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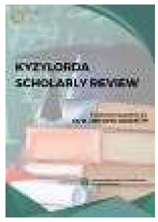

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ARTIFICIAL INTELLIGENCE IN QUALITY CONTROL: A REVIEW OF METHODS, APPLICATIONS, AND EMERGING DIRECTIONS

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Abstract. Today, Statistical Process Control (SPC) and manual inspection methods (classical SPC) employed in quality control (QC) can't manage the volume, velocity, and variety of the data generated by production systems. Artificial Intelligence (AI), which encompasses classical machine learning (ML), deep learning (DL), computer vision, generative modeling, and explainable AI (XAI), has become the key factor for automating the quality assurance process in both manufacturing and process industries, making it adaptive and predictive. This review categorizes the application of AI across the lifecycle of the QC process, including the examination of visual defects, prediction of maintenance issues and statistical process control, as well as anomaly detection and document/compliance management. The literature is classified based on the class of the technique and based on industrial sector, that is automotive and general manufacturing, electronics and semiconductors, pharmaceuticals, food processing, construction, with typical benchmark datasets used, performance results, and current issues like lack of data, class imbalance, explanation, and integration. The conclusion of this review states that transformer and convolutional vision models are predominant in defect detection; classical ensemble methods compete well in tabular sensor-based predictive maintenance and SPC; generative models are becoming more popular in tackling the problem of insufficient defects to train models for defect detection, and the need for interpretability is increasing for critical or regulated applications. Future work areas identified are federated and edge learning, human-in-the-loop inspection, and cross-sector benchmarking.

Keywords: Artificial Intelligence; Quality Control; Deep Learning; Machine Vision; Predictive Maintenance

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Introduction

Quality Control (QC) is a group of operational tasks aimed at ensuring processes, products, services, and products meeting defined standards and criteria. For most of the 20th Century, QC has been an operation based on manual physical and visual controls and gauges coupled with some sampling and Statistical Process Control (SPC) charts and Six Sigma. These methods are still useful, but limitations exist due to inspector fatigue, subjectivity, coverage not of the entire population, and can't model high-dimensional relationships between process parameters and defect outcomes [1], [2], [3].

This data deluge, spawned from pervasive sensing, Industrial Internet of Things (IIoT) connectedness, and cheap computation, is precisely why AI QC can be seen as an extension of Industry [4], [5]. With the help of machine learning and deep learning, it is possible to learn the discriminatory signature of a defect from an image, vibration signal, or log data, and to build vision systems that outperform rule-based ones in accuracy and generalization [6], [7], [8]. Simultaneously, approaches like Generative adversarial networks (GANs) address the long-standing bottleneck challenge of a lack of labeled defect images [9], [10]. For regulated industries, such as the automotive industry's safety regulations and the pharmaceutical industry, it is extremely important to create transparent and traceable decision-making processes – a need that is catered to by explainable artificial intelligence (XAI) techniques [11], [12], [13].

This subsequent review is a combination of almost eighty published applications of AI to the complete QC life cycle. Section 2 details the methods of the literature review. Section 3 discusses the main groups of AI techniques applied. Section 4 explores AI applications under the major headings of core QC functions: visual inspection, predictive maintenance, SPC and anomaly detection. Section 5 explores applications for each sector and industrial region, whilst Section 6 discusses the human dimension. Section 7 summarises the global challenges and Section 8 outlines areas of future research.

Methods

This survey adopts a narrative-synthesis methodology that draws upon the practice of systematic review. A comprehensive literature search, based on relevant keywords (e.g., 'AI quality control,' 'deep learning defect detection,' 'predictive maintenance machine learning,' 'explainable AI manufacturing,' 'GAN defect detection,' 'wafer defect classification,' 'pharmaceutical AI quality assurance'), was conducted over several leading academic archives and preprint servers, as well as industrial publications. The survey's timeframe ranges from 2011 to 2026. In particular, emphasis was given to systematic reviews as well as major well-cited primary studies published to date. Nonetheless, inclusion of recent preprints (2024–2026) was also provided to investigate trends like recent progress in visual transformers, as well as XAI in hardware, as well as the emerging area of Quality 5.0. The surveyed studies have been classified thematically into categories based on: (a) the specific Artificial Intelligence technique utilized, (b) the QC feature it focuses on, and (c) the sector where it has been applied (in Sections 3-5 respectively).

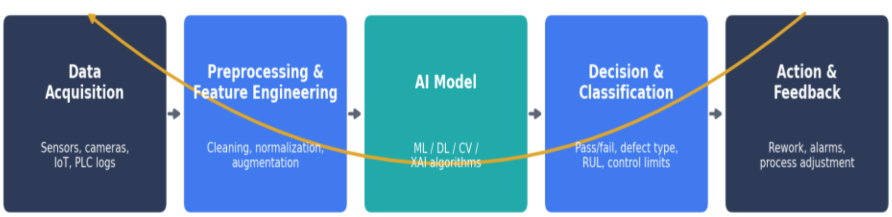

Figure 1. Generic closed-loop pipeline for AI-enabled quality control systems, from data acquisition through model-driven decisions and process feedback.

Results and Discussion

AI Techniques Used in Quality Control

QC applications utilizing AI rely upon a rather limited set of technique groups that reappear across multiple industries (Table 1). Machine learning models like support vector machines (SVMs), random forests (RFs), and gradient boosting machines are popular for their relatively low data requirements, speed, and internal diagnostics for diagnosing failure modes using features' importance [14], [15], [16]. The most successful approach to image-based inspection tasks is now deep learning, especially Convolutional Neural Networks (CNNs), to automatically learn the hierarchical visual features without manually designing the filter for use in classical machine vision [7], [8], [17]. More recent methods employ architectures used in object detection, such as You Only Look Once (YOLO) and attention-based transformer models, with the purpose of the algorithms to localise and detect multiple fault types in one processing pipeline [18], [19]. However, since defective samples often occupy only a small proportion compared to the conforming ones, deep generative models like Generative Adversarial Networks (GANs) are often used to synthesize realistic defect images and enhance the classifier's robustness while avoiding a large quantity of real defect samples [9], [10], [20], [21], [22]. A similar but also complementary paradigm is the self-supervised or unsupervised anomaly detection setting, where the model is only trained on data corresponding to the norm, and anomalies are reported during inference; this paradigm underlies popular standard benchmarks like MVTec Anomaly Detection ،and its 3D and multi-modal extensions [23], [24], [25], [26].

Finally, AI has matured from a mere academic curiosity to an actual enabler in the context of inspections that demand that decisions made by the AI be explainable/verifiable with a trace that could be accessed by regulators and quality engineers. Various forms of gradient-based attribution methods such as Gradient-weighted Class Activation Mapping (Grad CAM), perturbation-based methods such as Shapley Additive Explanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and, more recently, especially faithfulness-auditing methods have started to be reported consistently alongside accuracy metrics in recent papers.

Table 1. Principal AI technique families applied in quality control.

Technique family	Representative methods	Typical QC use	Key references
Classical machine learning	Random forest, SVM, XGBoost, gradient boosting	Predictive maintenance, SPC, tabular sensor classification	[14], [15], [16], [27]
Deep learning/computer vision	CNN, ResNet, YOLO, Vision Transformers, autoencoders	Visual surface/PCB/wafer defect detection and segmentation	[7], [8], [17], [18], [19], [28], [29]
Generative models	GAN variants, diffusion-style augmentation	Synthetic defect generation to offset data scarcity and class imbalance	[9], [10], [20], [21], [22], [30]
Unsupervised / self-supervised anomaly detection	Autoencoders, one-class classifiers, teacher-student networks, normalizing flows	Detecting rare or previously unseen defect types without labeled negatives	[23], [25], [26], [31]
Explainable AI	Grad-CAM, SHAP,	Auditable decisions	[12], [13],

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Technique family	Representative methods	Typical QC use	Key references
(XAI)	LIME, saliency maps, integrated gradients	for regulated or safety-critical inspection	[32], [33], [34], [35]
Natural language processing	NLP-based document parsing and classification	Compliance document review, deviation/CAPA management	[36]

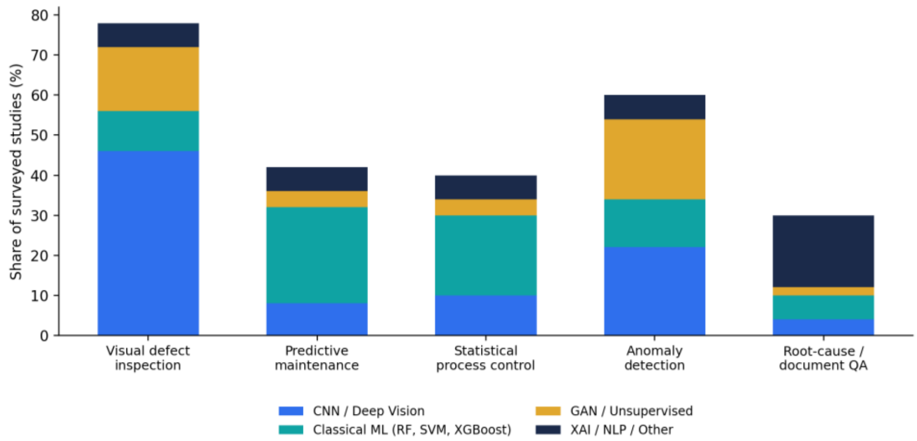

Figure 2. Illustrative distribution of AI technique families across core quality-control functions, synthesized from the reviewed literature.

AI Applications by Quality-Control Function

Visual Defect Inspection

The oldest and best-studied application of AI in QC is that of automatic visual inspection, where deep CNN-based classifiers and segmentation networks, which work to locate and identify surface defects in materials like steel, castings, textiles, wood, and ceramics, most of the time reach even higher accuracy and stability than the standard computer vision pipeline involving hand-crafted filters and thresholds [7], [17], [28], [37], [38]. In a systematic review, CNN-based methods are now leading the techniques, and encoder-decoder or attention-based architecture is more commonly applied to pixel-level defect segmentation rather than image-level classification [8], [17], [39]. For thin, high-volume items like printed circuit boards, the YOLO object detectors with data augmentation are often applied in combination to detect multiple defect types at once (short circuit, open circuit, missing hole, mouse bite), achieving precision and recall of over 90% [18], [19], [40], [41].

Predictive Maintenance

Predictive maintenance (PdM) leverages AI to anticipate equipment failure prior to failure propagation that could result in quality faults or production stoppages. Ensemble methods are widely used in PdM as sensor data (vibration, temperature, torque) is often tabular and of moderate size, whereas feature importance analysis can clearly illustrate to engineers which process variables are most causative of the failure. Popular techniques here include random forests and gradient boosting models, alongside SHAP analysis for clear visualization [15], [16], [42]. Recent systematic reviews of the PdM literature highlight the potential for IIoT sensor streams to work synergistically with ML tools to make the downtime and maintenance budget significant improvements over purely reactive or schedule-based approaches to the maintenance task.

Statistical Process Control (SPC)

Researchers have published a rising number of studies in which machine learning and traditional SPC charts are combined in order to analyze high-dimensional, auto-correlated, and non-stationary manufacturing data – i.e., data that neither follows the assumptions of independence nor normality of traditional SPC control charts [39], [43]. Recent deep learning methods (e.g., recurrent and attention architectures) were also implemented for control-chart pattern recognition, which significantly increased the capability of finding the mean and/orvariance jumps compared to existing rule-based Western Electric criteria [44]. The use of such data-driven hybrids-a kind of "SPC 4.0" or "smart SPC"-enables linking real-time monitoring data obtained by sensors to data-driven product quality predictive models in order to focus on preventive actions rather than corrective feedback [45], [46], [47].

Anomaly Detection and Benchmark Datasets

Because labeled defect examples are costly to collect and inherently rare, unsupervised anomaly detection—training only on defect-free ('normal') samples—has become a distinct and fast-growing subfield. Public benchmarks such as MVTec AD, its extension MVTec AD 2, and the 3D and multimodal variant MVTec 3D-AD have standardized evaluation and revealed that reconstruction-based and feature-embedding methods (e.g., teacher–student networks, normalizing flows) currently define the state of the art [23], [24], [25], [26], [31], [48], [49]. Table 2 summarizes commonly used public datasets referenced across the reviewed literature.

Table 2. Selected public benchmark datasets used in AI-based quality-control research.

Dataset	Domain	Approx. size	Notes/reference
MVTec AD	General industrial objects and textures (15 categories)	~5,000 images, 73 defect types	Benchmark for unsupervised anomaly detection and localization [24], [25]
MVTec AD 2	Extended industrial scenarios incl. transparent/reflective objects	8,000+ images, 8 scenarios	Addresses saturation of the original MVTec AD benchmark [48], [50]
MVTec 3D-AD	3D scans of 10 object categories	~4,100 3D scans + RGB	Supports multimodal (RGB + depth) anomaly detection [26], [49]
WM-811K	Semiconductor wafer maps	~811,000 wafer maps	Widely used benchmark for wafer defect-pattern classification [29], [51]
PCB defect datasets (e.g., PKU HCI Lab)	Printed circuit boards	Thousands of annotated images	Used for open-circuit, short-circuit, mouse-bite and similar defect types [18], [40], [41]

AI Applications by Industrial Sector

Beyond the functional lens of Section 4, the literature also clusters naturally by industrial sector, each with distinct data modalities, regulatory pressures, and defect taxonomies (Table 3; Figure 3).

Automotive and General Manufacturing

Within the automotive industry, for example, AI is used in live part tracking, computer-vision approaches for detecting failures, and predictive maintenance to enable zero-defect manufacturing – where convolution networks and principal component analysis were identified as the predominant technologies for defect detection and process analysis in both Industry 4.0 and 5.0 setups [52]. Wider reviews for different industrial sectors concur with this trend towards the enhancement of traditionally manual structural problem solving by real-time analytics and prediction modelling [2], [3], [53].

Electronics and Semiconductors

Electronics manufacturing has produced an especially large and mature body of AI-QC literature, driven by the availability of large annotated datasets (e.g., WM-811K wafer maps, PCB defect image sets) and by the high economic cost of yield loss. Studies report CNN- and YOLO-based detectors for PCB defects [18], [19], [40], [41], and CNN, autoencoder, and GAN-augmented pipelines for wafer-map defect-pattern classification, often addressing severe class imbalance through synthetic oversampling or targeted data augmentation [29], [54], [55], [56], [57]. Reviews emphasize that model transferability and imbalance-handling remain open engineering challenges even as reported accuracies climb into the high nineties on curated test sets [51], [55].

Pharmaceutical and Biopharmaceutical Manufacturing

While not directly involved in manufacturing processes, pharmaceutical quality control extends inspection processes (e.g., inspection of coating thickness or cracks in tablets, etc.) to document-based quality assurance activities (e.g., batch record inspection, deviations and subsequent CAPA [11], [36], [58], where more NLP tools are used, to some degree. Since pharma is under regulation, this invariably leads to discussions on AI Explainable & Auditable, in the context of discussions by FDA, EMA, and ICH on risk-based regulations concerning AI-enabled QC systems.

Food and Agricultural Processing

In food manufacturing, machine learning is applicable to defect & contaminant detection, ingredient & nutritional optimization, and packaging layer quality assurance, where neural networks have been most prevalent, and ensemble learning is a notable second option, along with nascent areas such as hyperspectral imaging, sensor fusion, and layered traceability through the use of blockchain on top of AI-based inspection [59], [60].

Construction and Other Sectors

Ideas about the QC system based on AI have been developed in terms of construction project management and materials inspection as well, where computer vision and predictive analytics have taken a role to guarantee quality assurance in relation to the large size, complexity, and the necessity of sustainability of current projects in a nature that is similar to that in manufacturing, except for project-based, non-repetitive production [61].

Table 3. AI-for-quality-control applications organized by industrial sector.

Sector	Representative AI applications	Common techniques	References
Automotive & general manufacturing	Body-panel and paint defect inspection, structured problem solving, zero-defect strategies	CNN vision, ANN, PCA-based monitoring	[52], [53], [61]
Electronics & semiconductors	PCB defect detection, wafer-map pattern classification, SEM image inspection	CNN, YOLO, autoencoders, GAN augmentation	[18], [19], [29], [40], [51], [54], [55], [56], [57], [62], [63], [64], [65], [66], [67]
Pharmaceutical & biopharma	Tablet coating inspection, batch-record and deviation review,	Machine vision, NLP, ANN/SVM regression	[11], [36], [58], [68], [69], [70],

Sector	Representative AI applications	Common techniques	References
	formulation optimization		[71], [72], [73], [74]
Food & agri-processing	Hyperspectral quality grading, contamination and defect detection, packaging QC	Neural networks, ensemble learning, sensor fusion	[59], [60]
Construction & other sectors	Structural inspection, material imperfection detection, predictive project QC	Computer vision, predictive analytics	[61]

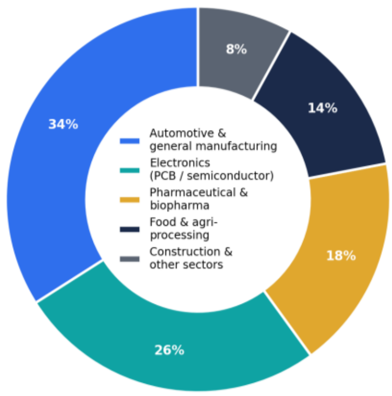

Figure 3. Approximate distribution of reviewed AI-for-quality-control studies by industrial application domain.

Explainability, Trust, and Human Factors

A recurring theme across sectors is that predictive accuracy alone is insufficient for industrial adoption: operators, quality engineers, and regulators need to understand why a model flagged (or missed) a defect. Explainable AI methods—including Grad-CAM-style saliency mapping, SHAP-based feature attribution, and LIME—are now commonly layered onto CNN-based inspection systems to link model outputs to physically meaningful defect regions or process variables [12], [13], [34], [35]. Recent work has gone further, proposing quantitative faithfulness audits that test whether a highlighted region actually drives a model's prediction rather than merely appearing plausible to a human reviewer [33].

Human-centered and edge-deployed XAI frameworks aim to make explanations accessible to shop-floor personnel without a machine learning background, for example by pairing segmentation outputs with natural-language explanations generated by vision-language models, and by optimizing model size for deployment on resource-constrained edge devices [32], [35]. In regulated industries such as pharmaceuticals, this trend intersects with formal quality-management requirements: reviews describe AI-enhanced document-control and change-control workflows that must remain auditable under frameworks such as ICH Q9 risk management [36].

Cross-Cutting Challenges and Limitations

Despite rapid methodological progress, several challenges recur across the reviewed literature

(Table 4). Foremost is data scarcity: because well-run production lines generate mostly conforming output, collecting enough labeled defect examples for supervised training is difficult, motivating the generative-modeling and unsupervised-anomaly-detection literature discussed in Sections 3 and 4 [9], [20], [29]. A second challenge is generalization: models trained on a specific product, camera setup, or lighting condition frequently underperform when deployed on a different line or facility, an issue especially pronounced for wafer and steel-surface inspection tasks [37], [54], [55].

A third challenge concerns interpretability and regulatory trust, particularly in pharmaceutical and automotive-safety contexts where opaque model decisions are difficult to justify to auditors [12], [70]. Fourth, integrating AI inference with legacy manufacturing execution systems (MES) and quality-management systems (QMS) remains nontrivial, since many shop-floor platforms were not designed for real-time model scoring or feedback loops [46], [53], [75]. Finally, organizational factors—resistance to change, uneven data-science skills, and unclear return-on-investment—are repeatedly cited as barriers to scaling pilot projects into production deployments [2], [3].

Table 4. Cross-cutting challenges in AI-enabled quality control.

Challenge	Description	Illustrative references
Data scarcity & class imbalance	Defective samples are rare relative to conforming products, limiting supervised model training.	[9], [10], [20], [29], [56]
Interpretability & regulatory trust	Black-box deep models are difficult to audit in safety-critical or regulated settings.	[12], [13], [34], [70]
Domain/equipment shift	Models trained on one line, product, or sensor configuration often generalize poorly to another.	[37], [54], [55]
Integration with legacy systems	Shop-floor PLCs, MES, and QMS platforms were not designed for real-time AI inference.	[46], [53], [75]
Computational constraints	Edge deployment requires model compression without sacrificing accuracy or explainability.	[32], [35]
Organizational readiness	Resistance to change and lack of cross-functional data science skills slow adoption	[2], [3]

Development Timeline and Future Directions

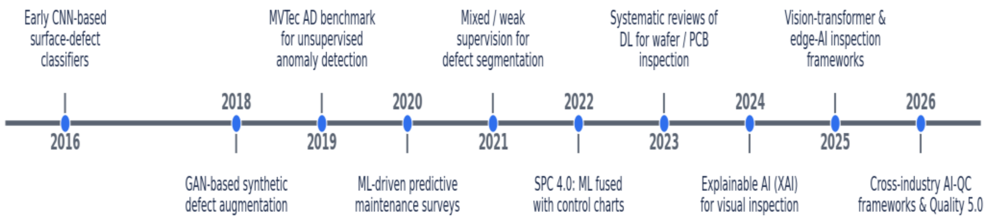

Figure 4. Indicative timeline of key methodological milestones in AI-enabled quality control, 2016-2026, synthesized from the reviewed literature.

As illustrated in Figure 4, the field has progressed from early CNN-based classifiers and GAN-based data augmentation, through the introduction of standardized unsupervised-anomaly-detection benchmarks, toward today's emphasis on explainability, vision transformers, and edge deployment. Several directions appear likely to shape the next phase of research and practice:

a. Federated and privacy-preserving learning, allowing manufacturers to pool model updates across sites or partners without sharing raw, potentially proprietary defect imagery [39].
b. Human-in-the-loop inspection, in which AI systems triage or pre-screen products while retaining human sign-off for ambiguous or high-stakes cases, particularly in pharmaceutical and safety-critical automotive contexts [34], [70].
c. Standardized, cross-sector benchmarking, extending image-centric datasets such as MVTec AD toward multimodal (vision, vibration, thermal) and cross-domain evaluation protocols [26], [31], [49].
d. Lightweight and edge-deployable explainable AI, combining model compression with human-readable explanations suitable for shop-floor, non-specialist users [32], [35].
e. Emergence of a broader "Quality 5.0" paradigm that positions AI as a collaborator with human expertise, emphasizing sustainability, resilience, and worker well-being alongside defect-detection accuracy [76].

Conclusion

Artificial intelligence has become deeply embedded in quality control across manufacturing and process industries, reshaping visual inspection, predictive maintenance, statistical process control, and anomaly detection. Deep learning and computer vision dominate image-based inspection tasks, classical ensemble methods remain strong performers for sensor-driven predictive maintenance and SPC, generative models help offset chronic defect-data scarcity, and explainable AI is increasingly treated as a deployment prerequisite rather than an optional add-on. Sector-specific pressures—yield economics in electronics, regulatory scrutiny in pharmaceuticals, traceability in food processing—shape how these general techniques are adapted in practice. The literature also converges on a consistent set of open challenges: data scarcity, weak cross-domain generalization, interpretability, legacy-system integration, and organizational readiness. Addressing these challenges through federated learning, human-in-the-loop workflows, standardized multimodal benchmarks, and edge-deployable explainable models is likely to define the next generation of AI-enabled quality-control systems.

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