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ARTIFICIAL INTELLIGENCE FOR QUALITY CONTROL IN ADDITIVE MANUFACTURING: METHODS, METRICS AND INDUSTRIAL READINESS

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Abstract: *Artificial intelligence (AI) is transforming quality control in additive manufacturing (AM) by introducing automation, predictive analysis, and higher accuracy throughout the production process. AI-powered methods address common 3D printing challenges such as defect detection, process variability, and equipment failures, enabling more reliable and efficient manufacturing. This paper reviews key applications of AI in AM quality control from 2018–2025, focusing on defect detection, predictive maintenance, and process optimization. The contribution of this study lies in mapping methods to AM processes, reporting performance outcomes, and identifying current limitations for industrial adoption.*
Key words: *Additive Manufacturing, Quality Control, Computer Vision, Predictive Maintenance, Zero-Defect Manufacturing.*

1. INTRODUCTION

Additive manufacturing (AM) is becoming one of the key technologies in modern production, but keeping a stable and reliable level of quality is still difficult. Small changes in process conditions, variations in materials, and complex shapes often lead to hidden defects. Traditional inspection methods such as visual checks or non-destructive testing are usually slow, expensive, and cannot stop problems once the part is finished [1, 2]. Therefore, there is a need for new approaches that can detect and prevent errors while printing is still in progress.

Artificial Intelligence (AI) is now offering practical tools to solve these challenges. By analyzing data from cameras and sensors, AI systems can detect problems earlier and with more accuracy than manual inspection [3, 4]. Deep learning models have been used to find surface defects, track process stability, and even predict when equipment is likely to fail [5, 6, 7]. Other approaches combine sensor data (images, acoustic signals, thermal information) to improve detection and reduce false alarms [8, 9, 10]. These methods show how AI can make production more efficient and less dependent on trial and error [11, 12].

The contribution of this paper is to give an updated review of AI techniques for quality control in AM between 2018 and 2025. The review connects each method to a specific AM process, highlights reported performance metrics, and points out where AI is already useful for industry [13, 14]. Unlike earlier reviews, this paper also discusses the current limits of AI, especially in metal AM, and shows how these methods fit into the idea of Zero-Defect Manufacturing and closed-loop control [15, 16].

The structure of the paper is as follows: Section 2 presents the role of AI in AM quality control with focus on defect detection, predictive maintenance, and process optimization. Section 3 explains the research method and criteria used to select the literature. Section 4 gives the main results and includes a comparative analysis of the studies. Section 5 concludes with the main findings, limitations, and directions for future work.

2. AI IN ADDITIVE MANUFACTURING QUALITY CONTROL

Quality control in additive manufacturing is carried out through a mixture of different approaches, which in practice often combine machine vision, sensor data, machine learning methods, and more traditional inspection techniques such as X-ray or ultrasound [8, 9]. The purpose of using these tools together is to keep track of the printing process while it is running and to collect large amounts of information that can later be used to detect irregularities and classify possible faults [1]. Instead of waiting for the part to be finished and then inspected, problems can be spotted much earlier. One typical example is the use of vision systems: cameras record each layer as it is printed, and the captured images are processed to highlight mistakes. This way, defective builds can be stopped on time, which not only saves material but also improves the overall efficiency of production.

2.1 Real-Time Defect Detection and Prediction

Large amounts of sensor data, such as thermal images, vibration signals, or acoustic emissions, can be analyzed to reveal defects before they become visible, which makes it possible to adjust the process while printing is still underway. This kind of early reaction is especially important in parts with complex geometries, where conventional inspection methods are either unreliable or too time-consuming to apply.

In many studies, researchers rely on machine learning techniques to link printing parameters with material behavior, which allows them to anticipate where and when flaws are likely to occur [10]. By approaching the process in this way, the final quality of 3D-printed products can be raised to a much higher level. Another important aspect is the ability to track not only the printed object but also the performance of the equipment itself. For example, algorithms have been shown to recognize malfunctioning components in the production system and at the same time detect and classify defective parts [5].

2.2 Predictive Maintenance and Process Optimization

Through the use of machine learning, past production data can be examined to spot patterns that indicate when equipment is likely to fail. In this way, maintenance can be scheduled before problems occur, and printing parameters can be adjusted to improve part quality while reducing unnecessary material use [12, 17]. Such an approach is closely connected to the idea of Zero-Defect Manufacturing, where the goal is to get the process right on the first attempt by detecting, predicting, and preventing faults instead of correcting them afterwards [15].

Over time, these methods contribute to the development of closed-loop quality control systems in which feedback from monitoring and predictive analysis is constantly fed back into the process. As a result, manufacturing becomes more reliable and productive, with fewer interruptions and more consistent outcomes [2]. In addition, the gradual integration of predictive maintenance with process optimization allows companies to reduce reliance on manual supervision and allocate resources more strategically across multiple production lines.

This trend also reflects the broader shift toward intelligent manufacturing systems, where adaptive learning mechanisms are embedded directly into equipment to ensure higher stability and continuous improvement.

This workflow is illustrated in Fig. 1, which shows the closed-loop framework of AI-enabled quality control in additive manufacturing.

3. DATA AND METHODS

The research design combined a clear set of inclusion and exclusion criteria with a structured methodology for identifying, selecting, and analyzing relevant studies on AI in additive manufacturing quality control.

3.1 Inclusion and exclusion criteria

To ensure that the review remained focused and methodologically consistent, a set of inclusion and exclusion criteria was applied. Studies were included if they met the following requirements:

- **Publication type**: peer-reviewed journal articles or full conference papers.
- **Publication period**: 2018–2025, to capture both foundational works and the most recent developments.
- **Research focus**: explicit application of artificial intelligence, machine learning, or deep learning methods to quality-related tasks in additive manufacturing.
- **Application domain**: additive manufacturing processes such as laser powder bed fusion (LPBF/SLM), directed energy deposition (DED), electron beam melting (EBM), and fused filament fabrication (FFF/FDM).
- **Quality relevance**: studies addressing in-situ/inline monitoring, defect detection and classification, process parameter optimization, predictive maintenance, or related quality control objectives.
- **Transparency**: a concrete and detailed methodological description to allow understanding of data sources, algorithms used, and performance outcomes.

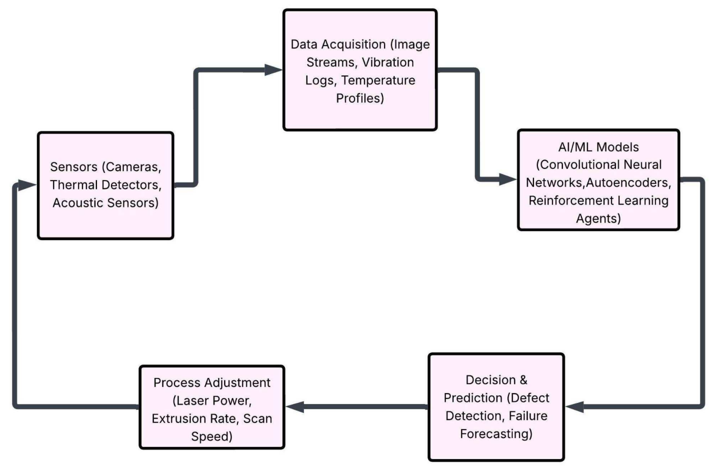

Fig. 1. Closed-loop quality control framework for AI-enabled additive manufacturing.

Exclusion criteria were applied to filter out papers that:

- Were editorials, opinion articles, or non-peer-reviewed sources.
- Focused solely on material design or supply chain aspects without direct relation to quality control in AM.
- Mentioned AI only in passing without presenting methods, experiments, or results.
- Lacked measurable outcomes or presented insufficient methodological details.

Applying these criteria ensured that only studies with clear technical contributions to AI-enabled quality control in AM were retained for detailed analysis.

3.2. Methodology

The literature search was conducted across Scopus, Web of Science, IEEE Xplore, and ScienceDirect, with Google Scholar used to capture additional sources. Search strings combined terms for additive manufacturing processes, artificial intelligence techniques, and quality-related outcomes (e.g., “additive manufacturing” OR “3D printing” AND “artificial intelligence” OR “machine learning” AND “quality control” OR “defect detection” OR “predictive maintenance”).

The initial pool contained about sixty publications. After removing duplicates and screening titles and abstracts, papers were evaluated in full text according to the criteria in Section 3.1, resulting in a final set of twenty-six studies. From each selected paper, information was systematically extracted on the investigated AM process, the applied AI approach, sensing modalities, reported performance metrics, and practical quality control outcomes. A narrative synthesis and comparative mapping were then applied to identify patterns, differences, and emerging trends, which form the basis for the results in Section 4.

4. RESULTS

The studies reviewed in this work show that modern computational approaches are playing an increasingly important role in improving quality control within additive manufacturing. Different processes and sensing techniques reveal how these methods can be used to identify defects while printing is in progress, forecast potential equipment failures, and fine-tune process parameters. To provide a clear overview, the findings are presented in three parts: real-time defect detection and process monitoring, predictive maintenance and process optimization, and a comparative analysis of the selected studies.

4.1 Real-time defect detection and process monitoring

A significant group of the reviewed studies focuses on real-time quality monitoring during additive manufacturing. Computer vision techniques, particularly convolutional neural networks (CNNs) and autoencoder-based architectures, have been widely adopted to identify surface defects, geometric deviations, and anomalies during printing [1, 6]. Vision systems allow rapid feedback by analyzing image streams from cameras installed inside the build chamber, enabling operators to prevent wasted material and reduce rework [5].

Beyond vision, sensor-based monitoring methods make use of thermal signatures, acoustic emissions, and vibration data to detect process instabilities. Research indicates that when different types of sensor data are combined and analyzed with advanced classifiers, defects can often be detected much earlier than by relying on visual inspection alone. This is especially important in complex geometries or in metal printing, where hidden flaws beneath the surface are a serious concern [4, 10].

More recent work has also drawn attention to hybrid monitoring strategies. In these cases, deep learning models trained on multiple sensor inputs have improved classification accuracy and reduced the number of false alarms during in-situ quality control [7, 9]. Taken together, these methods show that monitoring systems are not only able to catch visible defects but can also anticipate their development by recognizing patterns in the underlying process conditions. Practical demonstrations show that vision-based approaches are effective for complex processes such as LPBF, where anomaly detection can be achieved layer by layer during the build [1]. Hybrid systems combining imaging with acoustic and thermal signals further reduce false alarms and highlight instabilities earlier [7-9]. In FFF, classifiers and computer vision methods help to identify typical defects early and accelerate corrective action [10]. The diversity of these methods and their application across different AM processes is summarized in Fig. 2, which provides a taxonomy of AI techniques, related sensor modalities, and associated manufacturing processes.

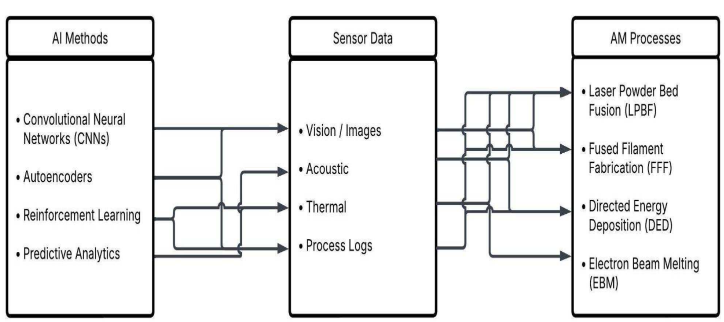

Fig. 2. Taxonomy of AI methods in additive manufacturing by process type and sensor modality.

4.2 Predictive maintenance and process optimization

A common topic across the reviewed studies is the effort to predict equipment failures in advance and to fine-tune process parameters in additive manufacturing. Models trained on historical sensor data make it possible to introduce predictive maintenance strategies that cut down on downtime and reduce the risk of unexpected interruptions [18, 19].

By recognizing degradation patterns, maintenance tasks can be scheduled in advance. Research on laser powder bed fusion and fused filament fabrication has shown that both supervised and reinforcement learning methods can pinpoint parameter settings that lead to higher part density, smoother surfaces, and more accurate geometries [4, 12]. These developments tie closely to the principles of Zero-Defect Manufacturing, which promotes preventing errors before they occur rather than correcting them afterwards [15].

Bringing predictive maintenance together with parameter optimization points toward the development of closed-loop control systems. In such systems, failures are not only anticipated but operating conditions are also adjusted in real time, ensuring that quality and efficiency remain consistent throughout the manufacturing process [2, 16]. Representative examples of these AI applications are shown in Fig. 3. For parameter optimization, studies illustrate how supervised and reinforcement learning can adjust laser power/scan speed in LPBF or extrusion rate/temperature in FFF to increase density and improve geometric accuracy [4, 12]. Predictive maintenance based on historical datasets has been used to plan service intervals and reduce unexpected machine downtime [18, 19].

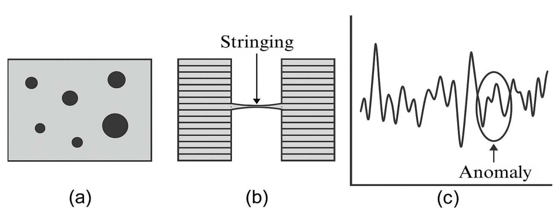

Fig. 3. Examples of AI applications in additive manufacturing quality control: (a) porosity detection in LPBF, (b) stringing detection in FFF, (c) vibration-based monitoring for equipment failures.

4.3 Comparative analysis of selected studies

Table 1 offers a comparative overview of the reviewed studies, outlining the main contributions of artificial intelligence techniques, their use in additive manufacturing processes, and the quality control outcomes that follow. What stands out most is the strong role of vision-based methods and deep learning, which dominate in real-time defect detection by spotting anomalies early and making it possible to intervene during the build itself. Alongside this, many studies focus on predictive maintenance and process optimization, where historical sensor data is processed through machine learning frameworks to forecast failures and fine-tune operating parameters.

A number of cross-industry reviews also underline that these approaches are not limited to additive manufacturing alone. Instead, they can be transferred to other production settings, making them relevant for developing safer and more efficient workflows while staying consistent with the wider goals of Industry 4.0.

4.4 Limitations and Industrial Adoption

Although recent studies demonstrate clear benefits of AI-enabled quality control, several limitations still restrict industrial adoption, particularly in metal AM. First, generalization across machines, materials, and geometries remains limited due to domain shift and small, non-representative datasets; models often require re-training when process conditions change [1, 13, 14]. Second, real-time constraints and controller integration are challenging: closed-loop actuation demands low-latency inference and access to proprietary machine interfaces that are not always available [15, 16]. Third, validation and certification barriers persist, especially in regulated environments, where explainability and traceability of AI decisions are necessary for compliance and operator trust [5, 20].

Finally, economic considerations—including the high cost of sensor retrofitting, the establishment and upkeep of data infrastructure, and the continuous maintenance of machine learning models—not only affect the expected return on investment but also significantly slow down large-scale deployment of AI-enabled quality control solutions in industry [4, 12]. Addressing these issues will require not only standardized data schemas and open interfaces to AM controllers but also robust domain adaptation techniques capable of handling variability across machines and materials, together with evidence from long-running industrial pilot projects in metal AM production lines that can demonstrate reliability, cost-effectiveness, and scalability under real operating conditions [13–16, 21].

Table 1

Comparative analysis of selected studies on AI in AM quality control

Reference	AI Method	AM Process	Sensors / Data	Industrial Outcomes / Improvements	Limitations
Scime & Beuth (2017) [1]; Mehta & Klarmann (2023) [6]	CNNs, autoencoders	LPBF	In-situ imaging	Early anomaly localization and layer-wise defect classification	Limited dataset, lab-scale validation
Sundaram & Zeid (2023) [5]	Deep learning CNN	Casting, AM workflows	Vision cameras	Automated inspection, reduced manual checks	No closed-loop integration
Jain (2024) [9]; Shafi et al. (2023) [7]	Hybrid vision + DL	Cross-industry / AM	Multi-sensor (vision, acoustic)	Real-time monitoring, reduced QC time, fewer false alarms (qualitative)	Limited transferability to AM
Al-Jubori & Al-Darraji (2023) [8]; Erokhin et al. (2023) [10]	ML classifiers + CV	FFF, automated AM	Imaging, process logs	Multi-modal defect recognition, taxonomy of defect types	No industrial deployment
Kim & Park (2023) [4]; Jin et al. (2020) [12]	ML, reinforcement learning	LPBF, FFF	Process parameters, datasets	Improved accuracy and part reliability (qualitative)	Requires large datasets
Kumar et al. (2022) [13]; Tercan & Meisen (2022) [14]	Systematic reviews	General AM	Various	Overview of ML/DL QC frameworks	Descriptive only, no metrics
Cascón et al. (2024) [15]; Wang et al. (2024) [16]	AI+ knowledge graph	Milling + AM	Force sensors, logs	Intelligent closed-loop QC, improved repeatability (qualitative)	Conceptual stage, limited validation

Patil (2025) [18]; Bernárdez et al. (2025) [19]	Predictive analytics	Manufacturing systems	Historical production data	Maintenance scheduling, downtime reduction (qualitative)	Mostly non-AM studies
Abd-Elaziem et al. (2024) [21]	ML optimization	LPBF (stainless steel)	Process parameters, thermal data	Improved reliability, defect prevention strategies	Lab setting only
Shiboldenkov & Nesterova (2020) [2]; Waltersmann et al. (2021) [20]	Smart manufacturing, resource-oriented AI	AM lifecycle	Resource usage data	Predictive maintenance, energy efficiency (qualitative)	No AM-specific validation
Abadi et al. (2024) [22]; Gavade (2024) [23]	AI for energy efficiency and automation	Cross-industry + AM	Mixed datasets	Improved efficiency, sustainable practices (qualitative)	Generalized, limited AM focus
Agrawal et al. (2025) [24]; Akhtar (2024) [25]	Exploratory AI frameworks	Food manufacturing, broader domains	Mixed	Transferable insights for AM QC	Indirect relevance to AM

The majority of recent studies emphasize computer vision and deep learning approaches for real-time defect detection and process monitoring, confirming their central role in AM quality control. At the same time, predictive maintenance strategies and Zero-Defect Manufacturing concepts are gaining momentum, with AI methods being applied to anticipate failures and optimize process parameters.

Cross-industry reviews further highlight the transferability of AI-driven quality control frameworks, reinforcing their relevance for securing and improving additive manufacturing workflows.

5. CONCLUSION

Artificial intelligence is increasingly shaping how quality control is carried out in additive manufacturing. Beyond detecting defects in real time, machine learning now contributes to predicting equipment failures and fine-tuning printing parameters. These capabilities extend quality assurance from the printed part itself to the wider production environment, helping to reduce downtime and keep production steady.

The gradual integration of monitoring, forecasting, and adjustment is opening the door to closed-loop control systems. In such systems, feedback is immediate, waste is reduced, and the process becomes more reliable.

This direction is closely aligned with Industry 4.0 goals, where manufacturing is guided by data and error prevention rather than correction. Despite the progress, some challenges remain. Scaling solutions across different AM processes, ensuring that systems can work together, and collecting datasets large enough to train robust models are still open issues.

Addressing these will require more careful algorithm design, the combination of multiple sensing methods, and validation in real industrial settings. If these steps are taken, AI can move from being a promising research topic to a routine tool, supporting more efficient, sustainable, and dependable additive manufacturing.

For near-term industrial adoption, we recommend starting with vision-based monitoring on critical builds, adding one additional sensing channel (thermal or acoustic) where feasible, and tracking a minimal set of KPIs (scrap rate, rework hours, downtime, and first-pass yield).

Where controller access exists, pilot a constrained closed-loop action (e.g., small laser power or scan-speed adjustments within predefined safety bounds). Standardizing data collection, documenting model updates, and reporting outcomes using comparable metrics will accelerate certification and replication across AM lines [1, 4, 12, 14-16].

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Inteligența artificială pentru controlul calității în fabricația aditivă: metode, metrici și pregătirea industrială

Rezumat: *Inteligența artificială (IA) transformă controlul calității în fabricația aditivă (FA) prin introducerea automatizării, a analizei predictive și a unei precizii sporite pe tot parcursul procesului de producție. Metodele bazate pe IA abordează provocările comune ale imprimării 3D, precum detectarea defectelor, variabilitatea procesului și defecțiunile echipamentelor, permițând o producție mai fiabilă și mai eficientă. Această lucrare oferă o trecere în revistă a principalelor aplicații ale IA în controlul calității FA în perioada 2018–2025, cu accent pe detectarea defectelor, mentenanța predictivă și optimizarea proceselor. Contribuția lucrării constă în corelarea metodelor cu procesele FA, prezentarea rezultatelor privind performanța și identificarea limitărilor actuale pentru aplicarea industrială.*

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