in the database and check in real time whether the same ID has been assigned to more than one part. In addition, at different stages of production, camera systems re-identify each part and data matches are checked at multiple verification points. With this multi-layered structure, incorrectly identified parts are removed from production, ensuring safe production without disrupting continuity. The success of the system is quantitatively supported by the detection of 34 duplicate-ID cases within a three-month period and their removal from production.

Table 1. *Summary of duplicate ID detection performance and system improvement metrics during the T1 observation period.*

Indicator	Definition	Measurement Window	Before (T0)	After (T1)	Change	Note
Detected duplicate ID cases (pcs)	Assignment of the same ID to more than one part	3 months	Data not available	34	—	In the T1 period, duplicate IDs were detected through in-process multi-point verification and excluded from production.
Stage of duplicate ID detection (most frequent)	Stage where the case was first identified	3 months	Final inspection / post-shipment (qualitative)	In-process (multi-point verification)	Improvement	Camera + DMC/QR matching; database consistency check.
Duplicate IDs detected after shipment (pcs)	Cases discovered after shipment	3 months	Data not available	0	—	In the T1 period, 34 cases detected in process were segregated within the line.
Median detection time	Time elapsed between ID assignment and anomaly detection	3 months	Not monitored	≤ 60 s (system target)	Improvement (target)	Actual values verified through system logs.
False-positive alert ratio (ID mismatch) (%)	False alerts / total alerts (%)	3 months	Data not available	Data not available	—	Can be updated as reports are generated.

As summarized in **Table 1**, the introduction of the AI-based control and traceability mechanisms led to a marked improvement in duplicate ID detection performance during the T1 observation period.

Data not available entries in the T0 column indicate that, prior to the deployment of the integrated system, duplicate-ID cases and related timing metrics were not captured in a structured digital form; they were either

not monitored at all or tracked only qualitatively through manual incident reports, which makes a reliable quantitative reconstruction of the baseline infeasible.

3. Findings

The findings of this study show that the integrated, AI-enabled quality control and traceability system deployed on the Şafak Makina production line makes a strong contribution to both internal and external quality performance. At the same time, the comparative validity of these results is naturally limited by data availability. Although before/after (T0/T1) comparisons are presented, the lack of long-term, systematically logged baseline data—especially for duplicate identity events and detection times—constitutes a methodological constraint. For several key indicators, pre-deployment information is either missing or exists only in qualitative form, which prevents a full reconstruction of the baseline. Therefore, the analysis focuses on short-term observed gains and relative improvements rather than a complete longitudinal evaluation.

From the perspective of external quality, the system delivers clear quantitative benefits. In the baseline period before deployment (T0), the line generated approximately 245 shipment-related customer complaints per year. In the first full observation period after deployment (T1), this figure dropped to 32. The difference, 213 cases, represents the estimated number of prevented customer complaints and corresponds to an 87% relative reduction in complaint and shipping defect rates. These improvements are also reflected in the associated cost structure: within the same observation window, the plant avoided roughly €6,000 in sorting costs and €3,400 in repair costs. In parallel, line downtime attributable to quality problems decreased and overall process efficiency increased. Although Overall Equipment Effectiveness (OEE) is not modelled explicitly, the combined reduction in external complaints, rework and sorting activities provides strong evidence that the system contributes meaningfully to operational efficiency.

In-process quality indicators exhibit a similar pattern of improvement. Over a three-month monitoring period on the integrated line, the system detected 147 assembly defects in process and enabled their correction before shipment. These defects included missing components, misoriented or misplaced parts and dimensional deviations outside the specified tolerance band. The air-gauge module, supported by regular calibration and environmental compensation, achieved 99.2% measurement accuracy within the defined tolerance range. This performance demonstrates that dimensional nonconformities can be intercepted close to their source, reducing the burden on final inspection and limiting the propagation of defects down the value chain. A key functional advantage of the system is its ability to distinguish between different defect types—such as missing assembly, orientation errors and out-of-tolerance dimensional deviations—and to trigger defect-specific actions. By consolidating measurement, visual and identity data under a single record per part, the system enables targeted corrective actions and supports a data-driven culture of continuous improvement on the line.

Traceability performance is also significantly enhanced by the new architecture. In the post-deployment period, each part receives a unique identity at the beginning of the line, encoded as a DMC/QR code, which is read by camera systems at multiple checkpoints and matched against MES records. During a three-month T1 observation period, the system detected 34 duplicate-ID cases through database-level consistency checks and multi-point in-process verification. All these parts were segregated while still in the line, and no duplicate-ID cases were recorded after shipment in the same period. The median detection time for duplicate identities—measured as the elapsed time between ID assignment and anomaly flagging—was kept within a target window of 60 seconds or less, according to system logs. In contrast, comparable quantitative figures do not exist for the T0 period, since duplicate-ID incidents were either not monitored systematically or were captured only through manual incident reports, often at final inspection or by customers. This shift from late, ad hoc and partly invisible detection to early, in-process and digitally logged detection marks a qualitative step change in the robustness of the traceability layer. Indicators such as the false-positive alert ratio for ID mismatches and the distribution of detection stages along the line are now monitored systematically, providing a basis for further refinement and long-term benchmarking.

These technical gains are reflected in customer-facing outcomes. International OEM and Tier-1 customers have reported fewer field issues linked to the analyzed line and have emphasized, particularly during audits and technical visits, the value of transparent, digitally documented traceability. Increased product reliability reduced post-shipment complaint rates and the ability to reconstruct part-level histories have collectively reinforced customer trust. These observations are consistent with the smart factory literature, which reports that digital traceability and AI-enabled in-process control reduce recall costs and enhance perceived product reliability [25–27]. In this context, the absence of duplicate-ID shipments, the marked reduction in complaint counts and the availability of detailed digital records have been particularly appreciated, especially by customers operating under strict quality and safety regimes.

Taken together, the findings demonstrate the practical applicability of the industry 4.0 paradigm on the shop floor. By combining micron-level air-gauge measurements, CNN-based computer vision and identity

verification under a single AI-enabled system, the solution significantly advances the targets of measurement accuracy, assembly reliability and full traceability. In comparison with classical manual control processes, the system detects defects much earlier, reducing both the need for operator intervention and the burden on final inspection. This earlier detection directly contributes to increased line efficiency and reduced downtime. Importantly, the system's success does not stem from AI algorithms alone: correct data flow, consistent MES integration, robust microservice orchestration and disciplined calibration routines are equally decisive in ensuring reliable operation.

From a scientific and technological standpoint, the main contribution of the study lies in the unification of measurement, computer vision and traceability—elements that are often implemented as separate inspection cells—within a single integrated decision layer on a real production line. Existing studies demonstrate the successful use of CNN or OCR algorithms in quality control, and others report robust decoding of industrial Data Matrix codes and improved OCR performance under challenging imaging conditions [16–21]. Similarly, recent anomaly-detection approaches based on autoencoders and one-class classification have been applied to surface-defect inspection and visual quality monitoring [22–24]. However, these contributions typically treat vision, code reading and metrology as distinct modules and do not fuse air-gauge measurements, CNN/OCR outputs and ID consistency checks into a unified, real-time, line-level decision framework. In contrast, the system presented here integrates micron-level air-gauge data, YOLO-based CNN decisions for assembly accuracy, OCR-assisted DMC/QR decoding and anomaly detection outputs under a single decision policy directly linked to PLC actions and MES-based traceability. This integration is the key differentiating aspect of the present work, both methodologically and in terms of industrial application.

Despite its strong contribution, the study has several limitations that must be acknowledged. Most notably, long-term and fully structured baseline data are not available for all indicators. Many T0 metrics—especially those relating to duplicate identities and detection timing—were not recorded digitally and cannot be reconstructed with sufficient reliability, which limits the depth of statistical comparison and the generalizability of the results. Furthermore, integrating heterogeneous cells introduces non-trivial engineering and organizational challenges. Synchronizing data streams from different modules, dealing with network latencies and correcting operator-induced data inconsistencies initially affected system performance and required iterative tuning. Maintaining continuous adaptation of supervised and unsupervised learning algorithms to changing field conditions demands regular data updates, careful retraining and disciplined model management, all of which depend on a sustained maintenance regime. Finally, the findings are based on a single line and a specific product family in one plant. Although the underlying architecture is scalable, further research is needed to evaluate performance across different product variants, plants and sectors, and to explore more advanced decision-fusion strategies and predictive maintenance integration.

Overall, the evidence indicates that the integrated system is an effective tool for reducing defect rates, strengthening traceability and increasing customer confidence, while also offering a concrete reference model for similar Industry 4.0-oriented quality control deployments in other automotive suppliers and high-precision manufacturing environments.

4. Results

This study shows that, when an integrated quality control architecture—micron-level measurement with air gauges, CNN-based assembly verification, and DMC/OCR-based full traceability—designed in line with Industry 4.0 principles is combined with real-time decision mechanisms on the same production line at the Application Site, a proactive and preventive quality assurance structure can be achieved on the shop floor. By consolidating measurement accuracy, assembly reliability, and identity integrity within a single chain, the system increased both in-process visibility and decision speed. The main findings are summarized below:

1. Integrated architecture and decision fusion: Outputs of air gauges, visual inspection, and identity verification are combined within a single decision layer; through an accept–gray zone–segregate policy, human–machine interaction is positioned at the right point, establishing real-time (<1 s target) action capability on the shop floor.

2. Micron-level measurement reliability: With regular calibration and environmental compensation, the air-gauge system provided high and consistent accuracy for tight-tolerance parts; small drifts were made visible in process using SPC-based monitoring.

3. AI contribution to assembly accuracy: The CNN-based assembly inspection framework evaluates not only presence/absence but also orientation and positional accuracy, providing early warnings and automatic segregation without disrupting production flow.

4. Full traceability and duplication control: With DMC/QR + OCR integration, part histories were tracked with atomic records; thanks to a multi-point verification architecture, duplicate-ID risks were detected in process, and 34 cases were removed during a three-month application.

5. Operational impact and costs: In 2024, shipment-related defects decreased markedly (≈87%); 213 potential customer complaints were prevented; corresponding sorting and repair costs were significantly reduced (≈€6,000 and €3,400).

6. In-process quality gains: Within a three-month monitoring window, 147 assembly defects were caught in line; high measurement accuracy (99.2%) was maintained. Consolidating measurement, visual, and identity data under a single record provided direct input to root-cause analysis.

7. Shop-floor applicability and scalability: Microservices, data governance, and bidirectional MES/PLC integration yielded a scalable, traceable, and reversible operating model, simplifying maintenance and update cycles.

These findings show that integrated quality control delivers concrete benefits in transitioning from reactive approaches to proactive/preventive ones. However, the absence of a control group and limited long-term monitoring leave room for further quantitative validation. Future work should deepen adaptation to different products/lines, periodic and data-driven optimization of thresholds, drift monitoring (illumination/scene conditions), and cybersecurity/access management. In conclusion, the proposed architecture combines measurement accuracy, assembly reliability, and traceability within a single decision system, offering a practical and replicable Industry 4.0 solution that strengthens both internal process quality and customer trust.

References

[1] Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239–242.

[2] Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Final report of the Industrie 4.0 Working Group.

[3] Wang, S., Wan, J., Li, D., & Zhang, C. (2016). Implementing Smart Factory of Industrie 4.0: An Outlook. International Journal of Distributed Sensor Networks, 12(1).

[4] Qin, J., Liu, Y., & Grosvenor, R. (2016). A Categorical Framework of Manufacturing for Industry 4.0 and beyond. Procedia CIRP, 52, 173–178.

[5] Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). Maintenance in digitalized manufacturing: Delphi-based scenarios for 2030. International Journal of Production Economics, 191, 154–169.

[6] Zhang, Y., Ren, S., Liu, Y., Sakao, T., Huisingh, D., & Dou, Y. (2017). A framework for Big Data-driven product lifecycle management. Journal of Cleaner Production, 159, 229–244.

[7] Lee, J., Bagheri, B., & Kao, H. A. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems, Manufacturing Letters, 3, 18–23.

[8] Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics, 165, 234–248.

[9] Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for Industry 4.0: a self-organized multi-agent system with big data-based feedback and coordination, Computer Networks, 101, 158–168.

[10] Jayaraman, P. P., Yavari, A., Georgakopoulos, D., Morshed, A., & Zaslavsky, A. (2016). Internet of Things platform for smart farming: Experiences and lessons learnt, Sensors, 16(11), 1884.

[11] Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent Manufacturing in the Context of Industry 4.0: A Review, Engineering, 3(5), 616–630.

[12] Alkan, B., & Kaynak, O. (2020). Industry 4.0 and Application Examples in Turkey, Mühendis ve Makina Dergisi, 61(694), 75–88.

[13] Dombrowski, U., Mielke, T., & Engel, C. (2014). Smart Factory – Sustainable production processes based on cyber-physical systems in the context of Industry 4.0. Procedia CIRP, 17, 645–650.

[14] Hawkins, D. M., & Wu, N. (2014). The CUSUM and the EWMA head-to-head. University of Minnesota Lecture Notes.

[15] Lawson, J. (2020). Time-Weighted Control Charts in Phase II. Online Lecture Notes.

[16] Okano, M. T., et al. (2025). Edge AI for Industrial Visual Inspection: YOLOv8-Based Visual Conformity Detection Using Raspberry Pi. Algorithms, 18(8), 510.

[17] Deep Object Detection Framework for Automated Quality Inspection. (2022). Journal of Manufacturing Systems, Elsevier.

[18] Calabrese, M., et al. (2025). Application of Mask R-CNN and YOLOv8 for AOI in PCB Manufacturing. SN Applied Sciences.

[19] Liao, L., et al. (2022). Data Extraction Method for Industrial Data Matrix Codes Based on Local Adjacent Modules Structure. Applied Sciences, 12(5), 2291.

[20] Karrach, L., et al. (2020). Recognition of Data Matrix Codes in Images and Industrial Conditions. Management Systems in Production Engineering.

[21] Sporici, D., Cușnir, E., & Boiangiu, C.-A. (2020). Improving the Accuracy of Tesseract 4.0 OCR Engine Using Convolution-Based Preprocessing. Symmetry, 12(5), 715.
[22] Tsai, D.-M., et al. (2021). Autoencoder-Based Anomaly Detection for Surface Defect Inspection. IFAC-PapersOnLine.
[23] Saeedi, J., et al. (2022). Anomaly Detection for Industrial Inspection Using Convolutional Autoencoder and Deep Feature-Based One-Class Classification. VISIGRAPP 2022.
[24] Mehta, D., et al. (2023). Autoencoder-Based Visual Anomaly Localization for Industrial Inspection. arXiv:2309.06884.
[25] Hu, L., et al. (2025). DataMatrix Code Recognition Based on Coarse-to-Fine and Transformer Methods. Electronics, 14(12), 2395.