

Artificial Intelligence in Manufacturing Quality Assurance: Applications, Challenges, and Opportunities for Emerging Industrial Economies

Arnold Niyonkuru

arnoldniyonkuru@gmail.com

Quality Assurance Technician, REMCO, Kigali, Rwanda

BSc candidate, Renewable Energy Science

Certified: UNIDO (Root Cause Analysis) · ALX (Data Analytics)

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ABSTRACT

Quality assurance (QA) in manufacturing has long depended on manual inspection, sampling, and rule-based checks, which are slow, vary between inspectors, and cover only part of production. This paper is a narrative review of how artificial intelligence (AI) is used in manufacturing QA. It covers deep-learning visual inspection, predictive quality models built on process data, anomaly detection, and predictive maintenance. It summarizes the benefits reported in the literature, the main limitations (labelled data, changing conditions, explainability, and computing cost), and the ISO 9001 context. It then considers what these findings mean for manufacturers in developing countries and in Rwanda, using national accounts data (manufacturing was about 8% of Rwanda's GDP in 2024 and grew 10% in 2025) and the Made in Rwanda policy, which has made product quality a national priority. The paper argues that AI should support QA professionals rather than replace them, and proposes an eight-step adoption roadmap built around small, well-defined pilot projects. It reports no new experimental data.

KEYWORDS *artificial intelligence, quality assurance, manufacturing, machine vision, defect detection, predictive quality, Industry 4.0, developing countries, Rwanda*

1 INTRODUCTION

Product quality is central to manufacturing competitiveness. Defects raise costs, shorten product life, and waste resources [21]. Researchers estimate that the cost of poor quality in manufacturing companies averages about 15% of sales, with a range from 5% to 35% depending on product complexity [4]. At that scale, even small gains in defect prevention matter commercially. In many plants, inspection still relies partly on people and on equipment that needs manual set-up and adjustment, which limits speed and adaptability [21].

Over the past decade, machine vision and deep learning have become among the most widely used approaches to automated defect detection. Reviews describe them as offering better inspection results and lower cost than traditional methods, while still depending on large amounts of training data [21]. More broadly, combining modern communication technologies with machine learning (ML) and deep learning supports data-driven, smarter manufacturing, and quality assurance is one area that can benefit strongly [18].

For manufacturers in emerging economies, the question is not only whether AI works but whether it is affordable, practical, and suited to local conditions. In Rwanda, the Made in Rwanda policy treats quality as a core part of improving the competitiveness of local products [9], which makes QA capability strategically important.

Research questions. This paper addresses three questions:

- (1) Which AI techniques are used in manufacturing QA, and what do they offer over traditional methods?
- (2) What limitations and risks affect their use?
- (3) How can manufacturers in emerging economies, such as Rwanda, adopt them realistically?

Scope and method. This is a narrative review, not a systematic one. Sources were identified through searches of publisher and repository websites in October 2026 and were selected for relevance, with preference for peer-reviewed reviews, original dataset papers, standards bodies, and government sources. Every source cited is listed in the References section.

2 BACKGROUND: TRADITIONAL QUALITY ASSURANCE

Traditional manufacturing QA combines incoming material checks, in-process checks, final inspection, and statistical process control, usually inside a quality management system. ISO 9001:2015 sets out requirements for such a system and is generic, meant to apply to any organization regardless of type or size [7].

These methods have well-known limits:

- **Reliance on manual work:** many traditional detection methods still depend on manual assistance and on instrument debugging before testing [21].

- **Sampling risk:** checking a portion of output means some defects can pass through.
- **Delay:** problems are often found after many defective units have been produced.
- **Scattered data:** records kept on paper or in separate spreadsheets make it hard to see patterns across batches, shifts, and machines.

3 AI TECHNIQUES IN MANUFACTURING QA

3.1 Computer vision for defect detection

Computer vision is the most widely applied AI technique in QA. Cameras capture images of products, and deep-learning models classify them as acceptable or defective, or locate defects such as scratches, pits, cracks, and missing components. Surveys describe several network families used for this purpose, including convolutional neural networks, autoencoders, residual networks, fully convolutional networks, and recurrent networks, as well as one-stage and two-stage object detectors [21].

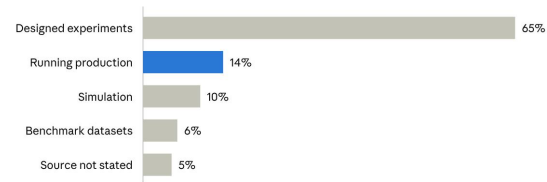
Published results vary widely. In the studies compared by Yang et al. [21], reported precision ranged from about 86% to 99%, depending on the product, the defect type, and the data. At the upper end, a custom convolutional network reached 99.86% inspection accuracy on images of casting products [17]. That is a single-dataset result under controlled conditions and should not be read as typical plant performance. The same survey notes that detection accuracy and speed still do not fully meet the needs of high-speed production in smart factories, and that changes in lighting, shooting angle, distance, noise, and partial occlusion make detection harder in real plants. A review of surface defect methods identifies real-time performance, small sample sizes, small targets, and unbalanced samples as the key recurring problems [3].

3.2 Predictive quality from process and sensor data

Predictive quality uses ML and deep learning to estimate product quality from process and product data, with the goal of producing insights that improve quality [18]. The estimates support decisions such as adjusting process parameters to avoid rejects. The same review distinguishes three tasks: describing relationships between process variables and quality, predicting a numerical quality value, and classifying quality, for example by defect type.

Tercan and Meisen reviewed 81 publications from 2012 to 2021 and found that the number of publications has risen steadily. Most of the studies used real manufacturing data, but the large majority of that came from designed experiments (65% of the publications) rather than from running production (14%). This suggests that many published results have not yet been tested under everyday plant conditions.

Only 14% of predictive-quality studies used data from running production
Source of training data, % of 81 publications reviewed (2012–2021)



Four publications (5%) did not state their data source.

Figure 1. Where the training data came from in predictive-quality research. Source: Tercan & Meisen [18]; 81 publications, 2012–2021. “Share not stated” = 4 of 81 (calculated).

3.3 Anomaly detection

When examples of defects are scarce, anomaly detection methods learn what normal production looks like and flag departures from it. Anomalies are events that differ from normal behavior and are not initially tied to a known defect [18]. The MVTec AD dataset, introduced at CVPR 2019, supports research in this area. It contains 5,354 high-resolution images across object and texture categories, with defect-free images for training and images with more than 70 types of defects for testing, together with pixel-precise annotations [1]. Its authors reported that their initial benchmark showed considerable room for improvement. Practitioners should note that the dataset license does not allow commercial use [10].

3.4 Predictive maintenance as a quality enabler

Worn or poorly calibrated equipment is a frequent cause of drift in product quality, so condition monitoring and predictive maintenance complement inspection. Predictive maintenance in the Industry 4.0 setting has been reviewed systematically by Zonta et al. [22], and a wider review of ML in factory operations covers quality control alongside predictive maintenance, process control, and logistics [6].

3.5 Language models and generative AI

Language models can help summarize audit findings and complaint records and can draft procedures. They can also produce confident but incorrect statements, so any output must be checked by qualified staff, and these tools should not be used to make product release decisions.

4 BENEFITS

The sources reviewed point to these main benefits:

- **Consistency and endurance:** automatic detection can work for long periods with high precision and efficiency, and it can adapt to environments unsuitable for people [21].
- **Earlier intervention:** predictive quality models allow early action in the process, which can reduce the reject rate and stabilize processes [18].
- **Less waste and lower cost:** automated detection research aims to reduce production cost and improve efficiency and product quality [21].

- **Better data for root-cause analysis:** every inspection result and image becomes a record that can be searched and compared over time.

These benefits should be read with caution. Much of the evidence comes from research settings, and published case studies tend to report successful projects. Table 1 collects the main figures used in this paper.

Table 1. Key evidence at a glance.

Measure	Figure	Source
Cost of poor quality in manufacturing	About 15% of sales on average (range 5%–35%)	[4]
Precision reported for deep-learning defect detection	About 86% to 99% across the studies compared	[21]
Predictive-quality studies reviewed	81 (2012–2021); 65% used designed experiments, 14% running production	[18]
MVTec AD anomaly benchmark	5,354 images; more than 70 defect types	[1]
Rwanda: manufacturing share of GDP	About 8% (2024)	[11]
Rwanda: manufacturing growth	10% (2025)	[12]

Figures are as reported in the cited sources; see the References for details.

5 CHALLENGES AND LIMITATIONS

Data. Deep-learning inspection depends on large amounts of labelled data [21], and rare defects produce small and unbalanced datasets [3]. Few published predictive-quality studies use data from running production [18].

Changing conditions. Lighting, camera angle, materials, and product variants change in real plants and can reduce accuracy [21]. Models therefore need monitoring and periodic retraining.

Explainability and trust. High-accuracy models are often black boxes, and their opacity affects trust, which is critical in decision-making [16]. A 2025 review found that applications of explainable AI in smart manufacturing remain under-developed, non-standardized, and fragmented [8].

Computing cost. Computation for deep-learning research has grown very quickly and has a carbon footprint, and its cost can exclude researchers and organizations from emerging economies. Schwartz et al. argue that efficiency should be reported alongside accuracy [15].

Cost, skills, and people. Cameras, lighting, computing hardware, and integration with production lines require investment. Few organizations have staff who combine manufacturing quality knowledge with data skills. Inspectors may fear job loss, so involving them early and presenting AI as a support tool improves acceptance.

Validation. A quality system built on ISO 9001 expects controlled and documented processes [7]. An AI tool used for acceptance decisions should be treated like any other inspection method: validated against defined criteria, run in

parallel with existing checks before it is trusted, and placed under change control.

6 CONTEXT: DEVELOPING COUNTRIES AND RWANDA

This paper does not report an AI deployment at any Rwandan facility. The points below are reasoned from the literature and from the policy context.

6.1 AI in manufacturing in developing countries

Adoption of advanced manufacturing technology is uneven. A UNIDO survey of manufacturing firms in Ghana, Thailand, and Viet Nam found that Industry 4.0 technologies had yet to diffuse widely in these economies, and the vast majority of the Ghanaian firms faced financial, managerial, and knowledge barriers to adopting new technology [5]. A 2026 policy brief in the UNIDO Insights series reports that AI is already improving quality control and productivity in manufacturing, but that adoption is uneven and many developing economies face persistent barriers: infrastructure constraints, skills gaps, limited access to finance, and restricted data availability [2]. UNIDO’s report *Bridging the AI Divide* makes the same general point: many developing countries face barriers that prevent them from adopting AI in manufacturing [20].

These barriers match the challenges in Section 5. They suggest that small, narrowly targeted QA pilots fit developing-country plants better than plant-wide transformation, which is the approach taken in the roadmap in Section 7.

6.2 Rwanda’s manufacturing sector in numbers

Official statistics show a manufacturing sector that is a modest share of the economy but growing quickly. Table 2 summarizes the latest figures from the National Institute of Statistics of Rwanda (NISR).

Table 2. Rwanda: manufacturing and the wider economy.

Indicator	Value	Period	Source
GDP at current market prices	Frw 23,387 billion (Frw 19,918 billion in 2024)	2025	[12]
Real GDP growth	9.4%	2025	[12]
Shares of GDP	Services 52%, industry 22%, agriculture 20%	2025	[12]
GDP per head (current US\$)	1,156 (1,091 in 2024)	2025	[12]
Industry growth	11%	2025	[12]
Manufacturing growth	10%	2025	[12]
Manufacturing value added	Frw 1,618 billion, about 8% of GDP (author’s calculation)	2024	[11]
Industry growth / manufacturing growth	16% / 13%	FY 2025/26	[13]
Fastest-growing manufacturing branches	Metal products, machinery and equipment +38%; non-metallic mineral products +38%; chemicals, rubber and plastics +18%	FY 2025/26	[13]

Indicator	Value	Period	Source
Declining branch	Furniture and other manufacturing -3%	FY 2025/26	[13]

The 8% share divides manufacturing value added (Frw 1,618 billion) by 2024 GDP (Frw 19,918 billion), both as published by NISR. FY = fiscal year.

Manufacturing is therefore roughly one-twelfth of the economy, and in 2025 it grew at about the same pace as GDP as a whole (10% against 9.4%). The fastest-growing branches in fiscal year 2025/26 make products whose dimensions, surfaces, and process settings can be measured, such as metal products, construction materials, and plastics. This makes them plausible early candidates for the vision and predictive-quality methods in Section 3. That is an inference from the sector mix, not an observation of any plant's practice.

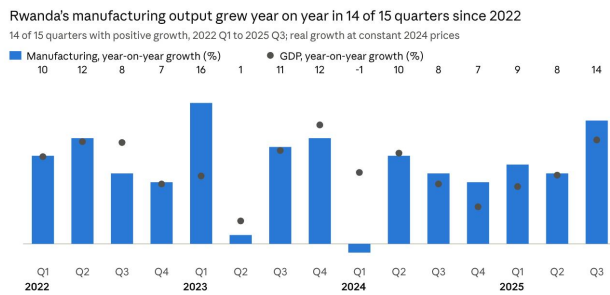


Figure 2. Rwanda: year-on-year growth in manufacturing and in GDP, by quarter, 2022 Q1 to 2025 Q3 (constant 2024 prices). Source: NISR [11], Table 2A.

6.3 Policy, opportunities, and constraints

Policy context. The Made in Rwanda campaign was launched in 2015 and approved by Cabinet as a policy in 2017 [14]. The Ministry of Trade and Industry describes the policy as a roadmap to raise economic competitiveness through value chain development, with targeted interventions that include improving quality. The Rwanda Standards Board leads on quality within it [9].

Why quality matters locally. A 2016 ministry survey, reported by The New Times, found that nearly 65% of respondents bought locally made products to support them, but that quality and availability remained a challenge [19]. Reliable QA is one way manufacturers can address that gap.

Opportunities. Newer plants can build digital data collection in from the start rather than retrofit older systems. Standard cameras, open-source software, and edge devices make small pilots possible without large capital spending. Products that are repetitive and visually inspectable, such as packaged foods, textiles and garments, and construction materials, are natural early candidates.

Constraints. Imported hardware is costly, local AI expertise is limited, and training needs are significant. Partnerships with universities and technology hubs in Kigali could help close these gaps.

6.4 Environmental and sustainability dimension

Better QA supports environmental goals. Defects waste materials and resources [21], so catching them earlier reduces the energy and material lost in scrap and rework. AI systems also use energy, so pilots should favor lightweight models and edge devices, following the Green AI principle of reporting efficiency alongside accuracy [15]. For a plant with on-site solar generation, low-power inspection hardware could be powered from that supply, which links AI-based QA to renewable energy use. This idea needs testing and is offered here as a direction, not a result.

7 A PRACTICAL ADOPTION ROADMAP

1. **Start with one problem.** Choose a costly, well-defined quality problem, such as a recurring visual defect, rather than adding AI in general.
2. **Digitize and clean data.** Record inspection results consistently, with images, timestamps, and defect labels.
3. **Pilot small.** Test a vision or analytics model on one line or product, running alongside human inspection.
4. **Measure.** Track detection rate, false alarms, scrap, rework, and time saved against a baseline.
5. **Keep people in the loop.** Inspectors review uncertain cases and help label data and improve the model.
6. **Validate and document.** Treat the tool as part of the quality system, with acceptance criteria and change control.
7. **Monitor and retrain.** Watch for drift when lighting, materials, or suppliers change.
8. **Scale gradually.** Expand to other lines only after the pilot proves its value, and build data skills in the QA team.

8 LIMITATIONS AND FUTURE DIRECTIONS

Limitations of this review. It is a narrative review, not a systematic one, so relevant studies may have been missed. It relies on published and publicly accessible sources, and it reports no new experimental data or plant results.

Future directions.

- Methods that need less labelled data and transfer more easily between similar products, a difficulty noted by Yang et al. [21].
- Online, real-time detection on the production line, and feedback of defect information into the process.
- Explainable AI designed for quality audits [8].
- Studies of AI adoption in QA at African manufacturers, since this search did not find such studies.

9 CONCLUSION

AI offers manufacturing QA a way to inspect more consistently, detect problems earlier, and use production data for continuous improvement. Its value depends on good data, careful validation, and the participation of QA professionals. For emerging industrial economies such as Rwanda, small and focused pilots offer a practical route to

these benefits without large upfront investment. QA professionals are well placed to lead the change because they understand both the quality problems and the production environment.

DECLARATIONS

Use of AI. This manuscript was prepared with the assistance of an AI language model (Claude, Anthropic). The author reviewed the text and takes responsibility for its content and for the sources cited.

Competing interests. The author is employed as a Quality Assurance Technician at REMCO. The views expressed are the author's own and do not represent REMCO. No funding was received for this work.

AUTHOR BACKGROUND

The author works in manufacturing quality assurance at REMCO in Kigali and holds a UNIDO certificate in root cause analysis (RCA) and an ALX certificate in data analytics. This combination of plant-level QA experience, structured problem-solving, and data skills is the perspective from which the paper approaches AI in manufacturing.

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