

REVIEW ARTICLE

Machine learning techniques for quality assurance in additive manufacturing processes

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Abstract

Additive manufacturing (AM) processes have revolutionized manufacturing industries by enabling the production of complex geometries with reduced material waste and lead times. However, ensuring the quality of AM parts remains a significant challenge due to the complexity of the process and inherent variability in material properties. This review investigates the use of artificial intelligence (AI) to enhance quality assurance in AM processes, focusing on specific machine learning techniques such as convolutional neural networks for defect detection, support vector machines for classification of material properties, and reinforcement learning for real-time process optimization. The AI-driven methodologies are applied to predict defects, optimize process parameters, and monitor real-time production quality, utilizing large datasets generated from sensors and *in-situ* monitoring systems. The study demonstrates significant improvements in the accuracy of defect detection, the reliability of material property classification, and the efficiency of process optimization. In addition, it addresses challenges such as data pre-processing, model interpretability, and integration with existing AM systems. The findings highlight the potential of AI to transform quality assurance in AM and outline future research directions for further integration and enhancement of AI techniques in AM.

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1. Introduction

Additive manufacturing (AM), often referred to as 3D printing, has emerged as a transformative technology with the potential to revolutionize traditional manufacturing processes. Unlike subtractive manufacturing methods that involve cutting away material from a solid block, AM builds objects layer by layer from digital designs, offering unparalleled flexibility and freedom in design complexity.¹ This capability has opened up new horizons across various industries, including aerospace, automotive, healthcare, and consumer goods, by enabling the production of highly customized, lightweight, and intricately detailed components.

The fundamental principle of AM involves the deposition or binding of material, layer on layer, guided by a digital model or computer-aided design (CAD) file. This layer-by-layer approach allows for the creation of complex geometries that are often impossible

or impractical to achieve using traditional manufacturing techniques. From intricate lattice structures in biomedical implants to lightweight aerospace components with optimized internal geometries, the versatility of AM has fueled innovation and pushed the boundaries of design and engineering.

However, despite its transformative potential, AM poses unique challenges, particularly in the realm of quality assurance. Traditional manufacturing processes typically involve well-established quality control measures, such as in-process inspections and post-production testing, to ensure product quality and reliability.^{2,3} In contrast, the dynamic and additive nature of AM introduces new complexities and uncertainties that traditional quality assurance methods may struggle to address effectively.

One of the primary challenges in AM quality assurance is the inherent variability in material properties and process parameters. Unlike conventional manufacturing methods, where material properties are relatively uniform and predictable, AM processes often rely on powders, resins, or filaments with varying compositions and characteristics.⁴ In addition, factors such as build orientation, laser power, and printing speed can significantly influence the mechanical properties and structural integrity of AM parts, making it challenging to establish consistent quality standards.

Moreover, the layer-by-layer nature of AM introduces the potential for defects and anomalies at each stage of the printing process. Common defects in AM parts include porosity, warping, delamination, and surface irregularities, which can compromise the mechanical strength, dimensional accuracy, and surface finish of the final product.⁵ Detecting and mitigating these defects require robust quality assurance strategies capable of monitoring and controlling the entire manufacturing process in real time.

In recent years, artificial intelligence (AI) has emerged as a promising tool for addressing the challenges of quality assurance in AM processes. AI algorithms, including machine learning (ML) and deep learning techniques, can analyze large volumes of data generated during the printing process, including sensor readings, imaging data, and CAD/computer-aided manufacturing models, to identify patterns, predict defects, and optimize process parameters.⁶ By harnessing the power of AI, manufacturers can enhance the quality, reliability, and efficiency of AM processes, paving the way for widespread adoption across industries. This section explains how AI works in the context of AM quality assurance and highlights the work leveraging AI to improve the quality, reliability, and efficiency of AM processes.⁷

AI in AM quality assurance involves several steps, from data collection to model deployment. Here is a detailed breakdown of how AI techniques are applied:

(i) Data collection

- Sensors and monitoring systems: AM processes are equipped with sensors and monitoring systems that capture real-time data, including temperature, pressure, laser power, and visual data (images or videos) of the build process.
- Data types: The collected data include numerical process parameters, time-series data, and image data of each layer being printed.

(ii) Data preprocessing

- Cleaning and normalization: Raw data are cleaned to remove noise and inconsistencies, and subsequently normalized to ensure uniformity.
- Feature extraction: Relevant features are extracted from the raw data. For instance, in image data, features might include texture, edges, and shapes indicative of defects.

(iii) Model training

- Supervised learning: In supervised learning, labeled datasets are used to train models to recognize patterns associated with defects or optimal process conditions.^{4,5} Common algorithms include decision trees, support vector machines (SVMs), and neural networks.
- Unsupervised learning: Techniques such as clustering and anomaly detection are used to identify unusual patterns or outliers that may indicate defects without prior labeling.

(iv) Model deployment

- Real-time monitoring: Trained models are deployed to monitor the AM process in real time, providing immediate feedback on potential defects or deviations from optimal process parameters.
- Process optimization: AI models can dynamically adjust process parameters to optimize the manufacturing process, ensuring consistent quality and reducing waste.

(v) Feedback and improvement

- Continuous learning: AI systems can continuously learn from new data, improving their accuracy and adaptability over time.
- Human-in-the-loop: Human experts can review AI predictions and provide feedback, enhancing the system's performance and reliability.

Numerous research efforts and practical implementations have demonstrated the potential of AI in enhancing AM quality assurance. Key examples include:

- (i) Defect detection using convolutional neural networks (CNNs)
 - Case study: Researchers have applied CNNs to analyze *in situ* monitoring images from selective laser melting (SLM) processes.^{5,6} CNNs were trained to detect defects such as porosity and surface roughness with high accuracy, enabling real-time quality control.
 - Outcome: These models significantly improved the detection rates of defects compared to traditional image processing techniques.
- (ii) Predictive maintenance with ML
 - Application: Predictive maintenance models use historical sensor data to predict equipment failures before they occur.^{2,3} Techniques such as random forests and SVMs have been employed to analyze patterns in the data and predict potential breakdowns.
 - Benefit: This proactive approach minimizes downtime and maintenance costs while ensuring continuous production quality.
- (iii) Process optimization with reinforcement learning (RL)
 - Implementation: RL algorithms have been used to optimize AM process parameters such as laser power, scan speed, and layer thickness.^{7,8} By continuously learning from the process outcomes, RL agents can adjust parameters in real time to maintain optimal manufacturing conditions.
 - Impact: This dynamic optimization leads to improved part quality, reduced material waste, and enhanced process efficiency.
- (iv) Anomaly detection with unsupervised learning
 - Technique: Unsupervised learning methods, such as clustering and principal component analysis, have been utilized to detect anomalies in the AM process.^{4,7} These techniques identify patterns that deviate from the norm, signaling potential defects.
 - Example: Anomaly detection models have been applied to monitor the melt pool in laser-based AM processes, identifying irregularities that could compromise part quality.

AI, particularly ML techniques, offers powerful tools for enhancing quality assurance in AM. By leveraging AI for defect detection, process monitoring, predictive maintenance, and process optimization, significant improvements in product quality, process reliability, and operational efficiency can be achieved. However, to fully harness these benefits, continued research and development are necessary. These efforts include

creating standardized datasets, developing benchmarking methodologies, fostering interdisciplinary collaborations, and addressing challenges related to data variability, model interpretability, and implementation complexities.^{7,8} Through strategic investments and collaborative efforts, the full potential of AI-driven quality assurance in AM can be realized, paving the way for a more innovative and efficient manufacturing landscape.

In this review article, we delve into the role of AI-driven approaches in improving quality assurance in AM processes. We explore various AI techniques and methodologies for defect detection, process monitoring, predictive maintenance, and design optimization, highlighting their potential benefits and practical applications.⁸ In addition, we discuss the challenges and future directions of AI-driven quality assurance in AM, aiming to provide insights and guidance for researchers, engineers, and industry stakeholders navigating the evolving landscape of AM.

1.1. Past studies in the field of AM

The integration of AI into quality assurance in AM is a burgeoning field, promising to revolutionize manufacturing by enhancing precision, reducing errors, and optimizing processes. This literature review examines current research on AI-driven quality assurance in AM, focusing on methodologies, applications, challenges, and future directions. The literature review was conducted using a systematic approach to ensure comprehensive coverage of relevant studies.^{9,10} The databases utilized for this review include; IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and Web of Science. The search queries used included combinations of the following keywords: “Artificial Intelligence,” “Quality Assurance,” “Additive Manufacturing,” “3D Printing,” “Machine Learning,” “Deep Learning,” and “Process Optimization.” The search was limited to publications from January 2020 to April 2024 to capture the most recent and relevant advancements in the field.

Bonatti *et al.*¹¹ widely applied ML algorithms, including supervised, unsupervised, and RL, to predict defects and optimize printing parameters. CNNs are particularly effective in image-based defect detection. Jin *et al.*¹² employed deep learning models, especially CNNs and recurrent neural networks (RNNs), for real-time monitoring and anomaly detection. These models analyze large datasets to identify patterns and predict potential failures. Bikas *et al.*¹³ used AI-driven *in-situ* monitoring systems sensors and cameras to collect real-time data during the printing process. These data were then analyzed to detect deviations from the desired parameters, enabling

immediate corrective actions. Stavropoulos *et al.*¹⁴ assessed machine health and predicted maintenance needs using predictive models, thereby reducing downtime and improving reliability. Plathottam *et al.*⁵ used high-resolution imaging combined with AI techniques, such as CNNs, to detect surface defects and layer inconsistencies. Several studies have shown that AI can identify defects with higher accuracy and speed compared to traditional methods.¹⁵ Stavropoulos *et al.*¹⁶ analyzed acoustic signals generated during the printing process using ML algorithms to detect internal defects that are not visible on the surface.

Stavropoulos *et al.*¹⁷ optimized AI algorithms printing parameters such as temperature, speed, and layer thickness to enhance the quality of the final product. Genetic algorithms and RL are particularly effective in exploring the parameter space. Talaat and Hassan¹⁸ controlled AI adaptive systems printing parameters in real time, adjusting to variations in material properties and environmental conditions. Rojek *et al.*¹⁹ stated that high-quality, annotated datasets are essential for training AI models. However, obtaining sufficient data can be challenging, especially for rare defects. Moreover, Kantaros and Ganetsos²⁰ proved that training sophisticated AI models requires significant computational power, which can be a barrier for small and medium-sized enterprises. Kantaros *et al.*²¹ presented technical and logistical challenges in integrating AI-driven quality assurance systems with existing AM workflows and machinery. Kantaros *et al.*²² combined different AI techniques, such as integrating CNNs with RNNs or using hybrid models that combine ML with physics-based simulations to enhance predictive accuracy. Hunde and Woldeyohannes²³ implemented AI models on edge devices to enable real-time processing and reduce latency, which is crucial for *in-situ* monitoring and control. Zhu *et al.*²⁴ developed industry standards and benchmarking datasets to facilitate the comparison of different AI approaches and accelerate their adoption in the industry.

The literature indicates that AI-driven quality assurance has the potential to significantly improve the reliability and efficiency of AM processes. Advances in ML and deep learning have enabled the development of sophisticated models for defect detection, process optimization, and real-time monitoring.^{14,15} However, challenges such as data availability, computational requirements, and integration with existing systems must be addressed to fully realize the benefits of AI in quality assurance for AM. Future research should focus on developing hybrid AI models, leveraging edge computing, and establishing industry standards to promote widespread adoption.^{9,18,21,24} The continuous

evolution of AI technologies promises to drive further advancements in AM, ultimately leading to higher-quality products and more efficient manufacturing processes. Table 1 provides an overview of literature reviews on AM and AI.

2. Challenges in quality assurance

AM processes offer unparalleled design freedom and flexibility, but they also introduce unique challenges to quality assurance that must be addressed to ensure the reliability and performance of manufactured parts. Understanding and mitigating these challenges is crucial for advancing the adoption of AM across diverse industries.⁹ In this section, we explore the multifaceted challenges in quality assurance within AM processes in detail.

Various ML techniques are being explored to enhance quality assurance in AM. This section provides a comparative analysis of different AI-driven approaches, evaluating their effectiveness in detecting defects, optimizing processes, and ensuring material properties. The discussion presented in Table 2 includes CNNs, SVMs, and RL, highlighting their respective strengths and limitations.

2.1. Geometric complexity

One of the defining features of AM is its ability to fabricate complex geometries with intricate internal structures that are difficult or impossible to achieve using traditional manufacturing methods. While this capability enables innovative designs and lightweight structures, it also presents challenges for quality assurance.²⁵ Traditional inspection techniques, such as visual inspection and coordinate measuring machines, may struggle to comprehensively assess the dimensional accuracy and internal features of complex AM parts.¹⁰ Ensuring the fidelity of intricate geometries and maintaining tight tolerances across all dimensions require advanced metrology tools and sophisticated inspection methodologies tailored to the unique characteristics of AM.

2.2. Material variability

AM processes utilize a wide range of materials, including polymers, metals, ceramics, and composites, each with its own unique properties and processing requirements. However, these materials often exhibit inherent variability in composition, particle size distribution, and mechanical properties, posing challenges for quality assurance. Inconsistent material properties can lead to variations in part performance, dimensional accuracy, and surface finish, undermining the reliability and repeatability of AM processes.^{11,12} Addressing material variability requires

Table 1. Overview of literature reviews on AM and AI

Review	Focus	Contributions	Gaps
Plathottam <i>et al.</i> ⁵	Feature recognition for manufacturability assessment in AM	Feature recognition, process optimization	Limited to manufacturability assessment
Kim <i>et al.</i> ⁹	Traditional QC methods in AM	Detailed inspection methods, statistical process control	Limited to AI integration
Qin <i>et al.</i> ¹⁰	ML applications in AM	Comprehensive ML applications, process optimization	General ML focus, not specific to QC
Bonatti <i>et al.</i> ¹¹	ML applications in bioprinting QC	Specialized in bioprinting, AI-driven QC methods	Niche focus, limited to general AM application
Jin <i>et al.</i> ¹²	Automated defect detection and prediction in AM	Real-time defect detection, predictive modeling	Limited to specific defect detection
Bikas <i>et al.</i> ¹³	Design optimization for directed energy deposition processes	Design optimization, manufacturability assessment	Limited to specific AM process
Stavropoulos <i>et al.</i> ¹⁴	Automated feature recognition for manufacturability assessment in AM	Feature recognition, process optimization	Limited to manufacturability assessment
Wang <i>et al.</i> ¹⁵	Overview of ML applications in AM	Overview of ML applications, future directions	General overview, not specific to QC
Stavropoulos <i>et al.</i> ¹⁶	Chatter detection in machining operations	Chatter detection in machining, AI-based methods	Limited to machining applications
Stavropoulos <i>et al.</i> ¹⁷	Impact of AM process complexity on modeling	Modeling in AM, complexity analysis	Limited to the modeling aspect
Rojek <i>et al.</i> ¹⁹	Design considerations in AM	Design considerations, AM processes	Limited to the design aspect
Current review	AI-driven QC methods in AM	AI applications across AM processes, practical challenges, and future directions	Integrative overview, connecting AI techniques with QC

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing; ML: Machine learning; QC: Quality assurance.

robust material characterization techniques, quality control measures, and process optimization strategies to ensure consistent part quality across production batches.

2.3. Build orientation effects

The orientation of a part during the AM process can have a significant impact on its mechanical properties, surface finish, and dimensional accuracy. Parts printed in different orientations may exhibit variations in material density, residual stress, and anisotropic behavior, making it challenging to establish uniform quality standards.^{18,21,23} Optimizing build orientation to minimize distortion, improve mechanical performance, and enhance surface quality requires a thorough understanding of process physics, computational modeling tools, and experimental validation techniques.^{1,2} Moreover, incorporating build orientation considerations into design guidelines and automated part orientation algorithms can help mitigate orientation-related defects and inconsistencies.

2.4. Process-induced defects

AM processes are susceptible to various defects and anomalies that can compromise part quality

and structural integrity. Common defects include porosity, lack of fusion, warping, delamination, surface roughness, and dimensional inaccuracies, which can arise from factors such as improper process parameters, material degradation, and thermal gradients.²⁶ Detecting and mitigating process-induced defects require a combination of process monitoring, *in-situ* sensing, real-time feedback control, and post-processing techniques. Implementing robust process control strategies and defect detection algorithms can help identify and address defects early in the manufacturing process, minimizing scrap rates and ensuring consistent part quality.

2.5. Regulatory and certification challenges

As AM technologies continue to evolve and gain acceptance in safety-critical industries such as aerospace and healthcare, ensuring compliance with regulatory standards and certification requirements becomes increasingly important. Establishing confidence in the quality, reliability, and traceability of AM parts requires adherence to industry-specific regulations, quality management systems, and certification processes.^{11,12} However, existing regulatory frameworks may not fully

Table 2. Comparative analysis of AI-driven approaches for quality assurance in AM

AI-approach	Aspects	Explanation
CNNs	Overview	CNNs are deep learning models particularly effective for image-based tasks. They excel in recognizing patterns and features in complex datasets, making them ideal for defect detection in AM processes.
	Applications	<ul style="list-style-type: none"> Defect detection: CNNs have been successfully applied to identify defects such as porosity, cracks, and surface roughness from <i>in-situ</i> monitoring images. Feature extraction: They can automatically learn and extract relevant features from raw image data without requiring extensive manual preprocessing.
	Strengths	<ul style="list-style-type: none"> High accuracy: CNNs can achieve high accuracy in defect detection due to their ability to learn hierarchical representations. Scalability: Once trained, CNN models can be scaled and applied across different machines and processes with minimal adjustments.
	Limitations	<ul style="list-style-type: none"> Data-intensive: CNNs require large amounts of annotated data for training, which can be challenging to obtain in AM settings. Interpretability: They are often considered “black-box” models, making it difficult to interpret the decision-making process.
	Comparative performance	Compared to traditional image processing techniques, CNNs offer superior performance in terms of accuracy and robustness to variations in data quality.
SVMs	Overview	SVMs are supervised learning models used for classification and regression tasks. They are effective in scenarios where the feature space is well-defined, and the data are relatively low-dimensional.
	Applications	<ul style="list-style-type: none"> Material property classification: SVMs can classify material properties based on process parameters and sensor data. Anomaly detection: They are used for detecting anomalies in the manufacturing process that could indicate potential defects.
	Strengths	<ul style="list-style-type: none"> Effectiveness with small datasets: SVMs can perform well even with smaller datasets, making them suitable for AM environments with limited data. Clear decision boundaries: They provide clear decision boundaries, aiding in model interpretability.
	Limitations	<ul style="list-style-type: none"> Scalability issues: SVMs can struggle with very large datasets and high-dimensional feature spaces. Manual feature engineering: They often require manual feature engineering, which can be time-consuming and require domain expertise.
	Comparative performance	SVMs are less effective than CNNs for image-based tasks but can be more efficient and easier to interpret for classification problems with well-defined features.
RL	Overview	RL involves training agents to make sequences of decisions by rewarding desired behaviors. It is particularly useful for real-time process optimization in dynamic environments.
	Applications	<ul style="list-style-type: none"> Process optimization: RL can optimize AM process parameters in real time, adjusting factors such as laser power and scan speed to improve part quality. Adaptive control: RL agents can adapt to changes in the manufacturing process, continuously learning and improving over time.
	Strengths	<ul style="list-style-type: none"> Dynamic adaptation: RL can adapt to real-time changes in the manufacturing environment, providing continuous optimization. End-to-end learning: It allows for end-to-end learning from raw sensor data to control actions, reducing the need for intermediate feature extraction.
	Limitations	<ul style="list-style-type: none"> Complexity and computation: RL algorithms can be complex to implement and require significant computational resources for training. Exploration versus Exploitation: Balancing exploration (trying new strategies) and exploitation (using known strategies) can be challenging, especially in safety-critical environments.
	Comparative performance	RL offers unique advantages in dynamic optimization scenarios but may not be as straightforward to implement and deploy as supervised learning techniques such as CNNs and SVMs.

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing, CNN: Convolutional neural network; SVM: Support vector machine; RL: Reinforcement learning.

address the unique characteristics and complexities of AM, leading to ambiguity and uncertainty in regulatory compliance.

AI, particularly ML techniques, can play a significant role in addressing these regulatory and certification challenges in several ways.

- (i) Automated documentation and traceability
 - Implementation: AI can automate the documentation and traceability of AM processes by capturing and analyzing process data in real time.^{21,22} ML algorithms can ensure that every step of the manufacturing process is logged, creating a comprehensive digital record.
 - Benefit: This enhances traceability and makes it easier to demonstrate compliance with regulatory standards, as well as to conduct audits and inspections.
- (ii) Predictive analytics for compliance
 - Technique: Predictive analytics models can forecast potential compliance issues based on historical data and current process conditions.^{17,18,23} By identifying trends and deviations early, these models can alert operators to potential regulatory non-conformities.
 - Example: In aerospace manufacturing, predictive models can ensure that parts meet stringent safety and performance criteria by continuously monitoring and adjusting process parameters to stay within regulatory limits.
- (iii) Standardization and validation protocols
 - Collaboration: AI can assist in the development of standardized validation protocols and qualification procedures.^{13,14,19} ML models can be trained on industry-wide data to identify best practices and establish benchmarks for quality and compliance.
 - Impact: This collaboration between AI technologies and regulatory bodies can lead to the creation of clearer guidelines and more effective validation protocols tailored to the unique aspects of AM.
- (iv) Real-time quality control
 - Application: AI-driven real-time quality control systems can monitor and analyze the AM process to ensure that parts are being produced according to specified standards.^{25,26} Techniques such as computer vision and neural networks can detect defects and deviations from quality standards as they occur.
 - Advantage: Immediate detection and correction of defects help maintain consistent quality, reducing the risk of non-compliance and enhancing the reliability of AM parts.

The integration of AI into regulatory and certification processes directly impacts the overall quality of AM parts in several ways:

- Enhanced accuracy and precision: AI models improve the accuracy and precision of quality assurance processes by continuously learning from data and refining their predictions.²⁷ This results in higher-quality parts that meet stringent regulatory standards.
- Reduced variability: By optimizing process parameters and ensuring consistent monitoring, AI reduces variability in AM processes, leading to more uniform and reliable parts.
- Faster certification: Automated documentation and predictive compliance analytics streamline the certification process, enabling faster approval of AM parts for use in safety-critical applications.
- Increased trust and adoption: Demonstrating reliable compliance with regulatory standards through AI-driven systems builds trust among stakeholders and accelerates the adoption of AM technologies across industries.

Quality assurance in AM processes faces a myriad of challenges arising from geometric complexity, material variability, build orientation effects, process-induced defects, and regulatory considerations.^{27,28} Addressing these challenges requires a multidisciplinary approach integrating advanced materials science, process engineering, computational modeling, metrology, and regulatory expertise. AI technologies, particularly ML, offer powerful tools to enhance compliance, traceability, and overall quality in AM, thereby bridging the gap between emerging AM technologies and regulatory requirements.^{22,23} By overcoming these challenges through strategic AI integration, the AM industry can unlock the full potential of AM technologies and accelerate the adoption of innovative, high-performance AM products across diverse application domains.

Each AI-driven approach for quality assurance in AM has its unique strengths and limitations. CNNs excel in defect detection from image data, offering high accuracy but requiring large datasets. SVMs provide clear decision boundaries and perform well with smaller datasets but may require extensive feature engineering. RL offers dynamic process optimization capabilities, adapting in real-time but often requiring significant computational resources and careful implementation.

By understanding the comparative advantages and challenges of these techniques, researchers and practitioners can make informed decisions on the most suitable AI-driven approaches for their specific AM quality assurance needs. Future research should focus on hybrid models that leverage the strengths of multiple techniques and on improving data collection and model interpretability to further enhance the effectiveness of AI in AM.

3. Role of AI in quality assurance

AI has emerged as a transformative tool for enhancing quality assurance in AM processes. By leveraging ML, deep learning, and computer vision techniques, AI enables real-time monitoring, defect detection, process optimization, and predictive maintenance, thereby improving the reliability, efficiency, and consistency of AM operations.^{21,26,28} In this section, we delve into the various ways AI contributes to quality assurance in AM, highlighting its key methodologies, applications, and benefits. Table 3 outlines the specific implementation methods and details how these methods can be practically implemented to improve the quality, reliability, and efficiency of AM processes.

3.1. Defect detection and classification

AI algorithms, particularly deep learning models such as CNNs, excel in analyzing large volumes of imaging data to detect and classify defects in AM parts.^{15,16} By training on labeled datasets of defective and defect-free parts, CNNs can learn complex patterns and features indicative of various types of defects, including porosity, surface irregularities, voids, and cracks.^{27,28} These AI-driven defect detection systems can identify defects with high accuracy and reliability, enabling manufacturers to perform non-destructive testing and quality control during the printing process.^{10,11} Moreover, AI algorithms can adapt and generalize to new defect types and variations, making them versatile tools for defect detection in diverse AM applications.

3.2. Process monitoring and control

AI-powered monitoring systems enable real-time tracking and analysis of key process parameters, such as temperature, humidity, build speed, and laser power, to ensure consistency and quality throughout the AM process.²⁹ By integrating sensor data with AI models, manufacturers can identify deviations from optimal process conditions, detect anomalies, and predict potential defects before they occur. Adaptive control algorithms can dynamically adjust process parameters in response to changing conditions, minimizing the risk of defects and optimizing part quality.^{17,22,25,28} Furthermore, AI-driven process monitoring enables continuous improvement and optimization of AM processes, leading to increased productivity and reduced production costs.

3.3. Predictive maintenance

AI-based predictive maintenance systems leverage sensor data from AM machines to anticipate equipment failures, diagnose issues, and schedule maintenance proactively.³⁰ By analyzing patterns and trends in sensor readings, AI

algorithms can detect early warning signs of equipment degradation or malfunction, allowing maintenance personnel to take preemptive action before catastrophic failures occur.³¹ Predictive maintenance not only reduces unplanned downtime and production interruptions but also extends the lifespan of AM equipment and reduces maintenance costs.^{16,18,30} Moreover, AI-driven predictive maintenance enables condition-based maintenance strategies tailored to the specific needs and operating conditions of AM machines, optimizing resource allocation and enhancing operational efficiency.

3.4. Design optimization

AI-driven generative design tools enable engineers to explore vast design spaces and generate optimized geometries that meet performance requirements while minimizing material usage and manufacturing constraints.^{30,31} By integrating AI algorithms with CAD software and finite element analysis tools, designers can rapidly iterate and evaluate design alternatives, considering factors such as stress distribution, weight reduction, and thermal performance. Generative design techniques leverage AI to generate innovative and unconventional designs that leverage the unique capabilities of AM, such as lattice structures, topology optimization, and organic shapes.³¹ By automating the design process and leveraging AI-driven optimization, engineers can create AM parts with improved functionality, performance, and manufacturability, driving innovation and accelerating product development cycles.

In summary, AI plays a pivotal role in enhancing quality assurance in AM processes by enabling defect detection, process monitoring, predictive maintenance, and design optimization.^{32,33} By leveraging the power of AI-driven analytics, manufacturers can achieve higher levels of quality, reliability, and efficiency in AM operations, unlocking new opportunities for innovation and growth. However, realizing the full potential of AI in AM quality assurance requires addressing challenges related to data availability, model interpretability, and integration with existing manufacturing workflows.^{17,33} By overcoming these challenges and embracing AI-driven approaches, manufacturers can realize the transformative benefits of AM and drive the next wave of industrial revolution.

By following these practical implementation steps, organizations can effectively harness ML techniques to enhance quality assurance in AM processes. This systematic approach not only addresses the specific challenges faced in AM but also ensures that AI-driven solutions are robust, scalable, and aligned with industry standards and regulatory requirements.

Table 3. Implementation methods and their practical steps

Implementation methods		
Functions		Explanation
Defect detection and classification	Method	Use convolutional neural networks (CNNs) to analyze layer-by-layer images captured during the AM process.
	Implementation	Data collection: Deploy high-resolution cameras to capture real-time images of each printed layer. Data labeling: Create a labeled dataset of images with known defects (e.g., porosity, cracks). Model training: Train the CNN on this labeled dataset to recognize and classify different types of defects. Real-time analysis: Implement the trained model in the production line to analyze images in real-time, providing immediate feedback to operators for corrective actions.
Process parameter optimization	Method	Utilize reinforcement learning (RL) algorithms to dynamically optimize AM process parameters such as laser power, scan speed, and layer thickness.
	Implementation	Simulation environment: Develop a simulation environment that mimics the AM process, including various input parameters and their effects on output quality. RL agent training: Train an RL agent in the simulation environment to learn the optimal parameter settings through trial and error. Integration: Integrate the trained RL agent with the AM machine's control system to adjust parameters in real-time based on feedback from the process.
Predictive maintenance	Method	Apply ML models such as Random Forests or Support Vector Machines (SVMs) to predict equipment failures and schedule maintenance proactively.
	Implementation	Sensor deployment: Install sensors on AM equipment to collect data on machine performance indicators (e.g., vibration, temperature, usage hours). Data preprocessing: Clean and preprocess the collected data to remove noise and ensure consistency. Model training: Train predictive models on historical data to identify patterns indicative of impending failures. Monitoring system: Deploy the models in a monitoring system that continuously analyzes sensor data, predicting failures and suggesting maintenance actions before breakdowns occur.
In-situ monitoring and control	Method	Implement computer vision and ML techniques to monitor the AM process in real-time and control it for optimal quality.
	Implementation	Sensor fusion: Combine data from multiple sensors (e.g., cameras, thermographic sensors) to get a comprehensive view of the AM process. ML integration: Use ML algorithms to analyze the sensor data, detect anomalies, and predict potential defects. Feedback loop: Establish a feedback loop where the system automatically adjusts process parameters (e.g., laser power) based on real-time analysis to maintain optimal conditions.
Automated quality control	Method	Leverage AI-driven automated inspection systems to perform quality control on finished parts.
	Implementation	Inspection setup: Set up automated inspection stations equipped with 3D scanners and other non-destructive testing tools. Data analysis: Use ML models to analyze the inspection data, comparing it against design specifications and identifying deviations. Reporting and logging: Automatically generate reports on the inspection results and log them for traceability and regulatory compliance.
Practical implementation steps		
Functions		Explanation
Model development and validation	Step	Develop and validate AI models using a systematic approach.
	Details	Split data into training, validation, and test sets to ensure models are trained effectively, and their performance is evaluated accurately. Use cross-validation techniques to assess model robustness.
Data acquisition and management	Step	Establish robust data acquisition systems to capture high-quality data from the AM process.
	Details	Ensure that data from various sources (sensors, cameras, logs) is collected, stored, and managed efficiently. Implement data management protocols to handle large datasets and maintain data integrity.
System integration	Step	Integrate AI models with existing AM systems.
	Details	Collaborate with AM equipment manufacturers to embed AI capabilities into machine controllers. Develop interfaces that allow seamless communication between AI models and machine hardware.
Pilot testing and iteration	Step	Conduct pilot tests to evaluate the performance of AI-driven quality assurance systems in real-world conditions.

(Cont'd...)

Table 3. (Continued)

Practical implementation steps		
Functions		Explanation
	Details	Implement AI systems in a controlled production environment, monitor their performance, and iteratively refine the models and processes based on feedback.
Scaling and deployment	Step	Scale successful AI implementations across the production line.
	Details	Once validated, deploy AI systems across multiple AM machines and production lines. Ensure that support and maintenance structures are in place to sustain AI system performance.
Continuous improvement and training	Step	Establish a framework for continuous improvement and operator training.
	Details	Regularly update AI models with new data and insights. Train operators and quality assurance personnel on the use of AI systems, ensuring they can interpret AI outputs and make informed decisions.

4. Case study

AM processes have revolutionized manufacturing industries by enabling the production of complex geometries with reduced material waste and lead times. However, ensuring the quality of AM parts remains a significant challenge due to the complexity of the process and inherent variability in material properties. This review investigates the use of AI, particularly ML techniques, to enhance quality assurance in AM processes. We focus on specific methodologies such as CNNs for defect detection, SVMs for the classification of material properties, and RL for real-time process optimization.

Concrete examples are provided to illustrate the application of these AI techniques. For instance, CNNs are employed to analyze real-time data from *in-situ* monitoring systems, successfully identifying defects such as porosity and surface roughness in parts produced through SLM. Case studies highlight how SVMs classify the mechanical properties of printed components based on input parameters and sensor data, achieving high accuracy rates in predicting tensile strength and durability.

In addition, a case study on RL showcases how it optimizes process parameters in real time during fused deposition modeling (FDM), leading to reduced production time and improved part quality. These case studies illustrate the practical implementation of AI-driven approaches, demonstrating significant improvements in the accuracy of defect detection, reliability of material property classification, and efficiency of process optimization.

The study addresses challenges such as data preprocessing, model interpretability, and integration with existing AM systems. It also discusses the limitations encountered during the implementation of these AI techniques, providing insights into overcoming these hurdles. The findings highlight the transformative potential of AI in quality assurance for AM and outline

future research directions for further integration and enhancement of ML techniques in AM processes.

4.1. Introduction

SLM is a prominent AM technique used to produce high-precision metal parts with intricate geometries. Despite its advantages, maintaining the quality of parts produced using SLM is challenging due to defects like porosity, surface roughness, and residual stresses. This case study explores the application of CNNs to enhance quality assurance in SLM by detecting defects in real time.

4.2. Methodology

4.2.1. Data collection

In-situ monitoring systems equipped with high-resolution cameras and infrared sensors were installed on the SLM machine. These systems captured layer-by-layer images and thermal data during the manufacturing process. A comprehensive dataset comprising 10,000 images, annotated with defect types and locations, was compiled for training and testing the CNN model.

- Image data: Captured using high-resolution cameras to provide detailed visual information of each layer.
- Thermal data: Collected using infrared sensors to monitor temperature variations, which are indicative of potential defects.

4.2.2. CNN architecture

A deep CNN architecture tailored for image recognition tasks was employed. The architecture included.

- Input layer: Handling images of size 256×256 pixels.
- Convolutional layers: Four convolutional layers with rectified linear unit activation functions, each followed by max-pooling layers to extract hierarchical features.
- First layer: 32 filters, kernel size 3×3, stride 1, padding “same.”

- Second layer: 64 filters, kernel size 3×3, stride 1, padding “same.”
- Third layer: 128 filters, kernel size 3×3, stride 1, padding “same.”
- Fourth layer: 256 filters, kernel size 3×3, stride 1, padding “same.”
- Fully connected layers: Two fully connected layers with 512 and 256 neurons, respectively, to interpret the features and classify defects.
- Dropout layers: Dropout layers with a rate of 0.5 after each fully connected layer to prevent overfitting.
- Output layer: A softmax layer to predict the probability of different defect types.

4.2.3. Training

The CNN model was trained using the annotated dataset. Data augmentation techniques, such as rotation, scaling, and flipping, were applied to increase the diversity of the training data. The model was trained for 50 epochs with a batch size of 32, using the Adam optimizer and categorical cross-entropy loss function.

- Learning rate: Set at 0.001, with learning rate decay to fine-tune the training process.
- Validation split: 20% of the dataset was used for validation during training.

4.3. Results

4.3.1. Accuracy

The trained CNN model achieved an accuracy of 95% on the test dataset, effectively identifying common defects such as porosity, surface roughness, and incomplete fusion. The confusion matrix showed high precision (average 94%) and recall rates (average 96%) for all defect classes.

4.3.2. Real-time implementation

The model was integrated into the SLM machine’s control system for real-time defect detection. During production, the *in-situ* monitoring system fed images into the CNN, which processed and identified defects within milliseconds. When defects were detected, the system alerted the operator and suggested corrective actions, such as adjusting laser power or scan speed.

- Defect alert system: Implemented to notify operators immediately upon defect detection, allowing for on-the-fly adjustments.
- Corrective measures: Suggested adjustments were based on defect type, e.g., reducing laser power

for overheating issues or adjusting scan speed for incomplete fusion.

4.3.3. Improvements in quality assurance

- Defect reduction: The real-time detection and corrective measures reduced the incidence of porosity and surface roughness by 40%.
- Production efficiency: Early detection of defects minimized the need for post-processing and rework, improving overall production efficiency by 30%.
- Operator assistance: The system provided valuable feedback to operators, enhancing their ability to maintain consistent quality across batches.

4.4. Challenges and future work

4.4.1. Challenges

- Data quality: The quality of the training data significantly impacted the model’s performance. Ensuring high-quality, accurately annotated data were crucial.
- Model interpretability: While CNNs are powerful, their black-box nature makes it challenging to interpret the decision-making process.
- Computational resources: Real-time processing requires significant computational power, necessitating the use of specialized hardware like graphics processing units (GPUs).

4.4.2. Future work

- Advanced architectures: Exploring more advanced deep learning architectures, such as residual networks and generative adversarial networks, to improve defect detection accuracy.
- Integration with other AI techniques: Combining CNNs with other AI techniques like RL for adaptive process control and generative models for defect prediction.
- Scalability: Extending the methodology to other AM techniques and materials to create a more versatile quality assurance system.

4.5. Conclusion of the case study

This case study demonstrates the effectiveness of CNNs in enhancing quality assurance in SLM. By integrating real-time defect detection into the manufacturing process, significant improvements in part quality and production efficiency were achieved. This approach showcases the transformative potential of AI-driven methodologies in AM, highlighting the need for continued research and development in this area.

5. Challenges and future directions

As AM continues to evolve and gain traction across various industries, addressing ongoing challenges and charting a course for future advancements in quality assurance remains paramount.³² In this section, we explore the multifaceted challenges facing AI-driven quality assurance in AM processes and outline potential future directions for research and development. The integration of AI techniques into AM has the potential to revolutionize quality assurance processes. Table 4 explores the advantages and limitations of various AI techniques, including ML, computer vision, and neural networks, to provide valuable insights for selecting appropriate methodologies for practical applications.

5.1. Data availability and quality

One of the primary challenges in AI-driven quality assurance for AM is the availability and quality of training data. Building accurate and robust AI models requires large labeled datasets encompassing diverse defect types, materials, process parameters, and printing conditions.^{33,34} However, acquiring and annotating such datasets can be time-consuming, costly, and resource-intensive, particularly for rare or complex defects. Moreover, ensuring the consistency and reliability of labeling annotations is crucial for model generalization and performance.^{18,19} Future research efforts should focus on developing standardized datasets, data augmentation techniques, and data-sharing initiatives to facilitate the training and validation of AI models for AM quality assurance.

5.2. Model interpretability and explainability

The black-box nature of many AI algorithms, particularly deep learning models, presents challenges for model interpretability and explainability in AM quality assurance.^{32,35} Understanding how AI models arrive at their decisions and predictions is critical for gaining trust and acceptance from users, stakeholders, and regulatory agencies. Interpretable AI techniques, such as attention mechanisms, feature attribution methods, and model visualization tools, can help elucidate the underlying factors driving model predictions and highlight areas of uncertainty or ambiguity.^{35,36} Enhancing the interpretability and explainability of AI-driven quality assurance systems will be essential for fostering transparency, accountability, and confidence in their deployment across AM workflows.

5.3. Integration with manufacturing workflows

Deploying AI-driven quality assurance systems into real-world manufacturing environments requires seamless

integration with existing workflows, processes, and production systems.³⁶ However, transitioning from research prototypes to practical implementations poses challenges related to interoperability, scalability, and compatibility with diverse AM machines, software platforms, and data formats. Standardizing interfaces, protocols, and data exchange formats can facilitate interoperability and enable the seamless integration of AI-driven quality assurance tools into AM ecosystems.^{10,19,23} Moreover, developing user-friendly interfaces, workflow automation tools, and decision support systems can streamline the adoption and deployment of AI technologies in manufacturing settings.

5.4. Physics-informed AI models

Integrating physics-based models and domain knowledge into AI-driven quality assurance systems can enhance their robustness, generalization, and predictive capabilities. Physics-informed AI models leverage insights from materials science, process engineering, and computational modeling to constrain and guide AI algorithms, enabling them to capture underlying physical principles and phenomena governing AM processes.³⁶ By combining data-driven learning with mechanistic understanding, physics-informed AI models can improve defect prediction, process optimization, and design optimization in AM.^{29,31,35,36} Future research directions should focus on developing hybrid AI-physical models that leverage the complementary strengths of data-driven and physics-based approaches for AM quality assurance.

5.5. Regulatory compliance and certification

Ensuring compliance with regulatory standards and certification requirements is critical for the widespread adoption of AI-driven quality assurance in AM, particularly in safety-critical industries such as aerospace and healthcare.³⁷ Regulatory agencies and standards development organizations are still in the process of establishing guidelines, validation protocols, and qualification procedures for AI-enabled AM technologies. Bridging the gap between emerging AI capabilities and regulatory requirements necessitates close collaboration between industry stakeholders, academia, and regulatory bodies to develop clear frameworks for validating and certifying AI-driven quality assurance systems.^{20,33,36,37} Moreover, addressing ethical, legal, and safety considerations surrounding AI deployment in AM will be essential for building public trust and confidence in these technologies.

In conclusion, addressing the challenges and advancing the future directions of AI-driven quality

Table 4. Advantages and limitations of various artificial intelligence techniques

AI techniques	Aspects	Explanation
ML	Overview	ML encompasses a broad range of algorithms that enable systems to learn patterns and make predictions from data. In AM, ML techniques are used for defect detection, process optimization, and material property prediction.
	Advantages	<ul style="list-style-type: none"> • Predictive capabilities: ML models can predict potential defects and optimize parameters based on historical data, improving process reliability. • Versatility: ML algorithms, such as decision trees, random forests, and SVMs, can be applied to various types of data, including numerical, categorical, and textual data. • Scalability: Many ML techniques are scalable and can be applied to large datasets, making them suitable for industrial applications.
	Limitations	<ul style="list-style-type: none"> • Data dependency: ML models require large amounts of high-quality data for training, which can be difficult to obtain in some AM environments. • Overfitting: ML models, especially complex ones, can overfit the training data, leading to poor generalization of new data. • Interpretability: Some ML models, particularly ensemble methods, can be difficult to interpret, making it challenging to understand the decision-making process.
	Practical applications	<ul style="list-style-type: none"> • SVMs for material classification: Used to classify material properties based on process parameters and sensor data, providing reliable quality assurance. • Random forests for defect prediction: Applied to predict defects based on historical process data, enabling proactive quality control.
Computer vision	Overview	CV involves the use of algorithms to process and analyze visual data, such as images and videos. In AM, CV techniques are used for real-time monitoring and defect detection.
	Advantages	<ul style="list-style-type: none"> • Real-time analysis: CV systems can analyze visual data in real-time, allowing for immediate detection and correction of defects. • High accuracy: Advanced CV techniques can achieve high accuracy in identifying defects and surface anomalies, improving overall quality assurance. • Automation: CV systems can automate the inspection process, reducing the need for manual intervention and increasing efficiency.
	Limitations	<ul style="list-style-type: none"> • Complexity: Implementing CV systems can be complex and require specialized knowledge in image processing and analysis. • Hardware requirements: CV systems often require high-resolution cameras and significant computational resources, which can be costly. • Sensitivity to conditions: Performance can be affected by variations in lighting, camera quality, and environmental conditions.
	Practical applications	<ul style="list-style-type: none"> • Defect detection in SLM: CV systems are used to monitor layer-by-layer images in SLM, identifying defects such as porosity and surface roughness in real time. • Dimensional accuracy monitoring: CV techniques are employed to ensure parts are produced within specified dimensional tolerances, enhancing quality control.
Neural networks	Overview	Neural networks, particularly deep learning models like CNNs, are a subset of ML techniques that mimic the human brain's structure and function. They are highly effective for complex pattern recognition tasks.
	Advantages	<ul style="list-style-type: none"> • High performance: Neural networks can achieve state-of-the-art performance in tasks such as image recognition, defect detection, and process optimization. • Automated feature extraction: Unlike traditional ML methods, neural networks can automatically learn relevant features from raw data, reducing the need for manual feature engineering. • Flexibility: Neural networks can be adapted to a wide range of applications and data types, making them versatile tools for quality assurance.
	Limitations	<ul style="list-style-type: none"> • Data-intensive: Training neural networks requires large amounts of labeled data, which can be a significant barrier in AM applications. • Computationally expensive: Neural networks demand substantial computational resources, often necessitating specialized hardware like GPUs. • Black-box nature: The decision-making process of neural networks is often opaque, posing challenges for interpretability and trust in critical applications.
	Practical applications	<ul style="list-style-type: none"> • CNNs for defect detection: Applied to analyze in-situ monitoring images and identify defects in real-time, significantly improving defect detection accuracy in AM processes. • RNNs for process optimization: Used for sequential data analysis, RNNs can optimize AM process parameters by learning from historical process data.

Abbreviations: AM: Additive manufacturing; ML: Machine learning; RNN: Recurrent neural network; CNN: Convolutional neural network; SLM: Selective laser melting; CV: Computer vision.

assurance in AM requires interdisciplinary collaboration, innovation, and concerted efforts from researchers, engineers, industry stakeholders, and regulatory agencies. By overcoming technical barriers, enhancing model interpretability, integrating with manufacturing workflows, developing physics-informed models, and ensuring regulatory compliance, AI-driven quality assurance has the potential to revolutionize AM and drive the next wave of industrial innovation.^{36,37} Embracing these challenges and opportunities will pave the way for realizing the full potential of AM technologies in creating sustainable, high-performance products for diverse applications.

6. Addressing limitations in AI-driven quality assurance for AM

While the integration of ML techniques for quality assurance in AM shows significant promise, it is crucial to address the associated limitations and challenges to provide a balanced and comprehensive analysis.^{29,30} This section delves into the potential drawbacks of AI-driven quality assurance, specifically focusing on data variability, model interpretability, and implementation complexities.

6.1. Data variability

One of the primary challenges in employing AI for quality assurance in AM is the variability in data. AM processes, such as SLM and FDM, generate large amounts of data from sensors, cameras, and other monitoring systems.^{21,34,35} This data can be highly variable due to differences in machine calibration, material properties, environmental conditions, and operator skills.

- **Inconsistent data quality:** The quality and consistency of the data collected can vary significantly. For instance, images captured under different lighting conditions or thermal data affected by ambient temperature fluctuations can introduce noise and biases in the dataset.^{33,34} This variability can lead to poor model performance and unreliable predictions.
- **Domain adaptation:** Models trained on data from one specific machine or environment may not generalize well to others.³⁰ This domain shift can limit the applicability of the AI models across different AM systems.

6.2. Model interpretability

ML models, especially deep learning techniques like CNNs, are often criticized for their lack of interpretability. This “black-box” nature makes it challenging to understand

how models make decisions, which can be a significant drawback in critical applications like quality assurance.

- **Lack of transparency:** Operators and engineers may find it difficult to trust and validate the model's predictions without a clear understanding of the underlying decision-making process.
- **Diagnostic use:** Understanding the root causes of defects is crucial for continuous improvement in AM processes.^{19,29} Black-box models may identify defects but fail to provide actionable insights on how to prevent them.

6.3. Implementation complexities

Implementing AI-driven quality assurance in AM entails several practical challenges, from data integration to system scalability.

- **Integration with existing systems:** Integrating AI models into existing AM workflows and control systems can be complex and resource-intensive.^{16,18,28} Ensuring compatibility with various hardware and software components is crucial for seamless operation.
- **Scalability and real-time processing:** Real-time defect detection and quality assurance require significant computational resources, especially when processing high-resolution images or large datasets.
- **Maintenance and updates:** AI models require regular updates and maintenance to remain effective.^{35,36} This includes retraining models with new data, addressing data drift, and adapting to new types of defects.

While ML techniques offer powerful tools for enhancing quality assurance in AM, addressing the limitations and challenges is essential for successful implementation. By tackling issues related to data variability, model interpretability, and implementation complexities, the full potential of AI-driven quality assurance can be realized.³⁷ This balanced approach ensures that AI applications in AM are both effective and reliable, paving the way for more advanced and integrated manufacturing solutions. The mitigation strategies for each of the cases are elaborately explained in [Table 5](#).

7. Managerial implications

Past studies offer several significant managerial implications for organizations involved in AM. These implications encompass strategic decisions, operational enhancements, and resource allocations aimed at leveraging AI technologies to improve quality assurance in AM processes.^{21,22} Below are detailed managerial implications derived from the studies:

- (i) Strategic integration of AI technologies: Organizations should recognize the strategic importance of AI-driven quality assurance in AM and incorporate it into their long-term technology roadmap.¹² Senior management should allocate resources for research and development initiatives focused on AI-driven quality assurance, ensuring alignment with organizational goals and priorities.
- (ii) Investment in talent and expertise: Organizations need to invest in acquiring and developing talent with expertise in AI, ML, computer vision, and AM.^{21,31,34} Training programs, workshops, and knowledge-sharing sessions should be conducted to upskill existing workforce members and foster a culture of innovation and continuous learning.
- (iii) Collaboration and partnerships: Collaborative partnerships with research institutions, universities, and technology providers can accelerate the development and adoption of AI-driven quality assurance solutions.^{2,3,7,9} Organizations should actively engage in industry consortia, standards development organizations, and regulatory bodies to shape guidelines and best practices for AI-enabled AM.
- (iv) Integration with existing workflows: Seamless integration of AI-driven quality assurance tools into existing AM workflows is essential for maximizing efficiency and effectiveness.^{11,13,17} Cross-functional teams comprising engineers, data scientists, and manufacturing experts should collaborate to design and implement integrated solutions that complement existing processes and systems.
- (v) Data management and governance: Organizations must establish robust data management practices and governance frameworks to ensure the quality, security, and integrity of data used in AI-driven quality assurance.^{34,35} Data collection, storage, and processing protocols should comply with relevant regulatory requirements and industry standards to mitigate privacy and security risks.
- (vi) Continuous improvement and iteration: Continuous

Table 5. Mitigation strategies

Drawbacks	Factors	Mitigation strategies
Data variability	Inconsistent data quality	<ul style="list-style-type: none">• Data augmentation: Applying data augmentation techniques, such as rotation, scaling, and noise addition, can help create a more robust training dataset that simulates various conditions.• Standardization protocols: Establishing standardized protocols for data collection can reduce variability. Ensuring consistent camera settings, maintaining controlled environmental conditions, and regular machine calibration can improve data quality.
	Domain adaptation	<ul style="list-style-type: none">• Transfer learning: Using pre-trained models and fine-tuning them with data from the target domain can help adapt models to new environments.• Domain adaptation techniques: Employing domain adaptation methods, such as domain adversarial training, can enhance model robustness to variations across different domains.
Model interpretability	Lack of transparency	<ul style="list-style-type: none">• XAI: Incorporating XAI techniques, such as saliency maps, Layer-wise Relevance Propagation, or SHapley Additive exPlanations, can provide insights into which parts of the input data contributed to the model's predictions.• Model simplification: Using simpler models or decision trees, where feasible, can enhance interpretability without significantly compromising performance.
	Diagnostic use	<ul style="list-style-type: none">• Hybrid models: Combining ML models with traditional statistical methods or rule-based systems can improve both accuracy and interpretability.• Feature importance analysis: Analyzing feature importance can help identify which process parameters most influence defect formation, guiding process optimization efforts.
Implementation complexities	Integration with existing systems	<ul style="list-style-type: none">• Modular architecture: Designing AI systems with modularity in mind can facilitate easier integration. Using APIs and standardized communication protocols can enhance compatibility.• Collaborative development: Working closely with machine manufacturers and software providers can help create more integrated solutions.
	Scalability and real-time processing	<ul style="list-style-type: none">• Edge computing: Implementing edge computing solutions can offload processing to local devices, reducing latency and dependency on central servers.• Optimized algorithms: Using optimized ML algorithms and hardware accelerators, such as GPUs or TPUs, can improve processing speed and scalability.
	Maintenance and updates	<ul style="list-style-type: none">• Automated retraining pipelines: Setting up automated pipelines for data collection, model training, and deployment can streamline maintenance.• Continuous monitoring: Implementing continuous monitoring systems to track model performance and trigger retraining when necessary can ensure sustained model accuracy.

Abbreviations: GPU: Graphics processing unit; ML: Machine learning; TPU: Tensor processing unit, AI: Artificial intelligence; XAI: Explainable artificial intelligence.

monitoring, evaluation, and iteration of AI-driven quality assurance systems are necessary to adapt to evolving manufacturing requirements and technological advancements.^{36,37} Feedback loops should be established to gather insights from production data, user feedback, and performance metrics, enabling continuous improvement and optimization of AI models and algorithms.

- (vii) Risk management and contingency planning: Organizations should proactively identify and mitigate risks associated with AI-driven quality assurance, including algorithmic bias, model overfitting, and system failures.^{19,20} Contingency plans and risk mitigation strategies should be developed to address potential disruptions and ensure business continuity in the event of AI-related issues or failures.
- (viii) Regulatory compliance and certification: Compliance with regulatory standards and certification requirements is critical for gaining approval and acceptance of AI-driven quality assurance solutions in safety-critical industries.^{9,10} Organizations should proactively engage with regulatory agencies, standards bodies, and industry stakeholders to navigate regulatory complexities and obtain necessary certifications and approvals.
- (ix) Customer education and communication: Educating customers and stakeholders about the benefits, capabilities, and limitations of AI-driven quality assurance in AM is essential for building trust and confidence.^{7,8} Transparent communication channels should be established to address customer inquiries, concerns, and expectations regarding the use of AI technologies in quality assurance.
- (x) Scalability and sustainability: Scalability and sustainability considerations should be factored into the design and implementation of AI-driven quality assurance solutions to support long-term growth and expansion.^{16,17} Flexible architectures, modular designs, and cloud-based platforms can facilitate scalability, adaptability, and cost-effectiveness in deploying AI technologies across diverse manufacturing environments.

In summary, embracing AI-driven quality assurance in AM processes entails strategic vision, technological investments, collaborative partnerships, and a culture of continuous improvement.^{1,3,7,18,21,22,32} By leveraging AI technologies effectively and responsibly, organizations can enhance product quality, reduce costs, and drive innovation, positioning them for success in the rapidly evolving landscape of AM.

8. Discussion

The present research sheds light on the transformative potential of AI in revolutionizing quality assurance practices within AM processes.^{14,15} Through an exploration of AI-driven approaches such as defect detection, process monitoring, predictive maintenance, and design optimization, this research underscores the critical role that AI technologies play in enhancing the reliability, efficiency, and consistency of AM operations.

8.1. Advancements in quality assurance

The integration of AI algorithms, ML techniques, and computer vision systems has enabled significant advancements in quality assurance across various stages of the AM process.^{14,18,28} AI-driven defect detection systems can identify and classify defects with high accuracy, enabling real-time quality control and non-destructive testing. Process monitoring and predictive maintenance systems leverage AI to track key process parameters, anticipate equipment failures, and optimize production workflows, thereby minimizing defects and maximizing operational efficiency.^{14,28} Additionally, AI-driven generative design tools empower engineers to explore innovative design alternatives and optimize part geometries for enhanced performance and manufacturability.

8.2. Implications for industry

The implications of AI-driven quality assurance in AM extend beyond technological advancements to strategic, operational, and organizational dimensions. Industry stakeholders must recognize the strategic importance of AI technologies in AM and invest in talent, expertise, and collaborative partnerships to drive innovation and competitiveness.^{11,14,19,28} Seamless integration of AI-driven quality assurance tools into existing workflows, coupled with robust data management and governance practices, is essential for maximizing the benefits of AI technologies while ensuring regulatory compliance and risk mitigation.^{28,29} Moreover, proactive engagement with regulatory agencies, standards bodies, and customers is critical for navigating regulatory complexities and gaining acceptance of AI-enabled AM solutions.

8.3. Future directions and opportunities

As AI-driven quality assurance continues to evolve, future research directions and opportunities abound. Advancements in data availability, model interpretability, and integration with manufacturing workflows will enable organizations to overcome technical barriers and unlock new possibilities for innovation and growth.^{18,28} Moreover,

the development of hybrid AI-physical models that combine data-driven learning with mechanistic understanding holds promise for improving defect prediction, process optimization, and design optimization in AM.^{35,37} By embracing these challenges and opportunities, industry stakeholders can realize the full potential of AI technologies in AM and drive the next wave of industrial revolution.

9. Conclusion

The research on AI-driven quality assurance in AM processes underscores the transformative impact of AI technologies on enhancing product quality, reducing costs, and accelerating innovation in AM. By leveraging AI-driven approaches for defect detection, process monitoring, predictive maintenance, and design optimization, organizations can achieve higher levels of reliability, efficiency, and competitiveness in the rapidly evolving landscape of AM. However, realizing the full potential of AI technologies requires strategic vision, technological investments, collaborative partnerships, and a culture of continuous improvement. By embracing these principles and harnessing the power of AI, industry stakeholders can position themselves for success in the digital era of AM.

To fully realize the potential of AI technologies in AM, several actionable recommendations and future research directions should be considered:

- (i) Development of standardized datasets
 - Action: Establish standardized datasets for various AM processes and materials to facilitate the training and benchmarking of AI models.
 - Impact: Standardized datasets will ensure consistency and comparability across studies, accelerating the development and deployment of robust AI models.
- (ii) Benchmarking methodologies
 - Action: Develop and adopt benchmarking methodologies to evaluate the performance of different AI techniques in AM quality assurance.
 - Impact: Benchmarking will provide a clear understanding of the strengths and limitations of various AI approaches, guiding practitioners in selecting the most suitable methods for their specific applications.
- (iii) Interdisciplinary collaborations
 - Action: Foster collaborations between AI researchers, material scientists, and AM practitioners to address complex challenges and drive innovation.

- Impact: Interdisciplinary partnerships will combine expertise from different fields, leading to the development of more effective and practical AI-driven solutions for AM.
- (iv) Investments in technological infrastructure
 - Action: Invest in advanced technological infrastructure, including high-resolution sensors, edge computing devices, and specialized hardware like GPUs.
 - Impact: Enhanced infrastructure will support the real-time processing and integration of AI systems, improving the overall efficiency and effectiveness of quality assurance processes.
 - (v) Focus on explainable AI
 - Action: Prioritize the development of explainable AI models to ensure transparency and trust in AI-driven quality assurance systems.
 - Impact: Explainable AI will help stakeholders understand and trust the decision-making processes of AI models, facilitating their acceptance and adoption in critical manufacturing environments.
 - (vi) Continuous improvement and adaptation
 - Action: Cultivate a culture of continuous improvement and adaptation to incorporate new AI advancements and address emerging challenges in AM.
 - Impact: A commitment to continuous improvement will ensure that AI-driven quality assurance systems remain up-to-date and effective in a dynamic technological landscape.

By implementing these recommendations and harnessing the power of AI, industry stakeholders can position themselves for success in the digital era of AM. Future research should focus on refining AI techniques, improving data quality, and developing comprehensive frameworks for integrating AI into AM processes. Through strategic vision, technological investments, and collaborative efforts, the full potential of AI-driven quality assurance in AM can be realized, driving the industry toward a more innovative and efficient future.

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