AI-Driven Quality Control in Manufacturing and Construction: Enhancing Precision and Reducing Human Error

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Abstract

In recent decades, the demand for higher quality and precision in manufacturing and construction has increased significantly due to globalization, customer expectations, and the complexity of modern projects. Traditional quality control (QC) systems, reliant on manual inspections and human oversight, often fall short in delivering consistency, speed, and accuracy. This review explores how artificial intelligence (AI) technologies are reshaping the landscape of quality control in both manufacturing and construction industries. The methodology employed in this review includes a synthesis of peer-reviewed journal articles, industry reports, and case studies published before 2018, focusing on practical applications of AI, such as machine learning (ML), computer vision, and robotics in quality assurance. Evidence from these sources was critically analyzed to extract common trends, successes, and challenges in implementing AI-driven QC solutions. The results indicate that AI systems outperform traditional QC processes in defect detection, predictive maintenance, and process optimization. In manufacturing, AI tools identify product anomalies in real-time with remarkable accuracy. In construction, drones, sensors, and ML algorithms ensure structural integrity, monitor progress, and minimize material waste. AI also facilitates adaptive learning, enabling systems to evolve and improve with continuous data input.The review concludes that AI-driven quality control enhances efficiency, reduces human error, and lowers operational costs in both sectors. However, successful integration demands robust infrastructure, skilled personnel, and regulatory frameworks to address ethical concerns and safety standards. Ultimately, AI's role in QC is not a replacement of human expertise but a complement that augments capabilities and fosters innovation.

Keywords: Artificial Intelligence (AI), Quality Control (QC), Machine Learning (ML), Computer Vision, Predictive Maintenance.

Significance | AI ensures consistency, accuracy, and safety in quality control for complex manufacturing and construction environments through real-time data analysis.

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1. Introduction

Quality control (QC) is a foundational element in manufacturing and construction industries, aimed at ensuring that final products meet predefined standards of quality, safety, and functionality. The traditional QC approach—centered around human inspection, checklists, and post-production assessments—has long been effective but increasingly shows limitations in scale, speed, and error reduction (Duarte et al., 2025). As industries face tighter tolerances, faster production cycles, and greater customization demands, the integration of artificial intelligence (AI) into QC

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systems has emerged as both a necessity and an opportunity. I's contribution to QC is multifaceted, involving technologies such as machine learning (ML), deep learning, computer vision, and autonomous systems. These innovations empower machines not just to collect and interpret data but to learn from it, thereby improving inspection accuracy, detecting patterns humans might miss, and predicting failures before they occur (Wang et al., 2016). Manufacturing sectors, including automotive, electronics, and aerospace, have been early adopters of AI in their QC processes. Meanwhile, the construction industry, often slower in adopting digital technologies, is increasingly leveraging AI tools like drones, sensors, and real-time data analytics to monitor quality and safety parameters at scale (Pop et al., 2023). In manufacturing, AI-driven QC often involves vision-based systems capable of identifying micro-defects in materials at speeds surpassing human inspectors. For instance, computer vision systems equipped with convolutional neural networks (CNNs) analyze thousands of images per second to detect inconsistencies in products such as semiconductors, printed circuit boards, or automotive components (Ashebir et al., 2024). Additionally, predictive maintenance algorithms assess real-time data from machines to identify anomalies and prevent breakdowns, improving production uptime and quality consistency (Kalusivalingam et al., 2020).

In construction, quality control has traditionally relied on visual assessments, measurement tools, and after-the-fact inspections. AI introduces a shift towards continuous, real-time monitoring through technologies such as LiDAR-equipped drones, wearable sensors, and intelligent construction management platforms. These systems monitor structural integrity, material usage, and compliance with design specifications (Lu et al., 1996). With machine learning, AI systems can recognize patterns in project data, flag potential issues early, and even suggest solutions, significantly enhancing project outcomes.The methodology underpinning this review involves a thorough analysis of journal articles, technical white papers, and case studies published before 2018 that document the integration and outcomes of AI in quality control. Sources were selected based on their relevance, empirical rigor, and contribution to the understanding of AI's role in industrial QC systems (Fan, 2022). Emphasis was placed on real-world applications and quantifiable benefits, including defect reduction, time savings, cost efficiency, and improved product reliability. I's ability to transform quality control is not merely a theoretical promise but a practical reality increasingly evident across industries. However, the road to implementation is not without hurdles. Barriers such as high initial costs, resistance to change, lack of skilled workforce, and concerns over algorithm transparency must be navigated carefully. Moreover, ethical considerations, especially in construction where human lives are at stake, must be addressed to ensure that AI systems are both reliable and accountable (Sim & Rogers, 2008).

As this review progresses, each section will delve deeper into the distinct contributions of AI to manufacturing and construction quality control. It will begin with an in-depth look at AI in defect detection, followed by predictive maintenance, quality management systems integration, and finally, the ethical and regulatory considerations surrounding AI deployment. Each subtopic will include extensive examples, critical analysis, and referenced data to provide a comprehensive understanding of the current landscape and future trajectory of AI-driven quality control.By examining both the technological innovations and the human factors at play, this review aims to provide a holistic overview of how AI is revolutionizing quality control. It is hoped that this will inform engineers, project managers, policymakers, and academic researchers interested in optimizing industrial outcomes while maintaining safety and sustainability.

2. AI in Defect Detection

Defect detection is one of the most immediate and impactful applications of artificial intelligence in quality control, particularly in manufacturing and, more recently, in construction (Table 1). Traditional defect detection methods—manual inspections, static imaging systems, and statistical sampling—often struggle with consistency, subjectivity, and scalability (Alamuru et al., 2024). These limitations become more pronounced in high-volume or high-precision manufacturing environments, where even minor defects can lead to significant product failures, recalls, or safety hazards. AI-driven systems, particularly those powered by machine learning and computer vision, address these shortcomings by offering continuous, real-time, and highly accurate monitoring capabilities. In manufacturing, visual inspection systems enhanced by AI have revolutionized how defects are identified (Boppana, 2022). Computer vision, a subfield of AI that allows machines to interpret and understand visual information, is particularly effective in this domain. Using high-resolution cameras and deep learning algorithms such as convolutional neural networks (CNNs), these systems can be trained on thousands of images to recognize a wide range of surface-level and internal defects—including cracks, scratches, discoloration, and structural irregularities (Higham et al., 2018). For example, in semiconductor manufacturing, where tolerances are measured in microns, AI systems have achieved near-perfect detection rates that surpass human accuracy (Srinivas et al., 2014). Furthermore, these systems continuously learn from new data, improving their defect-detection capabilities over time without requiring reprogramming or manual recalibration (Lee et al., 2014).

The implementation of AI in manufacturing defect detection extends beyond static imaging. Thermal imaging, X-ray scans, and

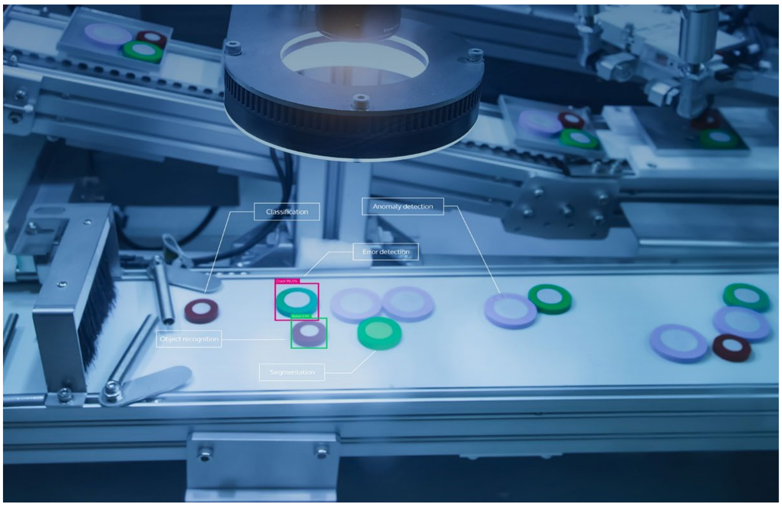

Figure 1. AI driven quality control in factories. (Courtesy of image from Khan et al., 2023).

ultrasonic sensors integrated with AI algorithms provide multi-modal inspection capabilities, enabling systems to detect hidden or subsurface flaws. This is particularly valuable in industries like aerospace and automotive manufacturing, where internal defects in components can have catastrophic consequences. In these contexts, AI models trained on historical defect data and failure modes can predict not just the presence of defects but also their potential impact on component performance (Senthil et al., 2013). Such predictive capabilities allow for immediate corrective actions, reducing waste and enhancing product reliability. Construction, though traditionally slower to adopt AI-driven technologies, has begun leveraging similar defect detection tools to improve on-site quality. One of the most transformative technologies in this sector is drone-based inspection, which uses high-definition cameras and LiDAR to scan large-scale structures such as bridges, buildings, and highways. These aerial systems collect vast amounts of visual and spatial data, which are then processed by AI algorithms to detect anomalies like cracks, corrosion, misalignments, or deviations from design specifications. Unlike human inspectors, who are limited by access, visibility, and fatigue, AI-powered drones can assess inaccessible or hazardous areas safely and efficiently (Elizabeth & Barshilia, 2024).

In addition to drones, mobile robotics equipped with AI systems are increasingly used in indoor construction environments. These autonomous machines can navigate construction sites and perform detailed inspections of floors, walls, plumbing, and electrical systems. Using image recognition and 3D mapping, they identify issues like incorrect installations, material defects, and unfinished components in real-time. This not only improves safety and quality but also ensures compliance with building codes and reduces the need for rework, which can be costly and time-consuming (Cognominal et al., 2021). One of the most significant advantages of AI in defect detection is its scalability and adaptability. Traditional quality control often relies on fixed protocols and sample-based testing, which may miss intermittent or batch-specific defects. In contrast, AI systems can monitor 100% of production or construction processes continuously, adapting their detection criteria based on environmental conditions, material changes, or evolving product designs. This dynamic adaptability leads to higher yields, fewer recalls, and better overall customer satisfaction (Abioye et al., 2021).

However, the implementation of AI in defect detection is not without challenges. Training AI models requires large volumes of labeled data, which can be time-consuming and expensive to

Table 1. AI techniques and their applications in manufacturing quality control.

AI techniques	Application area	Benefits	References
Convolutional Neural Networks	Surface defects detection in mental sheets	High accuracy in pattern recognition	Sani et al., 2024
Support vector machines	Classification path planning for industrial robots	Robust classification performance	Escobar et al., 2023
Decision trees	Inspection path planning for industrial	Fast and interpretable decision	George, 2024).

collect, especially in construction settings where defect scenarios vary widely. Moreover, there is a need for cross-disciplinary expertise—data scientists, engineers, and industry specialists must collaborate closely to ensure the AI models are accurate, reliable, and aligned with industry standards (Leberruyer et al., 2023). There is also the issue of false positives, where AI may mistakenly classify normal variations as defects. While these are preferable to false negatives, they can still disrupt operations if not calibrated correctly (Brynjolfsson & McAfee, 2014). Ethical considerations also emerge, particularly in scenarios where AI-driven decisions have safety implications. In construction, for instance, relying solely on AI to assess structural integrity could be risky without human oversight (Liang et al., 2024). Therefore, best practices emphasize the hybrid approach—AI systems perform initial detection, while trained professionals review and validate the findings. This collaboration not only improves accuracy but also builds trust in AI technologies across sectors traditionally skeptical of automation (Shneiderman, 2020).

Looking forward, the integration of AI with the Internet of Things (IoT) is poised to enhance defect detection capabilities even further. Smart factories and construction sites equipped with sensor networks can generate real-time data streams that AI systems analyze continuously (Figure 1). This fusion allows for predictive alerts, root cause analysis, and adaptive quality control measures. As AI models become more sophisticated, they will not only detect defects but also trace their origin, recommend process adjustments, and facilitate closed-loop quality management.AI in defect detection offers unparalleled advantages in precision, speed, and coverage for both manufacturing and construction industries. By reducing reliance on manual inspections and introducing intelligent, data-driven analysis, AI empowers organizations to achieve higher quality standards with lower costs and greater consistency. While challenges in implementation, data requirements, and ethical oversight remain, the long-term benefits of AI-driven defect detection make it an indispensable tool in the modern industrial landscape.

3. Predictive Maintenance and Quality Forecasting

Predictive maintenance and quality forecasting represent a paradigm shift in manufacturing and construction, driven largely by the integration of artificial intelligence (AI) and machine learning technologies. Traditionally, maintenance protocols followed reactive or preventive models—equipment was either repaired after failure or serviced at regular intervals based on estimates. Similarly, quality control focused on identifying defects after production or during manual inspections (Keleko et al., 2022). These reactive approaches led to unexpected downtimes, wasted resources, and inconsistent quality. AI, by contrast, enables systems to anticipate failures and quality issues before they occur, transforming maintenance and production into proactive and adaptive processes. The core of AI-driven predictive maintenance lies in its ability to analyze vast amounts of data from equipment sensors in real time (Aminizadeh et al., 2024). Manufacturing machines and construction tools are now commonly embedded with Internet of Things (IoT) sensors that continuously monitor parameters such as temperature, vibration, pressure, sound, and wear. AI algorithms—particularly those rooted in time-series analysis and neural networks—process this sensor data to detect patterns indicative of impending failures. For instance, an abnormal vibration pattern in a CNC machine spindle could indicate bearing degradation, prompting preemptive intervention before a critical breakdown occurs (IEEE, 2024). Similarly, changes in hydraulic pressure or electrical loads can reveal hidden wear in construction equipment.

In predictive maintenance, AI models are trained using historical operational data labeled with known failure events. These models then identify anomalies in real-time data streams, flagging potential risks. This approach not only minimizes unplanned downtime but also extends equipment life by ensuring timely and targeted servicing. For example, General Electric's “Predix” platform uses AI to predict failures in jet engines and industrial turbines, saving millions in repair costs and optimizing operational schedules (Roskladka & Miragliotta, 2024). In construction, companies like Caterpillar have adopted similar AI-driven strategies to monitor their heavy equipment fleets, significantly reducing operational disruptions and maintenance costs. I’s predictive capabilities also play a crucial role in quality forecasting. By analyzing process data—such as temperature, humidity, speed, material properties, and operator inputs—AI systems can identify the conditions that lead to quality deviations (Matveev, 2025). For example, in plastic injection molding, variations in mold temperature or pressure can cause warping or voids in final products. AI models trained on production data can forecast these outcomes before they manifest, allowing real-time process adjustments. This preemptive approach leads to higher first-pass yield rates and drastically reduces scrap and rework (Javaid et al., 2021).

Quality forecasting is particularly impactful in continuous and batch manufacturing industries such as pharmaceuticals, food processing, and chemical production. In these sectors, maintaining consistent quality is both regulatory and economically vital. AI systems such as support vector machines (SVMs), recurrent neural networks (RNNs), and decision trees are used to model complex cause-effect relationships across multiple variables (Lee et al., 2015). These systems do not merely predict outcomes—they recommend optimal process conditions, warn against deviations, and guide corrective actions in real time. In construction, the application of predictive quality models is relatively new but growing. For example, AI is being used to forecast concrete curing quality based on environmental conditions, mixing ratios, and material inconsistencies. Sensors embedded in curing slabs transmit data to AI systems that predict potential cracks or inconsistencies in structural integrity, allowing for timely mitigation (Luo et al., 2025). Similarly, predictive models are being used to monitor welding quality, where factors like arc speed, voltage, and electrode quality can affect structural strength. Early detection of non-conforming welds prevents costly structural failures and rework (Eagar et al., 2016).

One of the transformative aspects of AI in predictive quality control is its integration with digital twins. A digital twin is a virtual replica of a physical asset or process that mirrors its real-time status. In manufacturing, a digital twin of a production line can simulate how changes in parameters affect product quality, enabling virtual testing before physical execution. AI enhances this concept by continuously updating the model based on real-time data and predicting future outcomes (Tien, 2017). This fusion of AI and digital twins supports better decision-making, faster prototyping, and more efficient scaling. The economic benefits of AI-driven predictive maintenance and quality forecasting are substantial. Companies report increased equipment availability, reduced maintenance costs, fewer production delays, and enhanced product quality. A study by McKinsey & Company estimated that predictive maintenance using AI can reduce maintenance costs by 10–40% and unplanned outages by up to 50% (Molęda et al., 2023). These savings are especially critical in industries where downtime costs thousands of dollars per minute.

However, implementation challenges persist. Developing accurate AI models requires large volumes of high-quality data, which can be difficult to gather, especially in older facilities without sensor infrastructure. Additionally, there is a learning curve associated with integrating AI tools into legacy systems and workflows (W. Liang et al., 2022). Data privacy, cybersecurity, and workforce training also pose significant barriers. Many firms underestimate the cultural shift needed to move from reactive to predictive operations. Resistance from maintenance teams accustomed to manual methods can hinder adoption unless accompanied by strong change management strategies (Porter & Heppelmann, 2015). Despite these challenges, the trajectory of AI in predictive maintenance and quality forecasting is undeniably upward. As sensor costs decline, computational power increases, and AI algorithms grow more accessible, even small and medium enterprises are beginning to leverage these tools (S. M. Lee et al., 2019). Open-source platforms and cloud-based AI services further democratize access, making predictive capabilities more attainable across the industry spectrum.AI-driven predictive maintenance and quality forecasting are not just technological enhancements—they are strategic imperatives in a competitive industrial landscape. These technologies transform maintenance and quality assurance from cost centers into value-generating processes. They enable industries to move beyond reactive problem-solving toward anticipatory, intelligent operations. In doing so, they ensure greater reliability, efficiency, and quality across both manufacturing and construction sectors (Kekäle & Phusavat, 2010).

4. AI for Real-Time Process Optimization

Real-time process optimization is among the most powerful capabilities unlocked by AI in manufacturing and construction, allowing systems to continuously refine operations for peak performance. While traditional optimization relies on static models, rule-based systems, and human oversight, AI introduces dynamic, self-adjusting frameworks that learn and evolve with each cycle of production or construction activity (Okuyelu et al., 2024). These systems draw from vast streams of real-time data—generated by sensors, cameras, and other input devices—to make decisions that reduce waste, improve throughput, and ensure consistent quality.In manufacturing, AI-powered optimization begins at the sensor level. Sophisticated machine learning algorithms—particularly reinforcement learning, neural networks, and fuzzy logic systems—monitor conditions like temperature, pressure, load, flow rates, and material properties across multiple process stages. Instead of merely detecting anomalies, these algorithms adjust variables proactively to maintain optimal process conditions (Sarkar & Paul, 2025). For instance, in semiconductor manufacturing, AI systems balance temperature profiles and gas flow to maximize wafer yield while minimizing defects. This is crucial because even microscopic variations can impact the performance of final products (C. Liu & Chien, 2012).

One remarkable example is the use of AI in injection molding. The process is sensitive to material temperature, injection speed, and cooling time—all of which can affect product consistency. AI models analyze thousands of cycles in real-time, learning the specific dynamics of each mold, material, and machine. By doing so, they continuously adjust parameters to compensate for material inconsistencies, environmental conditions, or equipment wear (Elenchezhian et al., 2021). This ensures a higher first-pass yield and reduces post-production inspection and rework. In discrete manufacturing, such as automotive assembly, AI enables smart coordination between robots and human workers. Cameras and sensors monitor workstation activity, and AI algorithms dynamically schedule tasks based on delays, availability, and efficiency. These systems anticipate bottlenecks and reroute workflows, minimizing downtime. For example, Toyota's use of AI-enhanced automation allows its production lines to self-adjust in response to material delays or worker absences, maintaining overall productivity without managerial intervention (Borboni et al., 2023).

The use of AI in process optimization extends deeply into construction as well. Construction processes are often nonlinear and unpredictable, affected by weather, site conditions, labor variability, and equipment availability. Traditional project management tools lack the agility to respond to these dynamic challenges. AI, however, provides a level of responsiveness that radically improves operational flexibility. For example, AI platforms like ALICE use constraint-based modeling and machine learning to simulate and optimize scheduling for complex construction projects (Rane et al., 2023). These platforms evaluate thousands of potential sequences in real-time, recommending the most efficient path based on current progress and constraints. Moreover, real-time process optimization in construction benefits greatly from computer vision and drone-based AI. Drones equipped with cameras and LiDAR scan construction sites daily, feeding visual and spatial data into AI models that assess alignment, progress, and compliance with design blueprints. These insights are then used to optimize sequencing, identify potential delays, and reduce material wastage. A study by McKinsey showed that AI-driven process optimization in construction could reduce project overruns by up to 15% and improve labor productivity by 20–25% (Bayomi & Fernandez, 2023). AI's role in energy optimization is also critical. In both manufacturing plants and construction sites, energy consumption is a significant cost and environmental concern. AI models, especially those using deep learning and genetic algorithms, analyze equipment usage patterns, ambient conditions, and production schedules to manage energy consumption more efficiently. They can control HVAC systems, lighting, and machine idling to reduce energy wastage. For example, Siemens' MindSphere platform enables smart energy optimization in factories by integrating AI with IoT sensors, leading to significant energy savings and lower carbon emissions (Kulawiak, et al., 2021). In supply chain management, which is a vital support process for both sectors, AI enhances just-in-time operations by optimizing inventory levels based on demand forecasts, production schedules, and logistic constraints. Real-time data from sensors, barcode systems, and ERP platforms is analyzed to avoid overstocking, understocking, or shipment delays. AI enables dynamic inventory control and can reassign delivery schedules and sourcing routes based on real-time disruptions, such as supplier shortages or weather events. This flexibility has become increasingly critical in the post-pandemic era, where supply chains must adapt rapidly to changing conditions. Furthermore, the integration of AI with edge computing and 5G networks accelerates process optimization capabilities (Kaul et al., 2022). With edge AI, data is processed locally at the source—on a sensor or device—allowing near-instant decision-making without relying on centralized cloud infrastructure. This is particularly important in high-speed production environments where milliseconds count. For example, in high-frequency welding or 3D printing, AI models deployed at the edge can instantly modify heat application or print paths based on sensor input, ensuring accuracy and reducing material waste (Murzin, 2024).

However, as promising as real-time AI optimization is, it presents challenges. One key issue is the interpretability of AI decisions. Many machine learning models function as “black boxes,” making decisions without clear reasoning. This opacity can limit trust and hinder troubleshooting when something goes wrong. Research into explainable AI (XAI) is helping bridge this gap by making model predictions more transparent and understandable to human operators (Love et al., 2023). Another limitation is the dependency on data integrity and integration. Real-time optimization is only as good as the data it receives. Inconsistent or inaccurate sensor data can lead to poor decisions, while fragmented systems hinder full-scale optimization. Integration of legacy equipment with modern AI platforms requires significant investment in infrastructure, sensor deployment, and staff training. Many small and medium enterprises struggle with the capital and expertise needed to implement AI-based real-time optimization at scale (Shaban & Zeebaree, 2025). Despite these barriers, the trend is unmistakable. AI is shifting the paradigm from “control” to “co-creation”—where human operators and machines work in tandem, optimizing not only the product but the process itself in real-time. The result is a system that learns, adapts, and evolves—bringing industrial operations closer to true autonomy. As industries continue to digitize and interconnect, AI will become not just a tool but an embedded function within every aspect of the process chain (Khan et al., 2023).

5. AI in Defect Detection and Visual Inspection

Defect detection and visual inspection have long been the bedrock of quality assurance in both manufacturing and construction. However, traditional inspection methods—often reliant on manual labor or basic rule-based systems—suffer from inconsistencies, fatigue-related errors, and limitations in speed and scalability (Laofor & Peansupap, 2012). AI-driven visual inspection technologies offer a transformative alternative, leveraging computer vision and machine learning to identify defects with greater precision, speed, and consistency. These systems not only replace human oversight but often exceed it, detecting subtle anomalies invisible to the naked eye or conventional systems. Computer vision algorithms, trained on thousands of annotated images, form the core of AI-based defect detection. These algorithms, particularly convolutional neural networks (CNNs), are capable of distinguishing between acceptable and defective products by learning complex patterns of texture, color, shape, and structural alignment. In a steel manufacturing context, for instance, AI systems can detect surface imperfections such as cracks, pits, and inclusions that deviate from expected patterns—even when the deviations are minuscule (Thakfan & Salamah, 2024). Once trained,

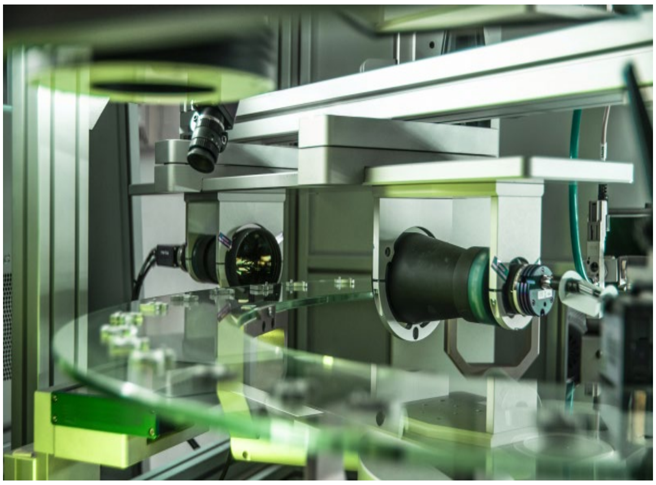

Figure 2. Improving Quality Control Using Artificial Intelligence. (Courtesy of image from Sani et al., 2024).

these systems inspect every item in real-time, providing instant feedback and even triggering process adjustments downstream to prevent recurrence.

In semiconductor production, where the margin for error is microscopic, AI-driven visual inspection tools can detect sub-micron defects in wafers using high-resolution imaging systems combined with deep learning. Unlike human inspectors, AI systems are not affected by fatigue or subjectivity, maintaining performance over millions of inspections (Rožanec et al., 2023). The same principle applies in textile manufacturing, where AI identifies variations in weave, dye, or stitch consistency at high speeds, significantly reducing material waste and return. Beyond the factory floor, AI has revolutionized visual inspection in construction. Unmanned aerial vehicles (UAVs), or drones, equipped with high-resolution cameras and AI software are used to survey construction sites daily. These drone-captured images are processed using deep learning algorithms to detect structural inconsistencies, cracks in concrete, misalignments, or unauthorized alterations. The algorithms compare the visual data against digital twin models and building information modeling (BIM) systems, flagging anomalies automatically. For example, Skanska and other major contractors use such systems to automate site inspections and verify that construction progress aligns with design specifications (Dandanelle & Tomasson, 2018).

Thermal imaging, combined with AI, is particularly effective in construction inspection. AI algorithms analyze thermal signatures from buildings or infrastructure to detect insulation gaps, leaks, or moisture intrusion. This approach is crucial in early defect identification in energy-efficient construction, where unseen thermal leaks can compromise building performance and sustainability ratings. Additionally, such inspections can be conducted without disrupting site operations, enhancing both safety and efficiency.AI-driven defect detection also enhances predictive maintenance strategies (Hanafi et al., 2024). In manufacturing, machine vision systems can monitor tool wear, surface finish quality, and component alignment continuously. By analyzing trends over time, these systems predict when a defect is likely to occur and recommend preventative maintenance actions. This predictive capability reduces unplanned downtime and extends the life of equipment. For instance, GE uses AI-powered inspection systems in its turbine production facilities to monitor blade wear and corrosion, improving uptime and reducing repair costs (George, 2024).

In the realm of visual inspection, AI's advantage lies in its ability to operate across the electromagnetic spectrum. In addition to visible light, AI can analyze X-ray, infrared, and ultrasonic imaging data, opening new avenues for non-destructive testing. In aerospace manufacturing, AI systems inspect X-ray images of critical components like turbine blades or wing spars for internal defects such as voids, delaminations, or micro-fractures. These defects are often invisible on the surface but can be catastrophic if undetected. The use of AI ensures consistent evaluation of complex imagery, minimizing the chance of human oversight (Adams et al., 2020). However, the success of AI in visual inspection depends heavily on the quality and diversity of training data. AI systems require extensive labeled datasets to learn what constitutes a defect and what does not. In practice, assembling such datasets can be time-consuming and expensive, particularly for rare defect types. Furthermore, changes in lighting, perspective, or camera calibration can affect model performance, requiring regular retraining or adaptation. This makes the integration of AI into defect detection more feasible for large firms with the resources to collect and maintain high-quality datasets (Javaid et al., 2021).

Another challenge lies in explainability. AI systems may correctly identify a defect but struggle to explain why a particular area is flagged. For quality control managers, this "black-box" behavior can be frustrating, particularly when false positives or negatives occur. As a result, research into explainable AI (XAI) has gained traction (Figure 2). XAI techniques, such as saliency maps or layer-wise relevance propagation, help visualize which features or regions of an image influenced the AI's decision, making the process more transparent and trustworthy (Bhati et al., 2024). Despite these limitations, the adoption of AI in visual inspection is accelerating. Real-world implementations demonstrate clear ROI through reduced labor costs, fewer recalls, improved throughput, and higher customer satisfaction. According to a 2020 Deloitte survey, 76% of manufacturers that adopted AI for visual inspection reported improved product quality and reduced defect rates, while 64% observed reduced inspection times (Escobar et al., 2023). The role of AI is also expanding from detection to classification and correction. Some advanced systems not only detect a defect but also classify its severity and recommend corrective actions. In CNC machining, for instance, if surface roughness exceeds thresholds, the AI system might suggest tool changes, speed adjustments, or lubrication enhancements. Similarly, in 3D printing, AI detects warping or under-extrusion in early layers and automatically recalibrates printer settings to prevent failure (Sani et al., 2024). In essence, AI has elevated visual inspection from a reactive quality gate to a proactive, continuous quality assurance tool. It blends speed, accuracy, and adaptability in ways that human inspection never could, creating a new paradigm where every unit—rather than a sample—is inspected in real-time, and defects are not just identified but understood, predicted, and prevented (Patel, 2024). As the technology matures, we can expect AI to further evolve into a collaborative partner in design and production, refining quality standards before the first unit is even manufactured.

6. Conclusion

AI is transforming quality control by enabling faster, more accurate, and proactive defect detection across industries. Techniques like saliency maps and layer-wise relevance propagation enhance transparency by revealing how AI systems make decisions. Despite challenges, adoption is rising due to tangible benefits—better product quality, reduced inspection times, and lower costs. As AI evolves beyond detection to classification and correction, it becomes a vital partner in refining production processes. With real-time, unit-level inspection and adaptive feedback, AI is redefining quality assurance. The future promises smarter, more resilient systems that anticipate and eliminate defects before they impact output.

Author contributions

M.M.H. conceptualized the study and developed the methodology. M.K. and M.B.B.R. prepared the original draft and contributed to the review and editing of the manuscript. M.M.H.K. performed data analysis and also participated in the review and revision of the writing.

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Competing financial interests

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