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Improving Quality Control in the Industrial Sector Using Artificial Intelligence Applications

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تحسين مراقبة الجودة في القطاع الصناعي باستخدام تطبيقات الذكاء الاصطناعي

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Abstract:
The increasing complexity of industrial production systems and the growing demand for high product quality have intensified the need for advanced quality control (QC) solutions beyond traditional inspection-based approaches. Artificial intelligence (AI) has emerged as a powerful enabler for transforming industrial quality control into a proactive, predictive, and data-driven function. This article presents a comprehensive review and conceptual analysis of improving quality control in the industrial sector through AI applications. It first establishes a conceptual framework that links classical QC principles with AI-driven quality management, highlighting the evolution from manual and statistical inspection methods to intelligent and adaptive systems. The study then examines key AI techniques and models, including machine learning, deep learning, computer vision, and expert systems, and their applications in defect detection, process monitoring, predictive quality assessment, and automated inspection. The role of industrial data and digital infrastructure is analyzed, emphasizing data acquisition, integration, and real-time analytics enabled by Industrial Internet of Things (IIoT) and big data platforms. Furthermore, the performance and impact of AI-driven QC systems are evaluated in terms of technical accuracy, operational efficiency, and economic benefits compared with conventional QC approaches. Finally, the article discusses major implementation challenges, ethical considerations, and future research directions for sustainable and intelligent quality control. The findings indicate that AI-enabled quality control can significantly enhance product quality, process reliability, and industrial competitiveness when supported by robust data governance, ethical frameworks, and organizational readiness.

Keywords: Artificial Intelligence, Industrial Quality Control, Machine Learning, Smart Manufacturing.

الملخص:
أدّت الزيادة المستمرة في تعقيد أنظمة الإنتاج الصناعية وارتفاع متطلبات جودة المنتجات إلى تنامي الحاجة إلى حلول متقدمة لمراقبة الجودة تتجاوز الأساليب التقليدية المعتمدة على الفحص. وقد برز الذكاء الاصطناعي كعامل تمكيني رئيسي لتحويل مراقبة الجودة الصناعية إلى وظيفة استباقية وتنبؤية وقائمة على البيانات. يقدم هذا البحث مراجعة وتحليلًا مفاهيميًا شاملًا لتحسين مراقبة الجودة في القطاع الصناعي من خلال تطبيقات الذكاء الاصطناعي. يبدأ البحث ببناء إطار مفاهيمي يربط بين مبادئ مراقبة الجودة الكلاسيكية ونظم إدارة الجودة المعتمدة على الذكاء الاصطناعي، موضحًا تطور مراقبة الجودة من أساليب الفحص اليدوي والإحصائي إلى أنظمة ذكية وتكيفية. كما يستعرض البحث أهم تقنيات ونماذج الذكاء الاصطناعي، بما في ذلك تعلم الآلة، والتعلم العميق، والرؤية الحاسوبية، والنظم الخبيرة، وتطبيقاتها في كشف العيوب، ومراقبة العمليات، والتقييم التنبؤي للجودة، والفحص الآلي. كذلك يناقش دور البيانات الصناعية والبنية التحتية الرقمية، مع التركيز على جمع البيانات وتكاملها والتحليلات الآنية المدعومة بإنترنت الأشياء الصناعي ومنصات البيانات الضخمة. علاوة على ذلك، يتم تقييم أداء وتأثير أنظمة مراقبة الجودة المعتمدة على الذكاء الاصطناعي من حيث

الدقة التقنية، والكفاءة التشغيلية، والعوائد الاقتصادية مقارنة بأساليب مراقبة الجودة التقليدية. وأخيرًا، يتناول البحث التحديات الرئيسة والاعتبارات الأخلاقية والاتجاهات البحثية المستقبلية نحو تحقيق أنظمة مراقبة جودة ذكية ومستدامة. وتشير النتائج إلى أن مراقبة الجودة المدعومة بالذكاء الاصطناعي قادرة على تحسين جودة المنتجات وموثوقية العمليات وتعزيز القدرة التنافسية الصناعية بشكل ملحوظ، شريطة دعمها بأطر حوكمة بيانات قوية، وضوابط أخلاقية واضحة، وجاهزية تنظيمية مناسبة.

الكلمات المفتاحية: الذكاء الاصطناعي، مراقبة الجودة الصناعية، التعلم الآلي، التصنيع الذكي

1. Introduction

Quality control is a critical function in industrial systems, directly influencing product reliability, customer satisfaction, and overall operational efficiency. Traditional quality control approaches, such as manual inspection, statistical process control, and sampling-based testing, have long supported industrial production; however, they are increasingly challenged by the growing complexity of manufacturing processes, higher production speeds, and stricter quality requirements. These conventional methods are often reactive in nature, detecting defects only after they occur, which can lead to increased rework, waste, and production costs [1,2].

In recent years, the rapid digitalization of industrial environments has generated vast volumes of data from sensors, machines, and production lines. This data-rich context has created new opportunities for enhancing quality control beyond the limitations of human-centered inspection and fixed statistical thresholds. Artificial intelligence (AI), with its ability to learn from data, identify complex patterns, and adapt to changing conditions, has emerged as a powerful tool for addressing these challenges. AI-based approaches enable automated inspection, real-time process monitoring, and predictive quality assessment, thereby supporting more proactive and data-driven quality management strategies [3,4].

The integration of AI into industrial quality control aligns closely with the principles of Industry 4.0 and smart manufacturing, where cyber-physical systems, Industrial Internet of Things (IIoT), and advanced analytics are used to optimize production performance. Techniques such as machine learning, deep learning, computer vision, and expert systems have demonstrated significant potential in detecting defects, monitoring process stability, and improving decision-making accuracy. By embedding these techniques within quality control systems, manufacturers can move from isolated inspection activities toward integrated and intelligent quality management frameworks [5,6].

Despite its significant potential, the adoption of AI in quality control also presents technical, organizational, and ethical challenges. Issues related to data quality, model interpretability, system integration, and workforce adaptation must be carefully managed to ensure reliable and responsible deployment. Therefore, a comprehensive understanding of AI applications in industrial quality control, covering conceptual foundations, enabling technologies, performance impacts, and implementation challenges, is essential. This article addresses these aspects by examining how artificial intelligence can be effectively leveraged to improve quality control in the industrial sector [7-9].

Several studies have addressed the use of artificial intelligence to improve quality control in industrial environments. According to [10], the article provided a comprehensive survey of deep-learning approaches for manufacturing defect detection across multiple product types and inspection scenarios. The study synthesizes how CNN-based architectures and related deep models outperform traditional machine-vision pipelines in complex defect patterns, while also highlighting practical barriers such as data labeling cost, class imbalance (rare defects), and deployment constraints on production lines. This work is widely used as a theoretical baseline for positioning AI-driven visual inspection as a core pillar of modern QC. In [11], the authors propose an AI-driven visual inspection framework leveraging deep learning. The method integrates a tailored convolutional neural network (CNN) for defect detection with a user-friendly software application suitable for deployment on the shop floor. The proposed model achieves an inspection accuracy of 99.86% on casting product image datasets.

The study [12] further investigates how blockchain technology enhances transparency across all tiers of the supply chain, thereby strengthening quality assurance. It also examines blockchain-enabled traceability systems, supported by the distributed ledger architecture, as a moderating mechanism linking the level of blockchain adoption to improvements in quality control performance. Overall, the findings offer novel insights into leveraging blockchain to improve operational performance and quality-delivery structures in the food manufacturing industry under evolving manufacturing conditions. The paper [13] is positioned as a perspective/position study that introduces the Zero-Defect Manufacturing concept and offers a clear, unified definition to establish a shared understanding of Zero-Defect Manufacturing. Recognizing persistent skepticism among researchers and practitioners, the paper formulates and addresses key argumentative questions to justify the transition from conventional QI methods to Zero-Defect Manufacturing. It further argues that this migration is already underway, supported by evidence reported in the literature, and concludes by outlining several future research directions, emphasizing substantial remaining opportunities across multiple domains.

This study contributes a consolidated and operationally grounded perspective on how artificial intelligence is transforming industrial quality control from periodic, inspection-centered activities into a continuous, predictive, and preventive quality management function embedded across the full production lifecycle. It advances the field by (i) proposing a coherent conceptual framework that positions AI as an enabler that strengthens, rather than displaces, established paradigms such as SPC, Six Sigma, and TQM through adaptive, data-driven decision-making; (ii) synthesizing the roles and capabilities of core AI methods (machine learning, deep learning, computer vision, and expert systems) for defect detection, real-time monitoring, predictive quality assessment, and automated inspection; and (iii) linking these capabilities to the enabling digital infrastructure (IIoT, big-data platforms, and real-time analytics) required to convert heterogeneous industrial data into actionable quality intelligence. Moreover, the study provides evidence-based insight into the multidimensional performance gains of AI-enabled QC (accuracy, efficiency, cost, and reliability) while explicitly identifying the implementation constraints, data integrity, interpretability, cybersecurity, workforce readiness, and ethical governance, and outlining forward-looking research directions (hybrid modeling, edge intelligence, uncertainty-aware decisions, and stronger governance) to build transparent, resilient, and sustainable AI-QC systems that enhance competitiveness and long-term industrial sustainability.

2. Conceptual Framework of Quality Control and Artificial Intelligence

Quality control (QC) has long been a fundamental pillar of industrial production, ensuring that products and processes meet predefined standards of performance, safety, and reliability. Traditional quality control systems are largely grounded in inspection-based approaches, statistical methods, and human expertise, such as Statistical Process Control (SPC), Six Sigma, and Total Quality Management (TQM). While these methodologies have proven effective in reducing defects and improving consistency, their reactive nature, limited adaptability, and dependence on manual intervention pose significant challenges in modern industrial environments characterized by high complexity, mass customization, and stringent quality requirements [14,15].

The rapid advancement of digital technologies, particularly Artificial Intelligence (AI), has introduced transformative opportunities for rethinking quality control paradigms. AI techniques, including machine learning, deep learning, computer vision, and intelligent decision-support systems, enable the processing of large volumes of heterogeneous industrial data in real time. This capability allows for predictive quality assessment, automated defect detection, continuous process monitoring, and adaptive decision-making that surpass the limitations of conventional QC systems [16,17].

Within the context of Industry 4.0 and smart manufacturing, quality control is no longer an isolated post-production activity, but an integrated, data-driven function embedded throughout the production lifecycle. AI-driven quality control frameworks shift the focus from defect detection to defect prevention, enabling proactive interventions and continuous improvement. Accordingly, developing a clear conceptual framework that contrasts traditional QC approaches with AI-enabled quality management systems is essential for understanding this transition. Table 1 presents a conceptual framework that systematically compares traditional quality control systems with AI-driven quality control across key dimensions, highlighting the theoretical foundations, operational mechanisms, and performance implications of AI integration in industrial quality management.

Table 1. Conceptual Framework of Quality Control and AI in Industrial Systems [16-23].

Dimension	Traditional Quality Control (QC)	AI-Driven Quality Control	Conceptual Contribution
Quality Control Philosophy	Reactive and inspection-based approach focused on defect detection after production	Proactive and predictive approach focused on defect prevention and continuous improvement	Shift from post-process inspection to intelligent, preventive quality management
Core QC Principles	Statistical Process Control (SPC), Six Sigma, Total Quality Management (TQM)	Data-driven optimization, adaptive learning, autonomous decision-making	Integration of classical QC principles with intelligent analytics
Inspection Methods	Manual inspection, rule-based checks, sampling-based testing	Automated inspection using machine learning, deep learning, and computer vision	Transition from human-dependent inspection to automated, high-accuracy systems

Data Utilization	Limited use of structured data and historical records	Extensive use of real-time, high-dimensional, and unstructured data	Enhanced exploitation of industrial big data for quality insights
Decision-Making Mechanism	Deterministic, rule-based, and human-centric decisions	Probabilistic, adaptive, and AI-assisted or autonomous decisions	Improved decision accuracy and responsiveness under uncertainty
Process Monitoring	Periodic and offline monitoring	Continuous, real-time monitoring with predictive capabilities	Early detection of anomalies and process deviations
Learning Capability	Static systems with limited adaptability	Self-learning and continuously improving models	Dynamic quality systems that evolve with process changes
Quality Management Framework	Isolated QC functions within production systems	Integrated smart quality management within Industry 4.0 ecosystems	Alignment of QC with digital transformation and smart manufacturing
Performance Outcomes	Moderate accuracy, higher inspection costs, delayed feedback	High accuracy, reduced costs, faster feedback loops	Superior operational efficiency and quality consistency

Traditional quality control philosophy is fundamentally reactive, emphasizing the identification and correction of defects after they have already occurred in the production process. This approach relies on inspection, testing, and corrective actions, which often lead to increased rework, scrap, and production delays. In contrast, AI-driven quality control introduces a proactive and predictive philosophy by leveraging historical and real-time data to forecast quality deviations before they materialize. Through predictive analytics and intelligent pattern recognition, AI systems enable early intervention, transforming quality control into a preventive mechanism that minimizes defects at their source and enhances overall production stability.

Conventional quality control systems are rooted in well-established principles such as Statistical Process Control (SPC), Six Sigma, and Total Quality Management (TQM), which focus on process stability, variance reduction, and continuous improvement. While effective, these principles often assume linear relationships and stable operating conditions. AI-driven quality control extends these foundations by incorporating adaptive learning, nonlinear modeling, and data-driven optimization. Machine learning algorithms can capture complex interactions among process variables, enabling dynamic quality optimization that responds to changing conditions while preserving the core objectives of traditional QC methodologies.

Inspection in traditional QC systems is predominantly manual or semi-automated, relying on human inspectors, predefined rules, and sampling-based procedures. These methods are limited by human fatigue, subjectivity, and scalability constraints, particularly in high-speed or high-volume production environments. AI-driven inspection methods, especially those based on computer vision and deep learning, enable automated, continuous, and full-scale inspection of products and processes. These systems can detect micro-defects, surface irregularities, and pattern deviations with high accuracy and consistency, significantly improving inspection reliability and reducing dependency on manual labor.

Traditional quality control systems typically rely on structured data, such as control charts, inspection reports, and historical production records. The limited scope and granularity of these data restrict the depth of quality analysis. In contrast, AI-driven quality control systems exploit large volumes of heterogeneous data, including sensor signals, images, acoustic emissions, and process parameters. Advanced AI algorithms can process high-dimensional and unstructured data, extracting meaningful features that enhance defect detection, process understanding, and root-cause analysis. This data-centric approach significantly expands the analytical capabilities of quality control systems.

Decision-making in conventional quality control is largely deterministic and rule-based, relying on fixed thresholds, control limits, and expert judgment. Such mechanisms are often rigid and struggle to cope with uncertainty and process variability. AI-driven quality control introduces probabilistic and adaptive decision-making frameworks, where decisions are informed by learned patterns, confidence levels, and predictive outcomes. These systems can recommend or autonomously execute corrective actions, improving responsiveness, reducing human bias, and enabling more robust quality decisions under complex and uncertain operating conditions.

Process monitoring in traditional QC systems is frequently periodic and offline, meaning that deviations are detected only after significant delays. This lag increases the risk of defect propagation and production losses. AI-enabled quality control systems support continuous, real-time process monitoring through intelligent sensors and analytics platforms. By identifying early warning signals and subtle anomalies, AI systems enable timely interventions that prevent quality deterioration. Predictive monitoring further enhances this capability by forecasting future process behavior based on current trends and historical data.

Traditional quality control systems are generally static, requiring manual recalibration or redesign when process conditions change. This lack of adaptability limits their long-term effectiveness in dynamic production environments. AI-driven quality control systems possess inherent learning capabilities, allowing models to continuously update and improve as new data become available. Through online learning and adaptive algorithms, these systems evolve alongside the production process, maintaining high performance despite changes in materials, equipment, or operating conditions.

In conventional industrial settings, quality control functions are often isolated from other operational systems, such as production planning and maintenance. AI-driven quality control frameworks are integrated within broader Industry 4.0 ecosystems, linking quality management with cyber-physical systems, Industrial Internet of Things (IIoT), digital twins, and enterprise information systems. This integration enables holistic quality management, where quality considerations are embedded across the entire production lifecycle and aligned with smart manufacturing and digital transformation strategies. Moreover, the combined impact of AI integration across all quality control dimensions results in significantly enhanced performance outcomes. AI-driven quality control systems achieve higher defect detection accuracy, reduced inspection and operational costs, faster feedback loops, and improved production efficiency. Moreover, these systems contribute to improved product consistency, customer satisfaction, and long-term sustainability. Compared with traditional QC approaches, AI-enabled frameworks provide a scalable and resilient solution capable of meeting the quality demands of modern industrial environments.

3. AI Techniques and Models Applied in Industrial Quality Control

The increasing complexity of industrial production systems, coupled with rising demands for product quality, reliability, and cost efficiency, has intensified the need for advanced quality control (QC) solutions. Traditional QC approaches, largely based on statistical methods, manual inspection, and rule-based decision-making, are often inadequate for modern manufacturing environments characterized by high data volumes, nonlinear process dynamics, and rapid operational changes. These limitations have accelerated the adoption of Artificial Intelligence (AI) as a key enabler for intelligent and automated quality control [24,25].

AI technologies offer the ability to analyze large-scale, heterogeneous industrial data in real time, uncover hidden patterns, and support predictive and prescriptive quality decisions. Techniques such as machine learning, deep learning, computer vision, and expert systems have been successfully applied to defect detection, process monitoring, predictive quality assessment, and automated inspection across various industrial sectors. Within the context of Industry 4.0, AI-driven quality control is no longer a standalone function but an integrated component of smart manufacturing systems that connect sensors, cyber-physical systems, and decision-support platforms [26,27]. Table 2 provides a structured overview of these techniques, highlighting their algorithms, application domains, data requirements, strengths, and limitations.

Table 2. AI Techniques and Models Applied in Industrial Quality Control [25-30]

AI Technique / Model Class	Typical Algorithms / Architectures	Primary QC Applications	Input Data Types	Key Strengths	Main Limitations / Risks
Supervised Machine Learning	SVM, Random Forest, XGBoost, Logistic Regression, k-NN	Defect classification, pass/fail decision, quality grading	Structured process parameters, sensor features	Strong baseline performance, relatively interpretable	Requires labeled data; sensitive to dataset shift
Unsupervised / Semi-Supervised Learning	k-means, DBSCAN, PCA, Isolation Forest, Autoencoders	Anomaly and novelty detection, early fault signals	Multivariate sensor data, time-series	Works with limited labels; detects unknown patterns	Higher false alarms; threshold sensitivity
Deep Learning for Vision	CNNs (ResNet, EfficientNet), U-Net, YOLO	Surface defect detection, automated visual inspection	Images, video streams, thermal/hyperspectral data	High accuracy for complex visual defects	Data- and compute-intensive; limited explainability

Deep Learning for Time-Series	LSTM, GRU, 1D-CNN, Transformers	Process monitoring, quality drift prediction	Sensor time-series, SCADA/PLC logs	Captures temporal dependencies effectively	Sensitive to noise and missing data
Reinforcement Learning	Q-learning, DQN, PPO	Adaptive process control, defect rate minimization	State-action signals from sensors and KPIs	Optimizes control policies dynamically	Safety constraints; deployment complexity
Expert Systems / Knowledge-Based AI	Rule-based systems, fuzzy logic, Bayesian networks	Compliance checks, root-cause analysis, decision support	Expert rules, QC records	Transparent logic; explainable decisions	Limited adaptability; knowledge engineering effort
Hybrid AI (Physics + Data)	Physics-informed ML, digital twins + ML	Robust quality prediction, what-if analysis	Process models combined with sensor data	Improved generalization and interpretability	Model integration complexity
Natural Language Processing (NLP)	BERT, topic modeling, text classifiers	QC document analysis, complaint mining	Inspection reports, NCRs, customer feedback	Extracts value from unstructured text	Domain adaptation required

In this direction, Supervised machine learning models, including support vector machines, random forests, gradient boosting methods, and logistic regression, are widely employed in industrial quality control for defect classification, pass/fail decisions, and quality grading. These models learn explicit mappings between process variables and quality outcomes using labeled datasets. Their strengths lie in relatively fast training, strong baseline performance, and, in some cases, interpretability, particularly for tree-based models. However, their effectiveness depends heavily on the availability and quality of labeled data, and their performance may degrade when production conditions change or data distributions shift.

Unsupervised and semi-supervised learning techniques, such as clustering algorithms, principal component analysis, isolation forests, and autoencoders, are commonly applied to anomaly detection and novelty identification in quality control. These methods are particularly valuable in scenarios where labeled defect data are scarce or incomplete. By modeling normal process behavior, they can identify deviations that signal potential quality issues. Nevertheless, these approaches often require careful threshold tuning and validation to balance sensitivity and false-alarm rates.

Deep learning models based on convolutional neural networks have revolutionized visual quality inspection in industrial environments. Architectures such as ResNet, U-Net, and YOLO enable accurate detection, localization, and segmentation of surface defects, cracks, voids, and structural inconsistencies. These systems outperform traditional vision-based methods in handling complex textures and varying lighting conditions. Despite their high accuracy and scalability, deep learning vision systems are computationally intensive and require large, well-annotated image datasets, raising challenges related to data acquisition and model explainability.

Recurrent neural networks, long short-term memory models, and transformer-based architectures are increasingly used for monitoring time-dependent industrial processes. These models capture temporal dependencies in sensor and operational data, enabling early detection of quality drift and predictive assessment of future quality states. Their ability to model dynamic behavior makes them suitable for complex, multistage production systems. However, they are sensitive to noisy or missing data and demand robust data preprocessing and stable data pipelines.

Reinforcement learning (RL) techniques provide a powerful framework for adaptive process control aimed at minimizing defect rates and optimizing quality-related objectives. By learning optimal policies through interaction with the production environment, RL agents can dynamically adjust process parameters in response to changing conditions. While promising, the deployment of RL in real industrial settings is constrained by safety considerations, exploration risks, and the need for high-fidelity simulations or digital twins to enable safe learning.

Expert systems and knowledge-based AI approaches rely on encoded expert knowledge, rules, and inference mechanisms to support quality decisions and compliance verification. These systems are particularly effective in standardized processes and regulatory contexts, offering transparency and explainability. However, they are labor-intensive to develop and maintain, and their rigid rule structures limit adaptability in rapidly evolving production environments.

Hybrid AI models combine data-driven learning with physics-based or process-oriented knowledge, such as digital twins and physics-informed machine learning. These approaches enhance generalization, robustness, and interpretability, particularly in data-limited or safety-critical applications. Although highly promising, hybrid systems involve significant integration complexity and require accurate process models, which may not always be readily available.

Natural language processing techniques are increasingly applied to analyze unstructured quality-related text, including inspection reports, nonconformance records, maintenance logs, and customer feedback. By extracting insights from textual data, NLP enhances traceability, root-cause analysis, and decision support. However, domain adaptation and data quality remain critical challenges, particularly when deploying pretrained language models in specialized industrial contexts.

4. Data Acquisition, Integration, and Digital Infrastructure for AI-Based QC

The effectiveness of artificial intelligence–based quality control systems depends not only on advanced algorithms but also on the availability of reliable industrial data and a robust digital infrastructure [31,32]. Modern manufacturing environments generate vast amounts of heterogeneous data from sensors, imaging systems, and process control platforms, which must be efficiently acquired, integrated, and analyzed to support intelligent quality decisions. Within the context of Industry 4.0, technologies such as the Industrial Internet of Things (IIoT), big data platforms, and real-time analytics provide the foundation for deploying AI-enabled quality control [33-35]. Figure 1 shows AI based QC components. This section introduces the key data and infrastructure requirements that enable scalable, responsive, and trustworthy AI-driven quality control systems in industrial applications.

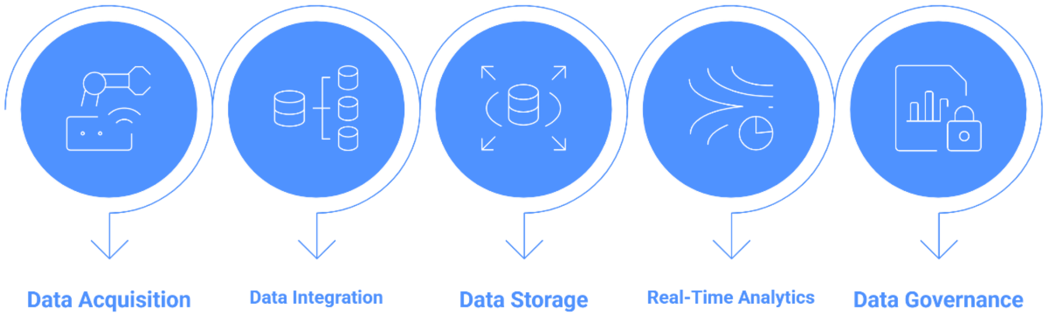

Figure 1. AI based QC components.

A. Industrial Data Acquisition and Sensing Architecture

Effective AI-based quality control begins with a robust data acquisition layer capable of capturing accurate, high-resolution, and representative information about products and processes. Industrial data sources typically include IIoT sensors (temperature, pressure, vibration, current), machine vision systems (RGB, thermal, hyperspectral cameras), and control system data from PLCs and SCADA platforms. The design of the sensing architecture must consider sensor placement, sampling frequency, calibration, and synchronization to ensure data reliability and temporal alignment. Poor data quality at this stage can propagate errors throughout the AI pipeline, undermining model accuracy and decision reliability. Consequently, systematic sensor validation and maintenance strategies are critical for sustaining long-term AI-QC performance.

B. Data Integration and Interoperability Across Shop-Floor Systems

Industrial environments generate heterogeneous data streams across multiple operational layers, creating significant integration challenges. AI-enabled QC requires seamless interoperability between operational technology (OT) systems on the shop floor and information technology (IT) systems at the enterprise level. Standards and middleware solutions such as OPC UA, MQTT, and RESTful APIs play a crucial role in enabling secure and consistent data exchange. Beyond connectivity, data integration involves harmonizing formats, aligning timestamps, and linking quality outcomes with upstream process parameters. This integration is essential for traceability, root-cause analysis, and closed-loop quality improvement across the production lifecycle.

C. Data Storage, Big Data Platforms, and Scalable Computing

The volume, velocity, and variety of industrial data necessitate scalable data storage and processing infrastructures. AI-based QC systems rely on big data platforms such as data lakes, time-series databases, and distributed computing frameworks to support both historical analysis and real-time operations. These platforms must ensure high availability, fault tolerance, and efficient data retrieval for model training, validation, and inference. Moreover, data lifecycle management, covering retention policies, data labeling, and versioning is essential for maintaining dataset integrity and reproducibility in quality analytics.

D. Real-Time Analytics, Edge–Cloud Architecture, and Deployment Pipelines

Quality control decisions often require low-latency responses to prevent defect propagation and production losses. Edge computing enables real-time analytics and AI inference close to machines, reducing communication delays and network dependency. Cloud platforms, in turn, support computationally intensive tasks such as large-scale model training, optimization, and system orchestration. An effective edge–cloud architecture balances responsiveness with scalability and cost efficiency. Additionally, deployment pipelines and MLOps practices, such as model version control, performance monitoring, and drift detection are critical to ensure that AI-QC systems remain reliable and adaptive under evolving production conditions.

E. Data Governance, Security, and Compliance for Quality-Critical Systems

Data governance forms the foundation of trustworthy AI-based quality control. Industrial QC systems must enforce strict data quality standards, access controls, and cybersecurity measures to protect sensitive operational information. Governance frameworks include role-based access, audit trails, and compliance with industry-specific standards and regulations. Furthermore, model governance, encompassing validation protocols, documentation, and accountability, ensures that AI-driven quality decisions are transparent, explainable, and aligned with organizational and regulatory requirements. Without robust governance, the scalability and acceptance of AI-enabled QC systems remain limited.

5. Performance Evaluation and Impact of AI-Driven Quality Control Systems

The adoption of artificial intelligence in industrial quality control has introduced new possibilities for improving product quality, operational efficiency, and cost effectiveness [36,37]. However, the successful deployment of AI-driven QC systems requires systematic performance evaluation to quantify their benefits and limitations relative to conventional quality control approaches. Performance assessment must extend beyond algorithmic accuracy to include operational, economic, and organizational impacts [38,39]. This section evaluates the performance and impact of AI-based quality control systems through multiple dimensions, including technical effectiveness, operational efficiency, economic benefits, system reliability, and comparative organizational outcomes [40,41].

A. Technical Performance Metrics and Model Effectiveness

The technical performance of AI-driven quality control systems is primarily evaluated using quantitative metrics such as accuracy, precision, recall, F1-score, defect detection rate, and false-alarm rate. Unlike traditional QC methods, which rely on fixed control limits and sampling-based inspection, AI models can detect complex, nonlinear patterns associated with defects and quality deviations. High detection accuracy and recall are particularly critical in safety- and quality-critical industries, where missed defects can result in significant losses. In addition, robustness to noise, variability, and changing production conditions is a key indicator of model effectiveness, distinguishing mature AI-QC systems from experimental implementations. Figure 2 outlines evaluation AI-Driven QC.

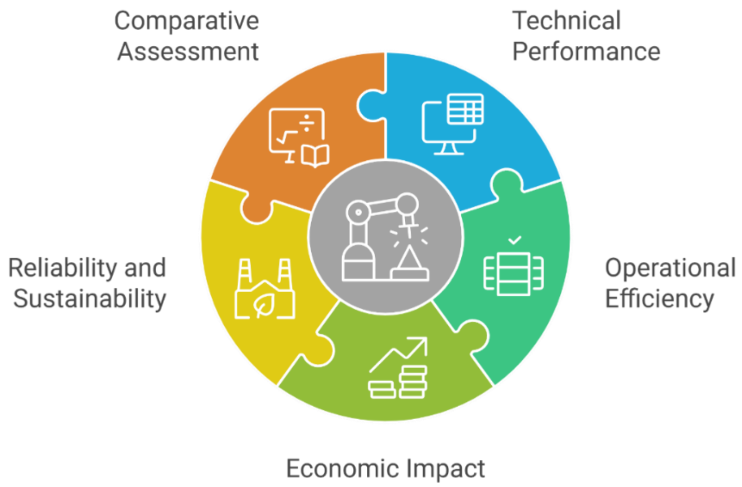

Figure 2. Evaluation AI-Driven QC.

B. Operational Efficiency and Process Improvement Outcomes

AI-driven quality control systems have a direct impact on operational efficiency by enabling continuous and automated inspection. Real-time monitoring reduces inspection time, accelerates feedback loops, and minimizes the propagation of defects along the production line. Compared with manual or periodic inspection, AI-based QC significantly reduces rework, scrap rates, and unplanned downtime. Furthermore, predictive quality assessment allows operators to intervene before quality deterioration occurs, enhancing process stability and throughput. These operational gains contribute to leaner and more responsive manufacturing processes.

C. Economic Impact and Cost–Benefit Analysis

From an economic perspective, AI-enabled quality control systems influence both direct and indirect costs. Although initial investments in sensors, computing infrastructure, and AI development may be substantial, long-term savings are achieved through reduced labor costs, lower defect-related losses, and improved resource utilization. Cost–benefit analysis typically evaluates metrics such as return on investment (ROI), payback period, and lifecycle cost reduction. In many industrial case studies, AI-based QC systems demonstrate favorable economic performance by shifting quality control from cost-intensive inspection to value-generating prevention and optimization.

D. Reliability, Robustness, and System Sustainability

Reliability and sustainability are critical for the long-term success of AI-driven quality control systems. Performance evaluation must account for system uptime, fault tolerance, resilience to data drift, and adaptability to process changes. Unlike traditional QC tools, AI models may degrade over time if underlying data distributions change. Therefore, continuous monitoring, retraining strategies, and model governance are essential to maintain stable performance. Systems that incorporate self-learning capabilities and robust validation mechanisms demonstrate higher sustainability and operational trustworthiness.

E. Comparative Assessment and Organizational Impact

Beyond technical and economic metrics, AI-driven quality control systems have a significant organizational impact. Compared with conventional QC approaches, AI systems shift quality decision-making from human-centric judgment to data-driven and AI-assisted processes. This transition alters workforce roles, requiring new skills in data interpretation, system supervision, and AI governance. When effectively managed, AI adoption strengthens quality culture, supports continuous improvement initiatives, and enhances organizational competitiveness. Comparative assessment highlights that AI-driven QC is not merely a technological upgrade but a strategic transformation of quality management practices.

The performance evaluation of AI-driven quality control systems demonstrates their substantial advantages over conventional QC approaches across technical, operational, and economic dimensions. AI-based systems achieve higher defect detection accuracy, improve operational efficiency through real-time and predictive monitoring, and deliver long-term cost savings despite higher initial investments. Their reliability and sustainability depend on robust data pipelines, continuous model management, and organizational readiness. Moreover, the organizational impact of AI-driven QC extends beyond automation, reshaping quality culture and decision-making processes. Overall, systematic performance evaluation confirms that AI-enabled quality control represents a critical enabler for achieving superior quality, efficiency, and competitiveness in modern industrial environments.

6. Challenges, Ethical Considerations, and Future Directions in AI-Enabled Quality Control

The integration of artificial intelligence into industrial quality control systems has created new opportunities for achieving higher accuracy, efficiency, and consistency in manufacturing processes. However, the deployment of AI-enabled quality control is accompanied by significant technical, organizational, and ethical challenges that must be carefully addressed to ensure reliable and responsible operation. Issues related to data quality, model interpretability, cybersecurity, workforce adaptation, and governance directly influence the trustworthiness and effectiveness of AI-based QC systems. At the same time, rapid advances in digital technologies are opening new research directions and application pathways for more intelligent, sustainable, and resilient quality control. This section introduces the key challenges and ethical considerations associated with AI-enabled quality control and outlines emerging trends that are shaping its future development in industrial sectors.

A. Implementation Challenges

The integration of artificial intelligence into industrial quality control systems has created new opportunities for achieving higher accuracy, efficiency, and consistency in manufacturing processes. However, the deployment of AI-enabled quality control is accompanied by significant technical, organizational, and ethical challenges that must be carefully addressed to ensure reliable and responsible operation. Issues related to data quality, model interpretability, cybersecurity, workforce adaptation, and governance directly influence the trustworthiness and effectiveness of AI-based QC systems. At the same time, rapid advances in digital technologies are opening new research directions and application pathways for more intelligent, sustainable, and resilient quality control. This section introduces the key challenges and ethical considerations associated with AI-enabled quality control and outlines emerging trends that are shaping its future development in industrial sectors.

- **Data quality and representativeness.**
  AI-QC performance is fundamentally bounded by data quality. Industrial datasets often suffer from sensor noise, missing values, label errors, class imbalance (defects are rare), and non-stationarity caused by changes in raw materials, tooling wear, operator behavior, or environmental conditions. These issues can inflate false alarms or, more critically, increase missed-defect rates. Robust AI-QC therefore depends on disciplined data engineering: calibration, synchronized timestamps, standardized data schemas, rigorous labeling protocols, and continuous data quality monitoring.
- **Model drift and generalization under process change.**
  Even high-performing models can degrade when the production regime changes (new supplier, new batch, different machine settings). Drift can be gradual (tool wear) or abrupt (equipment maintenance, line changeover). Without drift detection, periodic revalidation, and controlled retraining, AI-QC becomes unreliable. Operationally, this requires MLOps procedures tailored to manufacturing: data/model versioning, audit trails, rollback plans, and retraining triggers tied to process KPIs.
- **Interpretability and diagnosability.**
  Many AI models, especially deep learning for vision or multivariate time-series, behave as black boxes. In quality control, decisions must be explainable for root-cause analysis, corrective actions, and compliance. Lack of interpretability undermines trust on the shop floor and complicates fault investigation. Practical solutions include using interpretable baselines where possible (trees/linear models), deploying explainability tools (feature attribution, saliency maps), and, most importantly, building "diagnostic interfaces" that connect model outputs to actionable process variables and known failure modes.
- **System integration and real-time constraints.**
  AI-QC must integrate with PLC/SCADA, MES/ERP, vision hardware, and traceability systems while meeting strict latency and uptime requirements. Challenges include edge deployment, network reliability, compute constraints, and deterministic timing. Poor integration can create bottlenecks, misaligned timestamps, or incomplete traceability, reducing the value of AI insights. Successful deployment typically relies on robust edge–cloud design, streaming pipelines, and well-defined interfaces between OT and IT layers.
- **Cybersecurity and operational resilience.**
  AI-QC expands the attack surface: connected sensors, cameras, edge devices, model servers, and data pipelines. Threats include data poisoning, model theft, adversarial perturbations in vision inspection, and ransomware targeting production systems. Security must be treated as a quality prerequisite: segmentation, authentication, encryption, patch management, least-privilege access, and continuous monitoring. In critical industries, resilience planning (fail-safe modes, manual override, redundancy) is equally important.
- **Workforce adaptation and change management.**
  AI-QC alters roles, inspectors may become exception handlers, process engineers become model stewards, and operators interact with AI recommendations. Resistance can occur if AI is perceived as surveillance or job displacement. Adoption improves when organizations invest in training (data literacy, AI interpretation), clarify accountability, and co-design workflows with end-users so the system supports, not replaces, human expertise.

B. Ethical Considerations

- **Accountability and responsibility for quality decisions.**
  When AI flags defects or recommends parameter changes, responsibility must remain clear: who approves actions, who audits outcomes, and how errors are handled. Governance should define decision boundaries (assistive vs. autonomous), escalation rules, and documentation standards.
- **Fairness and worker impact.**
  AI-driven monitoring can unintentionally become worker surveillance, affecting performance evaluations or disciplinary actions. Ethical deployment requires transparent policies about what

data are collected, why, and how they are used. Systems should be designed to improve process capability rather than penalize individuals for systemic issues.

- **Transparency, auditability, and compliance.**
  Regulated sectors (aerospace, medical devices, automotive safety) require traceable and auditable QC decisions. Ethical compliance includes maintaining complete audit trails for datasets, model versions, thresholds, and any post-deployment changes. If explainability is limited, organizations should compensate with stronger validation, controlled operating envelopes, and independent verification.
- **Data privacy and confidentiality.**
  QC data may include proprietary process recipes, supplier-sensitive parameters, or camera footage that captures people. Ethical practice involves minimizing personal data collection, applying anonymization where feasible, and enforcing strict access controls. Confidentiality is also critical across multi-site or outsourced manufacturing.
- **Safety and risk of over-automation**
  Over-reliance on AI can lead to "automation bias," where operators accept model outputs uncritically. Ethical system design should support calibrated trust: confidence indicators, uncertainty reporting, human-in-the-loop approvals for high-risk decisions, and clear fallback procedures.

C. Future Directions and Emerging Trends

- **Hybrid (physics + data) and digital twin–enabled quality control.**
  Combining first-principles process models with machine learning improves generalization, supports constraints, and enhances interpretability. Digital twins can simulate "what-if" scenarios, accelerate safe optimization, and provide synthetic data for rare defect conditions.
- **Edge AI and low-latency inspection at scale.**
  More QC inference will move to edge devices for real-time responsiveness and reduced bandwidth costs, especially for high-frame-rate vision and high-frequency sensors. This trend will drive interest in model compression, efficient architectures, and hardware-aware deployment.
- **Self-supervised and weakly supervised learning for defect scarcity.**
  Because defects are rare and labeling is expensive, future AI-QC will increasingly rely on self-supervised pretraining, anomaly detection, and semi-supervised approaches. These methods reduce dependency on large labeled datasets and improve portability across lines and factories.
- **Uncertainty-aware and risk-sensitive QC.**
  Next-generation systems will quantify uncertainty, not just provide binary decisions. Probabilistic outputs, conformal prediction, and risk-based thresholds can support better trade-offs between false rejects and missed defects, aligned with safety and cost objectives.
- **Sustainable quality control and energy-aware AI.**
  Sustainability will shape QC objectives: reducing scrap, rework, material waste, and energy consumption. AI-QC evaluation will increasingly incorporate environmental KPIs (waste reduction, carbon impact) alongside traditional quality metrics. Efficient model training/inference will also matter for greener deployment.
- **Standardization and stronger AI governance in manufacturing.**
  Expect wider adoption of formal model governance: validation protocols, dataset documentation, model cards, continuous monitoring, and standardized reporting for industrial AI systems, making AI-QC more reliable, auditable, and scalable.

AI-enabled quality control represents a transformative advancement for industrial quality management, but its long-term success depends on addressing both technical and ethical dimensions of implementation. Challenges such as unreliable data, model drift, limited interpretability, cybersecurity risks, and workforce adaptation can significantly undermine system performance if left unmanaged. Ethical considerations, including accountability, transparency, worker impact, data privacy, and safety, are equally critical for building trust and ensuring responsible use of AI in quality-critical environments. Looking forward, developments in hybrid modeling, edge AI, uncertainty-aware decision-making, and sustainability-oriented quality metrics are expected to enhance the robustness and societal value of AI-driven quality control. By aligning technological innovation with strong governance and ethical frameworks, AI-enabled QC can evolve into a reliable, transparent, and sustainable cornerstone of modern industrial systems.

7. Conclusion

This study has comprehensively investigated the improvement of quality control in the industrial sector through the application of artificial intelligence, highlighting a fundamental shift from traditional, inspection-based practices toward intelligent, data-driven quality management. By establishing a clear conceptual framework, the analysis demonstrates how classical quality control principles, such as SPC, Six Sigma, and TQM, are not replaced but rather enhanced through AI-enabled predictive, adaptive, and preventive approaches. This evolution redefines quality control as a continuous and proactive function embedded across the entire production lifecycle. The article of AI techniques and models confirms that machine learning, deep learning, computer vision, and expert systems play a pivotal role in modern quality control by enabling accurate defect detection, real-time process monitoring, predictive quality assessment, and automated inspection. When supported by robust data acquisition mechanisms and integrated digital infrastructures, such as IIoT systems, big data platforms, and real-time analytics, AI-based QC systems can effectively exploit heterogeneous industrial data to deliver timely and reliable quality insights.

Furthermore, the evaluation of performance and impact reveals that AI-driven quality control systems outperform conventional approaches across multiple dimensions, including detection accuracy, operational efficiency, cost reduction, and process reliability. These measurable benefits justify the growing industrial adoption of AI-enabled QC, despite the initial investments required. However, the analysis also underscores that successful implementation depends on addressing critical challenges related to data quality, model interpretability, cybersecurity, workforce adaptation, and ethical governance. In this direction, the future of AI-enabled quality control lies in the development of more transparent, resilient, and sustainable systems through hybrid modeling, edge intelligence, uncertainty-aware decision-making, and stronger AI governance frameworks. By aligning technological innovation with ethical responsibility and organizational readiness, artificial intelligence can serve as a strategic enabler for achieving superior quality, competitiveness, and long-term sustainability in modern industrial sectors.

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References:

[1] S. Rezvani Boroujeni, H. Abedi, and T. Bush, “Enhancing glass defect detection with diffusion models: Addressing imbalanced datasets in manufacturing quality control,” *Computer and Decision Making: An International Journal*, vol. 2, pp. 687–707, 2025.

[2] C. A. Escobar, J. A. Cantoral-Ceballos, and R. Morales-Menendez, “Quality 4.0: Learning quality control, the evolution of SQC/SPC,” *Qual. Eng.*, pp. 1–26, 2024.

[3] A. Papavasileiou, G. Michalos, and S. Makris, “Quality control in manufacturing – review and challenges on robotic applications,” *Int. J. Comput. Integr. Manuf.*, pp. 1–37, 2024.

[4] C. Chang, F. Di Maio, R. Bheemireddy, P. Posthoorn, A. T. Gebremariam, and P. Rem, “Rapid quality control for recycled coarse aggregates (RCA) streams: Multi-sensor integration for advanced contaminant detection,” *Comput. Ind.*, vol. 164, no. 104196, p. 104196, 2025.

[5] K. Agrawal, P. Goktas, M. Holtkemper, C. Beecks, and N. Kumar, “AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance,” *Front. Nutr.*, vol. 12, p. 1553942, 2025.

[6] C.-M. Rosca, G. Rădulescu, and A. Stancu, “Artificial intelligence of Things infrastructure for quality control in cast manufacturing environments shedding light on Industry changes,” *Appl. Sci. (Basel)*, vol. 15, no. 4, p. 2068, 2025.

[7] J. A. Heredia Álvaro and J. G. Barreda, “An advanced retrieval-augmented generation system for manufacturing quality control,” *Adv. Eng. Inform.*, vol. 64, no. 103007, p. 103007, 2025.

[8] J. Lario, J. Mateos, F. Psarommatis, and Á. Ortiz, “Towards Zero Defect and Zero Waste manufacturing by implementing non-destructive inspection technologies,” *J. Manuf. Mater. Process.*, vol. 9, no. 2, p. 29, 2025.

[9] A. Das, “Water pollution and water quality assessment and application of criterion impact loss (CILOS), geographical information system (GIS), artificial neural network (ANN) and decision-

learning technique in river water quality management: An experiment on the Mahanadi catchment, Odisha, India," *Desalination Water Treat.*, vol. 321, no. 100969, p. 100969, 2025.
[10] X. Yin, Y. Chen, A. Bouferguene, H. Zaman, M. Al-Hussein, and L. Kurach, "A deep learning-based framework for an automated defect detection system for sewer pipes," *Autom. Constr.*, vol. 109, no. 102967, p. 102967, 2020.
[11] S. Sundaram and A. Zeid, "Artificial Intelligence-based smart quality inspection for manufacturing," *Micromachines (Basel)*, vol. 14, no. 3, p. 570, 2023.
[12] B. Al Kurdi *et al.*, "Analyzing the role of blockchain technology in enhancing quality control with mediating role of traceability systems," in *Advances in Science, Technology & Innovation*, Cham: Springer Nature Switzerland, 2025, pp. 65–73.
[13] F. Psarommatis, J. Sousa, J. P. Mendonça, and D. Kiritsis, "Zero-defect manufacturing the approach for higher manufacturing sustainability in the era of industry 4.0: a position paper," *Int. J. Prod. Res.*, vol. 60, no. 1, pp. 73–91, 2022.
[14] D. B. Olawade, J. Teke, K. K. Adeleye, K. Weerasinghe, M. Maidoki, and A. Clement David-Olawade, "Artificial intelligence in in-vitro fertilization (IVF): A new era of precision and personalization in fertility treatments," *J. Gynecol. Obstet. Hum. Reprod.*, vol. 54, no. 3, p. 102903, 2025.
[15] O. Morales Matamoros, J. G. Takeo Nava, J. J. Moreno Escobar, and B. A. Ceballos Chávez, "Artificial intelligence for quality defects in the automotive industry: A systemic review," *Sensors (Basel)*, vol. 25, no. 5, p. 1288, 2025.
[16] M. Puttegowda and S. Ballupete Nagaraju, "Artificial intelligence and machine learning in mechanical engineering: Current trends and future prospects," *Eng. Appl. Artif. Intell.*, vol. 142, no. 109910, p. 109910, 2025.
[17] S. B. Dhal and D. Kar, "Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: a comprehensive review," *Discov. Appl. Sci.*, vol. 7, no. 1, 2025.
[18] R. Taiwo, A.-M. Yussif, and T. Zayed, "Making waves: Generative artificial intelligence in water distribution networks: Opportunities and challenges," *Water Res. X*, vol. 28, no. 100316, p. 100316, 2025.
[19] X. Yang *et al.*, "Artificial intelligence-driven food quality prediction: Applying machine learning ensemble models for dynamic forecasting of pork pH and meat color changes," *Food Chem.*, vol. 492, no. Pt 2, p. 145383, 2025.
[20] K. J. Topping, E. Gehringer, H. Khosravi, S. Gudipati, K. Jadhav, and S. Susarla, "Enhancing peer assessment with artificial intelligence," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, 2025.
[21] H. L. Khan, S. Khan, S. Bhatti, and S. Abbas, "Role of artificial intelligence in quality assurance in ART: A review," *FandR*, pp. 1–7, 2022.
[22] C. Yu, "Artificial intelligence-based drug production quality management data," *Math. Probl. Eng.*, vol. 2022, pp. 1–14, 2022.
[23] D. Müller, M. März, S. Scheele, and U. Schmid, "An interactive explanatory AI system for industrial quality control," *Proc. Conf. AAAI Artif. Intell.*, vol. 36, no. 11, pp. 12580–12586, 2022.
[24] N. R. Mavani, J. M. Ali, S. Othman, M. A. Hussain, H. Hashim, and N. A. Rahman, "Application of artificial intelligence in food industry-a guideline," *Food Eng. Rev.*, vol. 14, no. 1, pp. 134–175, 2022.
[25] T. Miller *et al.*, "Integrating artificial intelligence agents with the Internet of Things for enhanced environmental monitoring: Applications in water quality and climate data," *Electronics (Basel)*, vol. 14, no. 4, p. 696, 2025.
[26] T. V. Andrianandrianina Johanesa, L. Equeter, and S. A. Mahmoudi, "Survey on AI applications for product quality control and predictive maintenance in industry 4.0," *Electronics (Basel)*, vol. 13, no. 5, p. 976, 2024.
[27] S. S. Aminabadi *et al.*, "Industry 4.0 in-line AI quality control of plastic injection molded parts," *Polymers (Basel)*, vol. 14, no. 17, p. 3551, 2022.
[28] A. Ettalibi, A. Elouadi, and A. Mansour, "AI and computer vision-based real-time quality control: A review of industrial applications," *Procedia Comput. Sci.*, vol. 231, pp. 212–220, 2024.
[29] R. Hoffmann and C. Reich, "A systematic literature review on artificial intelligence and explainable artificial intelligence for visual quality assurance in manufacturing," *Electronics (Basel)*, vol. 12, no. 22, p. 4572, 2023.

[30] M. Elahi, S. O. Afolaranmi, J. L. Martinez Lastra, and J. A. Perez Garcia, "A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment," *Discov. Artif. Intell.*, vol. 3, no. 1, 2023.

[31] A. Pathak, "Leveraging AI for better data quality and insights," *Journal of Computer Science and Technology Studies*, vol. 7, no. 3, pp. 291–300, 2025.

[32] R. Bin Mofidul, M. M. Alam, M. H. Rahman, and Y. M. Jang, "Real-time energy data acquisition, anomaly detection, and monitoring system: Implementation of a secured, robust, and integrated global IIoT infrastructure with edge and cloud AI," *Sensors (Basel)*, vol. 22, no. 22, p. 8980, 2022.

[33] Y. Sulema, A. Pester, B. Laforge, and F. Andres, "Augmented reality user's experience: AI-based data collection, processing and analysis," in *Augmented Reality and Artificial Intelligence*, Cham: Springer Nature Switzerland, 2023, pp. 31–46.

[34] N. Bangad *et al.*, "A Theoretical Framework for AI-driven data quality monitoring in high-volume data environments," *arXiv [cs.AI]*, 2024.

[35] A. Aldoseri, K. N. Al-Khalifa, and A. M. Hamouda, "Methodological approach to assessing the current state of organizations for AI-based digital transformation," *Appl. Syst. Innov.*, vol. 7, no. 1, p. 14, 2024.

[36] L. Gao *et al.*, "An AI-driven strategy for active compounds discovery and non-destructive quality control in traditional Chinese medicine: A case of Xuefu Zhuyu Oral Liquid," *Talanta*, vol. 287, no. 127627, p. 127627, 2025.

[37] N. Hoggas, O. Hioual, and A. Hebboul, "AI-driven quality control techniques in manufacturing processes to enhance Six Sigma approach," *Int. J. Six Sigma Compet. Advant.*, vol. 15, no. 3, pp. 291–314, 2025.

[38] I. Pysmennyi, R. Kyslyi, and K. Kleshch, "AI-driven tools in modern software quality assurance: an assessment of benefits, challenges, and future directions," *Technology audit and production reserves*, vol. 3, no. 2(83), pp. 44–54, 2025.

[39] M. O. Almangoush, T. M. Baayou, M. E. Esmail, and H. A. Alfitees, "Crises and risks in engineering project management: Identification and classification, crisis triggers and early warning indicators, lessons learned and implications," *LJSDR*, vol. 1, no. 1, pp. 01–14, 2025.

[40] C. Giachino, M. Cepel, E. Truant, and A. Bargoni, "Artificial intelligence-driven decision making and firm performance: a quantitative approach," *Manag. Decis.*, vol. 63, no. 10, pp. 3454–3476, 2025.

[41] M. Soori, R. Dastres, F. K. G. Jough, and M. K. Kolamroudi, "Smart quality control of Industry 4.0 by artificial intelligence-powered robot vision, a review," in *Artificial Intelligence of Things (AIoT)*, Elsevier, 2025, pp. 255–285.