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REVIEW

A Review of the Application of Machine Learning in Additive Manufacturing

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ABSTRACT: Additive manufacturing (AM) has emerged as a transformative technology in modern manufacturing, offering unprecedented capabilities for producing complex geometries and customized components. However, the widespread adoption of AM is hindered by insufficient quality control, stemming from the multi-factor coupling characteristics of the manufacturing process. Machine learning (ML) presents a promising solution by enabling data-driven approaches to process optimization, quality prediction, and defect detection. This review examines the application landscape of ML techniques in AM through comprehensive analysis of recent literature. The study categorizes ML applications into four primary domains: real-time process monitoring and control, process parameter optimization and prediction, material property prediction, and quality inspection and defect identification. Random Forest (RF), neural networks (NN), and Support Vector Machines (SVM) emerge as the most widely adopted algorithms, demonstrating strong performance in handling high-dimensional, nonlinear relationships between process parameters and product quality. The analysis reveals that while ML methods have achieved significant success in offline prediction tasks, most research remains at the supervised learning stage, lacking cross-material adaptability, real-time feedback control capabilities, and model interpretability. The review identifies critical gaps in current research, including the need for closed-loop autonomous control systems, transfer learning across different materials and machines, and physics-informed ML models that integrate domain knowledge. This work provides a comprehensive reference for researchers and practitioners, highlighting both the achievements and limitations of ML applications in AM, and proposing future directions toward intelligent, autonomous, and high-reliability AM systems.

KEYWORDS: Additive manufacturing; machine learning; quality control; process optimization

1 Introduction

In the current wave of manufacturing transformation and upgrading, achieving efficient fabrication of complex structures, reducing the cost of customized production, and shortening product development cycles remain major challenges for traditional manufacturing industries [1]. AM has emerged as a promising solution to these issues [2]. Unlike conventional manufacturing, which relies on molds, tools, and material removal or forming processes, AM directly fabricates three-dimensional components through layer-by-layer material deposition [3]. This fundamental difference has reshaped the manufacturing paradigm and significantly expanded design freedom. By minimizing traditional manufacturability constraints, AM enables the direct fabrication of complex geometries such as internal channels, deep cavities, and lightweight structures, making it particularly attractive for aerospace, biomedical, and automotive applications [4,5].

With the maturation of metal AM and the increasing capability to process high-performance materials such as titanium alloys and nickel-based superalloys, AM has evolved from a rapid prototyping tool into a viable technology for manufacturing end-use components.

However, one persistent challenge in AM is the anisotropic behavior of printed parts. Because AM components are built layer by layer under highly directional thermal gradients, repeated reheating cycles, and non-uniform solidification conditions, their microstructure and mechanical response often differ significantly with build orientation [6,7]. This anisotropy may manifest in tensile strength, ductility, fatigue resistance, residual stress, and even thermal expansion, thereby limiting the reliability of AM parts in structural applications. The degree of anisotropy is also strongly influenced by process parameters. For example, build orientation directly determines the loading direction relative to interlayer boundaries; laser power, scan speed, hatch spacing, and layer thickness affect melt-pool geometry, cooling rate, and grain growth; and scan strategy influences thermal accumulation, residual stress evolution, and texture formation. As a result, understanding and controlling anisotropy has become a critical prerequisite for achieving stable quality and reliable performance in AM.

Despite these advantages, the broader industrial adoption of AM is still hindered by insufficient quality control. The AM process involves strong multi-factor coupling, where variables such as laser power, scanning speed, layer thickness, shielding atmosphere, and powder characteristics jointly influence melt-pool behavior, solidification dynamics, and final part quality [8]. In addition, the complete AM workflow—from CAD model preparation and support design to slicing, energy deposition, layer-by-layer fabrication, support removal, and post-processing—contains numerous interdependent variables whose effects may accumulate over time. For example, thermal accumulation in earlier layers can influence the solidification behavior of later layers, while local energy fluctuations may induce porosity that subsequently acts as an initiation site for fatigue cracks. Such complex process–structure–property relationships make quality prediction and process control highly challenging.

In recent years, advances in sensing and data acquisition technologies have accelerated the transition of AM from experience-driven practice toward data-driven manufacturing. Modern AM platforms are increasingly equipped with high-speed cameras, infrared thermography systems, and interlayer scanning devices, enabling real-time acquisition of process information such as melt-pool geometry, temperature-field evolution, and powder-bed morphology. A single build can generate gigabytes of heterogeneous data spanning multiple temporal and spatial scales, from microsecond-level melt-pool dynamics to hour-level part formation, and from micrometer-scale microstructures to centimeter-scale geometries. However, abundant data do not automatically translate into actionable knowledge. Extracting key features from high-dimensional spatiotemporal data, quantifying the influence of process variables on quality, and predicting defects before they occur all require analytical tools beyond conventional modeling approaches.

ML provides a powerful data-driven framework to address these challenges. Unlike traditional methods that often depend on explicit physical modeling, ML can establish predictive relationships directly from data by learning statistical patterns between inputs and outputs. Different ML techniques offer complementary advantages: deep NN can automatically extract hierarchical features, ensemble methods can integrate heterogeneous information, and transfer learning can support knowledge reuse across materials and devices. Against this background, this review aims to systematically summarize recent applications of ML in AM, covering process monitoring, parameter optimization, material-property prediction, and quality inspection. By synthesizing representative achievements, current limitations, and future directions, this work seeks to clarify the role of ML in promoting AM toward more intelligent, autonomous, and high-reliability manufacturing systems.

2 Materials and Methods

2.1 AM

AM technology, with its unique method of building three-dimensional solids layer by layer, offers unprecedented possibilities for realizing complex structural components and functionally graded materials. Current mainstream AM processes include various technical routes such as laser-based selective melting, material extrusion, material jetting, binder jetting, and electron beam forming [9]. These methods differ significantly in energy source type, material morphology, forming mechanism, and applicable scenarios. For example, laser and electron beam processes are suitable for high-energy forming of high-melting-point metals, while extrusion and jetting technologies show broad applicability in polymer, composite material, and multi-material printing [10]. Although various technical paths emphasize different aspects of forming accuracy, manufacturing efficiency, and material adaptability, they all share the core challenges of multi-physics coupling, dynamic process response, and microscopic defect control. Traditional physics-based modeling methods often fall short in handling such nonlinear, high-dimensional problems.

In terms of specific process implementation, laser AM relies on high-energy beams to locally melt powder, involving a complex thermo-fluid-solid coupling process; extrusion processes extrude molten material through nozzles, controlled by temperature, speed, and path planning; material jetting technology focuses on microdroplet deposition, emphasizing droplet behavior and deposition precision control; binder jetting and lamination processes focus on layer bonding and adhesion mechanisms [11]. Although these processes differ in principle, they generally suffer from narrow process windows, high defect sensitivity, and difficulty in ensuring consistent forming [12]. Therefore, it is urgent to introduce data-driven methods to mine potential patterns from massive manufacturing data, to compensate for the shortcomings of traditional modeling in real-time response and multivariate optimization, and to promote the evolution of AM towards intelligence and high reliability.

Fig. 1 illustrates the standard workflow of AM, comprising five key steps: First, a 3D digital model is created in CAD software; then, the model file is converted to the STL standard format; next, slicing software is used to decompose the model into layer-by-layer slice data; finally, AM equipment physically shapes the model by stacking materials layer by layer according to the slice information, ultimately obtaining a 3D physical product. The entire process embodies the complete transformation from digital design to physical manufacturing, and is a visual representation of the core concept of AM technology: "layered manufacturing, layer-by-layer stacking."

Beyond the classical viewpoint that AM enables the fabrication of three-dimensional objects from digital models through a layer-by-layer material addition strategy, the engineering logic of "layer design–layer deposition–layer consolidation" is also crucial when AM is used to build multi-layer functional structures. In particulate-based AM routes (e.g., powder bed fusion and binder jetting), powder size distribution, particle shape, and surface characteristics influence packing density and spreading behavior, and thereby affect defects and bonding quality. In addition to technical feasibility, AM is increasingly evaluated from techno-economic and sustainability perspectives. Levelized cost concepts used in energy systems, which relate the present value of costs to delivered output, provide a useful analogy for structuring AM cost/energy accounting across the full process chain. In other engineering domains, swarm intelligence methods have been used for parameter estimation by treating the task as a stochastic search over a high-dimensional parameter space. Similar population-based optimization ideas can be adopted for AM parameter calibration and robust process setting under uncertainty. Among the seven ASTM AM categories, a dedicated review summarizes how void size and distribution depend on deposited track geometry, layer shape, and infill strategy, and organizes void-reduction approaches into pre-deposition planning, *in-situ* control, and post-processing treatments [13]. Reported analyses indicate that extrusion temperature, printing speed, raster/infill strategy, and cooling history jointly determine interlayer bonding, residual stress, and defect formation, thereby providing a practical framework for parameter selection and quality assurance in engineering-grade polymer AM. Multi-physics modeling is another key enabler for understanding and optimizing AM Reviews of multi-physics simulation in other advanced manufacturing processes emphasize common coupling strategies and show that prediction accuracy is sensitive to material models and boundary-condition assumptions, which is directly relevant when building predictive AM models. AM also plays a growing role in biomedical manufacturing. Research on advanced wound dressings shows how choices of biopolymers and microstructures influence antimicrobial function, moisture management, and tissue regeneration, offering transferable design cues for AM/bioprinting of porous scaffolds and customized medical constructs. Automated defect inspection studies based on scanning electron microscopy (SEM) illustrate a workflow including image preprocessing, feature extraction, and classification/decision stages for systematic defect identification. Finally, among AM routes with high geometric fidelity. Medical applications of material jetting have been reported for anatomical models, surgical planning, and device prototyping, reinforcing its value for patient-specific manufacturing where accuracy and surface finish are critical. A recent review on ML and data-driven predictive analysis in power systems emphasizes that robust predictive modeling must cope with multimodal inputs, nonlinearity, and uncertainty—concepts that are directly transferrable to AM quality prediction and process-risk assessment when building reliable digital twins of the print process.

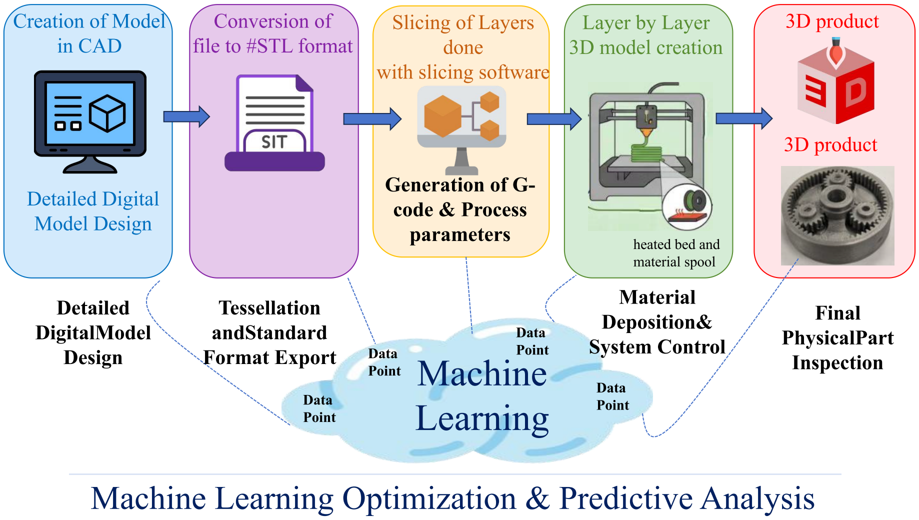

Figure 1: AM process.

At the material–process interface, interlayer bonding and adhesion govern mechanical integrity, especially in binder- and lamination-based AM. Bioinspired adhesion chemistry suggests that molecular motifs can modulate wetting and interfacial cohesion, motivating surface functionalization and binder design to enhance bonding stability in multi-layer builds. Complementing deterministic modeling, generative AI can learn complex distributions and represent uncertainty; multimodal generative models reviewed for wildfire-spread prediction (GANs, VAEs, transformers) motivate analogous AM uses such as synthesizing realistic process states, augmenting scarce defect data, and enabling rapid what-if robustness analyses. AM's geometric freedom also supports application-specific devices difficult for subtractive methods, as demonstrated by additively manufactured 3D optical markers designed for durable underwater deployment. Because AM planning inherently trades off quality, throughput, energy, and microstructure/defect control, it can be framed as multivariate optimization with explicit cost–benefit regularization. In laser-based AM, process parameters (e.g., energy density, defocusing distance) critically shape melt-pool geometry, microstructure, and defect formation, underscoring the need for careful process-window design and monitoring.

For scalable deployment, system-level reliability and digitalized workflows become equally important. Robotic integration and AI-enabled predictive maintenance can reduce downtime and maintenance cost, supporting stable, repeatable AM production lines. For fiber-reinforced and composite AM architectures, rigorous stability criteria and constitutive modeling—such as coupled Legendre–Hadamard conditions for Cosserat solids/shells—provide guidance for model development and verification. Upstream, controllable AI-assisted CAD generation (e.g., hierarchical neural coding with transformer-based completion) can accelerate design exploration while producing AM-ready geometries under constraints. Downstream, multi-sensor monitoring faces cross-sensitivity; strategies for decoupled multimodal sensing can inform AM sensor-suite design and data fusion for closed-loop control, while deep reinforcement learning offers a route to threshold-free maintenance decision-making that balances lifecycle cost and reliability. For outcome prediction, hybrid surrogate learning with global optimization (e.g., SA–PSO-tuned SVR) illustrates transferable pathways to improve predictive reliability for AM distortion or dimensional deviation. Theoretical frameworks such as DR-PDEE further clarify validity limits of reduced-order, data-driven models under partial observability—an intrinsic challenge in AM monitoring; related layerwise, scale-progressive filtering ideas from inverse analysis suggest ways to separate global drift from local defect signatures in sensor fields. In binder jetting, coordinated control of feedstock, binder spreading/saturation, and post-processing is central to final performance; at the equipment level, interpretable adaptive controllers (e.g., optimized fuzzy logic with intermediate states) provide templates for robust state management and fault handling. Finally, functionally graded materials highlight how property gradients can mitigate stress concentrations and improve compatibility, reinforcing the value of integrating graded-material design with AM process planning and data-driven validation.

2.2 Overview of Machine Learning Methods

ML is a discipline that investigates how computers can emulate human learning processes to acquire knowledge, optimize decision-making, and enhance system performance [14]. According to different learning paradigms, ML can be categorized into four main types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. As shown in Fig. 2, supervised learning relies on labeled data (X, Y) to train models $f_\theta(X) \approx Y$ for predicting unseen data. Unsupervised learning, on the other hand, deals with unlabeled data X, aiming to discover underlying structures such as clusters or lower-dimensional representations $(X \to Z)$. Semi-supervised learning leverages a small amount of labeled data (X_l, Y_l) together with a large set of unlabeled data X_u to reduce labeling costs while enhancing model performance. Reinforcement learning enables an agent a_t to interact with the environment state s_t and learn an optimal policy π^* by maximizing cumulative rewards:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_t r_t\right] \tag{1}$$

Supervised learning is suitable for classification and regression tasks with high accuracy but requires extensive labeled data. Unsupervised learning can reveal hidden patterns in data but often lacks interpretability. Semi-supervised learning balances labeling cost and predictive performance.

ML models offer diverse data-driven tools for solving complex problems in AM. Among them, ensemble learning models, such as random forests, cleverly utilize "double randomness" to enhance robustness and generalization ability by constructing numerous decision trees and making collective decisions. They can not only establish complex nonlinear mappings between process parameters and forming quality with high precision, but their inherent feature importance analysis function can also reveal key influencing factors for researchers, thus overcoming the overfitting limitations of single decision trees and demonstrating powerful effectiveness in parameter optimization and knowledge discovery.

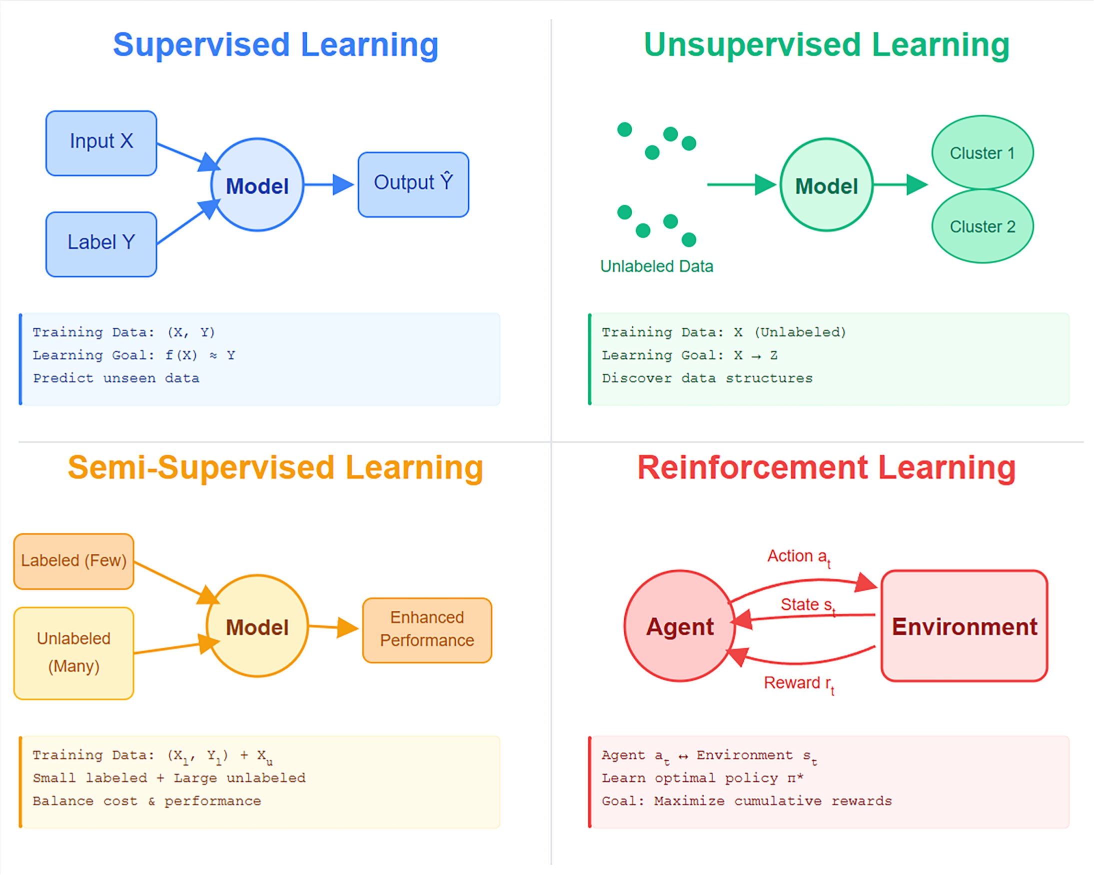

Figure 2: Comparative diagram of the four core paradigms in ML.

When processing unstructured data such as images and sound, convolutional NN dominate due to their biomimetic hierarchical structure. Through convolutional kernels with “local connectivity” and “weight sharing,” they can automatically extract features from raw pixel data from shallow to deep—from basic edge textures to complex morphological patterns. This end-to-end feature learning capability allows them to achieve superior accuracy and automation in visual tasks such as melt pool monitoring, powder surface analysis, and defect identification without relying on tedious and subjective manual feature engineering, becoming the core of intelligent *in-situ* monitoring.

For challenges requiring dynamic sequential decision-making, reinforcement learning offers a fundamentally different paradigm. It models the manufacturing process as a learning system where an agent continuously interacts with its environment: the agent executes actions based on its current state and learns the optimal strategy from reward signals received from the environment. Its core lies in the trade-off between “exploration” and “exploitation,” with the ultimate goal of maximizing long-term cumulative rewards through trial and error. This makes reinforcement learning particularly suitable for scenarios lacking explicit physical models but where results can be evaluated, such as dynamic optimization of printing paths and online adaptive control of process parameters, laying the algorithmic foundation for achieving fully autonomous intelligent closed-loop AM systems.

2.3 Literature Search Strategy and Selection Criteria

This review was conducted to systematically summarize recent research on the application of ML in AM. The literature collection and screening process was designed to support the four analytical domains adopted in this review, namely: (1) real-time process monitoring and control, (2) process parameter optimization and prediction, (3) material property prediction, and (4) quality inspection and defect identification. These four domains constitute the main analytical framework of the manuscript.

Literature was retrieved from Web of Science, Scopus, ScienceDirect, IEEE Xplore and Google Scholar. The literature search focused primarily on recent studies published between 2023 and early 2026, while a limited number of earlier foundational references published from 2012 onward were retained to provide background on AM technologies and general ML concepts. This time window reflects the rapid development of ML-enabled AM research in recent years and is consistent with the distribution of the references cited in this review, where the early references mainly provide background context and the majority of application-oriented studies are concentrated in the more recent literature.

The search strategy was based on combinations of AM-related and ML-related keywords. Representative search terms included: “AM,” “laser powder bed fusion,” “wire arc AM,” “defect detection,” “quality inspection,” “process monitoring,” “parameter optimization,” “material property prediction,” “ML,” “deep learning,” “,” “support vector machine,” “NN,” and “reinforcement learning.” These keywords were selected to match the scope of the present review and to capture studies involving both general AM workflows and specific data-driven modeling tasks.

The inclusion criteria were defined as follows: (1) the study focused on the application of ML methods in AM; (2) the paper reported a clear AM process, material system, or manufacturing task; (3) the work contained identifiable ML techniques, such as classification, regression, optimization, or decision-making methods; and (4) the paper provided sufficient technical detail to support qualitative comparison across studies.

The exclusion criteria included: (1) duplicate records; (2) studies unrelated to AM; (3) papers that mentioned ML only superficially without substantive methodological content; (4) studies lacking sufficient technical information for meaningful comparison; and (5) publications outside the thematic scope of the four analytical domains considered in this review. After screening and thematic classification, the final corpus used in this review consisted of 66 cited references, among which 44 representative application-oriented studies formed the core qualitative basis for the comparative discussion. The earlier references were mainly used to introduce AM background, manufacturing principles, and general ML concepts, whereas the later references were used to analyze recent advances in ML-driven AM applications.

No formal quantitative meta-analysis was performed in this study. The main reason is the substantial heterogeneity among the selected studies in terms of AM process type, material system, sensor modality, dataset size, target variables, and evaluation metrics. Under such conditions, direct statistical aggregation would not be sufficiently robust or comparable. Therefore, this work is positioned as a structured qualitative review with comparative analysis, with emphasis placed on identifying major research trends, commonly adopted algorithms, representative achievements, and persistent limitations across the four application domains.

3 Research on the Application of ML in AM

ML methods discussed in this review include RF, an ensemble learning method based on multiple decision trees; SVM, a supervised learning method for classification and regression; K-Nearest Neighbors (KNN), a distance-based learning algorithm; and NN, data-driven models capable of capturing complex nonlinear relationships. For image-based tasks, Convolutional Neural Networks (CNNs) are particularly effective, while methods such as Generative Adversarial Networks (GANs) can support data generation and augmentation.

This paper analyzes the literature on the application of ML in AM, collecting and analyzing multiple relevant research papers. Recent studies have further expanded the application of ML in additively manufactured metallic systems, particularly in process monitoring, parameter optimization, and material-property prediction. These developments highlight the growing importance of ML in improving the quality, reliability, and performance of metal AM components. Through in-depth analysis of the literature, the research results are divided into four main categories: process monitoring and real-time control, process parameter optimization and prediction, material property prediction, and quality inspection and defect identification. As shown in Fig. 3, six mainstream AM technologies (including laser powder bed melting, electron beam, and direct energy deposition) are used as data input sources. Six ML algorithms (RF, NN, CNN, SVN, decision tree, and reinforcement learning) are used for intelligent analysis, resulting in four major application directions (real-time monitoring, parameter optimization, material performance prediction, and defect detection). Industrial deployment of ML-enabled AM, especially in aerospace and medical fields, depends not only on model accuracy but also on qualification cost, certification requirements, and repeatable part-level reliability. Therefore, the transition from laboratory research to large-scale application will require stronger integration between ML models and validation frameworks that can support traceability, process qualification, and safety-critical manufacturing standards. These are ultimately deployed in industrial fields such as aerospace, medical, automotive, and electronics. The feedback loop marked in the figure indicates that the application results are continuously fed back to the technology and algorithm levels, forming a closed-loop optimization system, fully demonstrating the multi-layered application ecosystem of the deep integration of ML and AM.

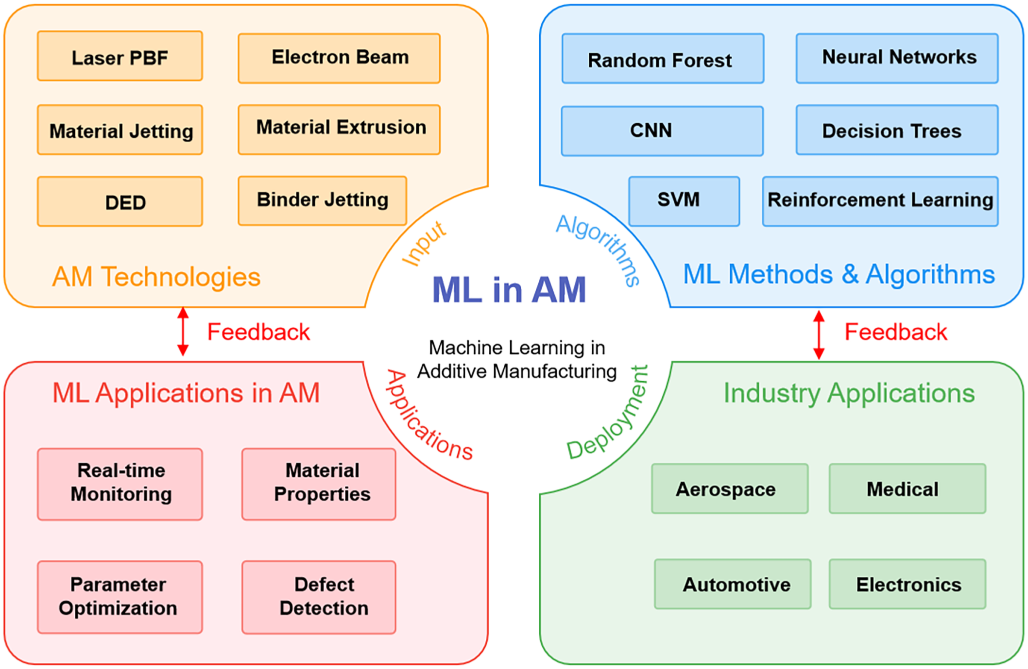

Figure 3: ML in AM.

Although, NN, and SVMs are among the most frequently adopted algorithms in AM research, their prevalence does not necessarily indicate universal superiority. Their relative performance depends strongly on the task type, data modality, sample size, and computational constraints. Therefore, Table 1 summarizes the comparative characteristics of these representative algorithms across major AM application domains.

Table 1: Comparative analysis of RF, NN, and SVM for different AM tasks.

Algorithm	Typical AM Applications	Common Data Types	Predictive Performance Characteristics	Training Data Requirement	Computational Efficiency	Main Advantages	Main Limitations
RF	Process parameter optimization, material property prediction, process monitoring based on engineered sensor features	Structured tabular data, extracted statistical features, process variables	Generally robust and stable on small- to medium-sized datasets; often achieves strong accuracy for regression and classification when data are noisy or heterogeneous	Low to moderate	High training and inference efficiency	Good generalization, resistant to overfitting, interpretable feature importance, less sensitive to scaling	Limited ability to learn highly complex spatial or image features; performance may plateau on high-dimensional raw data
NN	Quality inspection, defect identification, image-based monitoring, multimodal process prediction, complex process–property mapping	Images, thermal fields, time-series signals, multimodal high-dimensional data	Often superior for highly nonlinear and image-based tasks; strong representation capability and end-to-end learning potential	High	Moderate to low, depending on model depth and hardware support	Excellent nonlinear fitting ability, automatic feature extraction, suitable for complex and multimodal AM data	Requires larger datasets, longer training time, greater hardware support, and has lower interpretability
SVM	Defect classification, parameter prediction, small-sample regression or classification, feature-based monitoring	Medium-dimensional tabular data, engineered features, limited-size datasets	Competitive accuracy on small and medium datasets, especially when class boundaries are well defined or features are carefully designed	Low to mode-rate	Moderate; can become expensive for very large datasets	Effective in high-dimensional feature spaces, suitable for limited data, strong theoretical foundation	Sensitive to kernel and hyperparameter selection, limited scalability, less suitable for raw large-scale image learning

3.1 ML for Real-Time Control in AM

In the AM process, real-time monitoring and control are critical to ensuring product quality. By applying ML techniques for intelligent process monitoring, abnormalities can be detected and addressed in a timely manner, thereby improving product consistency and reliability, as shown in Fig. 4 and Table 2. Following this, Kishor et al. [15] further explored sensor-based monitoring and control of the manufacturing process. The RF and ML methods applied in their research demonstrated strong performance in handling complex data. Building upon these findings, Xie et al. [16] conducted an in-depth investigation into three CMKT methods, focusing on semantic alignment. Their work adopted RF and ML techniques and offered new approaches to addressing key challenges in this domain. Pereira et al. [17] focused on implementing real-time corrective strategies. By applying SVMs, ML techniques, and NN, the study achieved significant research outcomes. Mattera and Nele [18] concentrated on ML approaches and also achieved notable results through the application of RF and ML algorithms.

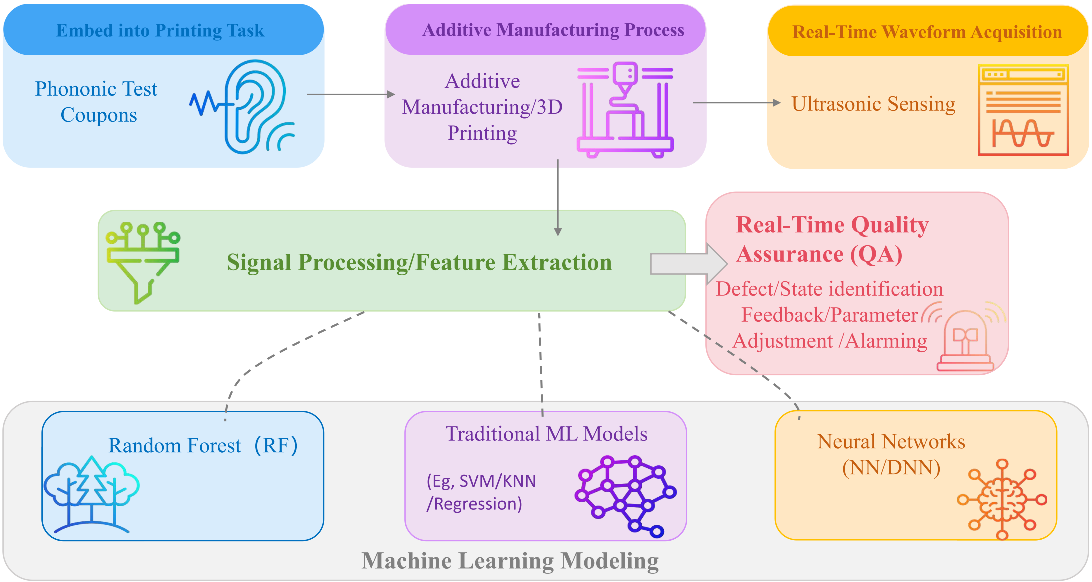

Figure 4: PTCs for real-time quality assurance in AM/additive manufacturing.

Table 2: Representative studies on ML for real-time process monitoring and control in AM.

Author	Year	Specific ML Methods/Frameworks	Core Innovation
Kishor et al. [15]	2025	RF	Is to use sensors-based monitoring and controlling the process
Xie et al. [16]	2025	Cross-modality knowledge transfer framework	Three cmkt methods: semantic alignment
Pereira et al. [17]	2025	Support vector machine, NN	And employing real-time corrective strategies
Mattera and Nele [18]	2025	RF	ML approaches
Ramalho et al. [19]	2025	RF, deep learning	Classified onset of instabilities with similar to 85% accuracy (f1-score)
Xie et al. [20]	2025	Reproducible ML framework	Towards reproducible ML-based process monitoring and quality prediction research

(Continued)

Table 2 (continued)

Author	Year	Specific ML Methods/Frameworks	Core Innovation
Le et al. [21]	2026	RF, SVM, decision tree	ML-based prediction models of single weld bead attributes in wire arc additive manufac
Al and Martinez-Hernandez [22]	2025	RF, logistic regression, SVM	Filament type recognition
Wang et al. [23]	2024	ML-enabled sensing framework	Sub-surface thermal measurement in AM via ML-enabled high-resoluti
Awd et al. [24]	2024	Mechanistic ML	Mechanistic ML
Maucher et al. [25]	2024	Reinforcement learning, NN	Qualification method with a corresponding device is introduced
Anand et al. [26]	2025	Gradient roosting, XGBoost, RF, NN	Application and Comparison of ML Models

In addition, numerous scholars have made substantial contributions to this research direction. Ramalho et al. [19] applied RF to classify the onset of instabilities and achieved an accuracy (F1-score) of approximately 85%. Xie et al. [20] proposed a framework toward reproducible ML-based process monitoring and quality prediction. Le et al. [21] developed ML-based prediction models for single weld bead characteristics in wire arc AM. Al and Martinez-Hernandez [22] used RF to study filament type recognition. Wang et al. [23] introduced a ML-enabled high-resolution subsurface thermal measurement technique for AM. Awd et al. [24] developed a mechanistic ML approach, while Maucher et al. [25] used reinforcement learning to propose a qualification method accompanied by a corresponding device. Anand et al. [26] developed and compared RF, Gradient Boosting, XGBoost, and NN models for predicting grinding parameters in additively manufactured Ti-6Al-4V alloy, and found that XGBoost provided the most accurate overall prediction performance.

From a methodological perspective, research in this field primarily employs ML algorithms such as ML, RF, and NN. ML is widely used due to its flexible modeling methods and broad applicability; RF, with its good generalization ability and strong resistance to overfitting. In practical applications, these studies mainly focus on multiple aspects such as molten pool monitoring, temperature field tracking, acoustic signal analysis, and visual inspection, achieving comprehensive monitoring of the AM process through multi-sensor fusion and multi-modal data processing.

3.2 ML for Process Parameter Optimization and Prediction

The selection of process parameters directly affects the quality and performance of AM products. Optimizing and predicting process parameters using ML methods can effectively shorten the process development cycle, reduce trial and error costs, and improve manufacturing efficiency. de Araújo et al. [27] conducted innovative research in this field in 2025. They used RF, ML, and other ML algorithms, providing an important methodological foundation for subsequent research. Subsequently, as shown in Fig. 5 and Table 3, Mo et al. [28] further explored a hybrid framework integrating experiments. The RF, ensemble learning, and SVM methods used in the study showed good performance in handling complex data. Based on this, Niu et al. [29] conducted in-depth research on multi-scale target detection of metal surface defects in AM based on reinforcement. This work used RF and reinforcement learning techniques, providing new ideas for solving key problems in this field. Zhang et al. [30] focused on reducing distortion in a bridge sample from 0. Significant research results were achieved through the application of RF, ML, and ensemble learning methods. Ko et al. [31] focused on d-ecomposer: sustainable part decomposition. Significant research results were achieved through the application of RF, reinforcement learning, and ML methods. In addition, many scholars have made important contributions in this direction. Wang et al. [32] studied trained on 48 high-fidelity cfd simulations using the RF method; generalizes readily to unmasked cold spray configuration; Xia et al. [33] proposed surrogate modelling of thermal and residual stress fields in cold-spray AM using; Song et al. [34] developed high-cycle fatigue life prediction of AM inconel 718 alloy via ML; Mohamed et al. [35] studied the L-PBF high-strength A205 Al alloy using the reinforcement learning method; Zhang et al. [36] proposed modelling and prediction of process parameters with low energy consumption in wire arc AM; Pelzer et al. [37] developed acquiring process knowledge in extrusion-based AM via Interpretable ML; from a methodological perspective, research in this field mainly employs ML algorithms such as RF, ML, and ensemble learning.

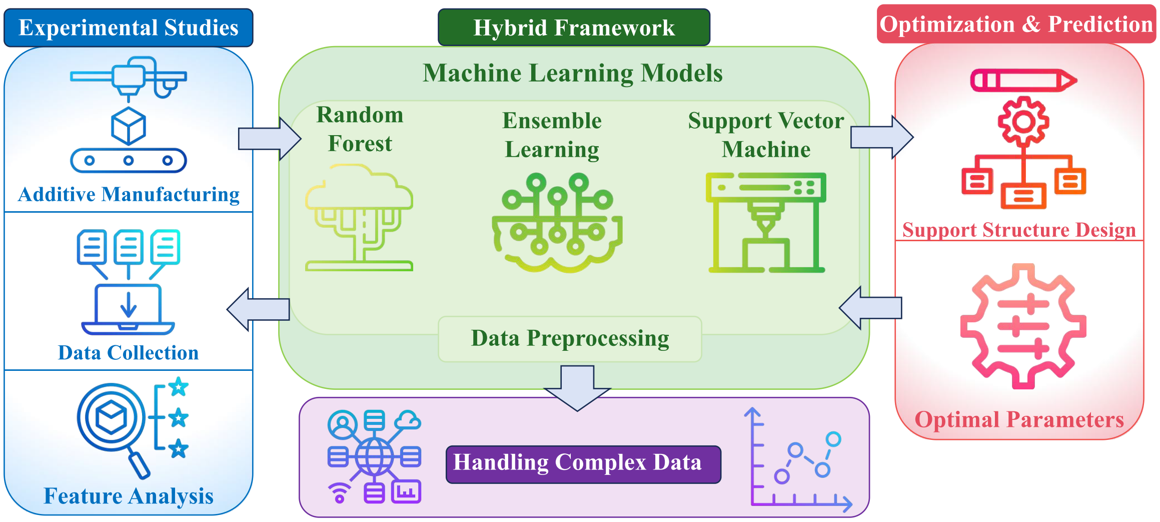

Figure 5: A hybrid framework integrating experiments in handling complex data.

Table 3: Representative studies on ML for process parameter optimization and prediction in AM.

Author	Year	Specific ML Methods/Frameworks	Core Innovation
de Araújo et al. [27]	2025	ML-based algorithm selection framework	The first empirical investigation of algorithm selection for 3dip problems; to use, typically a packing algorithm
Mo et al. [28]	2025	RF, ensemble learning,SVM	A hybrid framework integrating experiments; integrating experiments
Niu et al. [29]	2025	RF, reinforcement learning	Multi-scale target detection of metal surface defects in AM based on rein
Zhang et al. [30]	2025	ML-based predictive framework ensemble learning	Reduces distortion in a bridge sample from 0

(Continued)

Table 3 (continued)

Author	Year	Specific ML Methods/Frameworks	Core Innovation
Ko et al. [31]	2025	ML-based life-cycle assessment framework reinforcement learning	D-ecomposer: sustainable part decomposition
Wang et al. [32]	2025	RF, KNN	Trained on 48 high-fidelity cfd simulations; generalizes readily to unmasked cold spray configurations
Xia et al. [33]	2025	ML-based surrogate model ensemble learning	Surrogate modelling of thermal and residual stress fields in cold-spray AM using
Song et al. [34]	2025	Generative adversarial network, NN	High-cycle fatigue life prediction of AM inconel 718 alloy via ML
Mohamed et al. [35]	2025	Reinforcement learning	Has been experimentally validated on l-pbf high-strength a205 Al alloy
Zhang et al. [36]	2024	ML-based predictive model,ensemble learning, NN	Modelling and prediction of process parameters with low energy consumption in wire arc additive manu
Pelzer et al. [37]	2023	Interpretable ML	Acquiring process knowledge in extrusion-based AM via interpretable machine lear

Although recent studies demonstrate successful use of ML in algorithm selection, defect detection, surrogate modeling, and fatigue prediction, most models lack cross-material adaptability, real-time feedback control, and interpretability.

3.3 ML for Predicting Material Properties

Material performance prediction is an important research direction in the field of AM. By establishing the mapping relationship between process parameters and material properties through ML algorithms, product performance can be predicted before manufacturing, guiding material selection and process design. Li et al. [38] conducted innovative research in this field in 2025, studying the young's modulus of different variants of in 718 alloy in AM and trad. This study used ML algorithms such as RF and ML, providing an important methodological foundation for subsequent research. Based on this, as shown in Fig. 6 and Table 4, Soms et al. [39] conducted in-depth research on the ML algorithms based approach on prediction of mechanical behavior of pla/brass composites. This work used RF, SVM, and decision tree techniques, providing new ideas for solving key problems in this field. The research by Rifino et al. [40] focuses on significant challenges by eliminating manual trials for maximizing adhesion. Significant research results were achieved through the application of RF, ML, and SVM methods. In addition, many scholars have made important contributions in this direction. Oh and Yoo [41] studied ML-assisted design of composite em collimators considering AM cons using ML methods; Akbari et al. [42] developed benchmarking ML models for predicting mechanical properties, incorporated physics-aware featuriz; Riensche et al. [43] proposed a physics and data integrated modeling approach, consisting of two steps; Zhu et al. [44] developed ML-based hardness prediction of high-entropy alloys. From a methodological perspective, research in this field mainly adopts ML algorithms such as RF, ML, and SVM. Among them, RF is widely used due to its good generalization ability and strong resistance to overfitting, and a total of 11 papers have adopted this method.

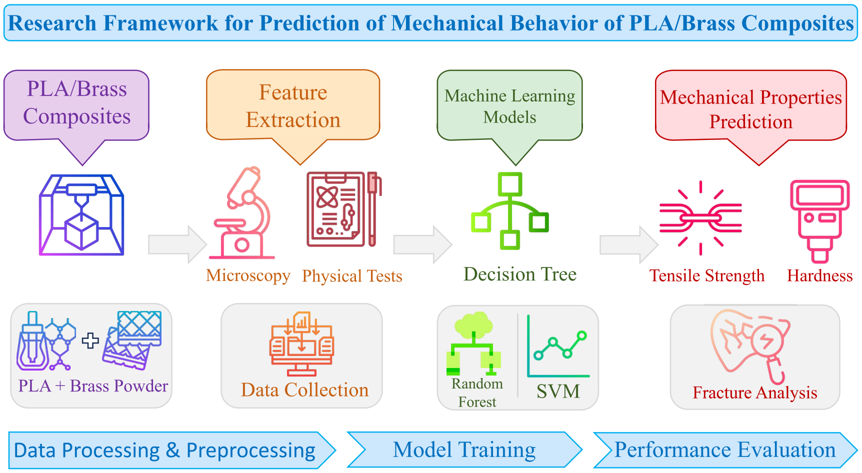

Figure 6: Research framework for prediction of mechanical behavior of PLA/brass composites.

Table 4: Representative studies on ML for material property prediction in AM.

Author	Year	Specific ML Methods/Frameworks	Core Innovation
Li et al. [38]	2025	RF	Study on the young's modulus of different variants of in 718 alloy in AM and trad
Soms et al. [39]	2025	RF, SVM, decision tree	ML algorithms based approach on prediction of mechanical behaviour of pla/brass composites
Rifino et al. [40]	2025	RF, support vector machine	Significant challenges; by eliminating manual trials for maximizing adhesion
Oh and Yoo [41]	2026	ML-assisted design framework, NN	ML-assisted design of composite em collimators considering AM cons
Akbari et al. [42]	2024	Benchmarking framework, physics-aware featurization	For benchmarking ml models for predicting mechanical properties; incorporates physics-aware featurization specific to mam
Riensche et al. [43]	2024	Physics-based ML	Physics and data integrated modeling approach; consists of two steps
Zhu et al. [44]	2023	RF, GANs, NN	ML-based hardness prediction of high-entropy alloys

Although existing studies prove that ML can significantly improve material-property prediction and AM design efficiency, the majority of the work remains at the prediction level rather than enabling autonomous manufacturing.

Equations and mathematical expressions must be inserted into the main text. Equations should be created using either MathType or Word's built-in equation editor, with a single editor applied consistently throughout the article, and formulas must not be inserted as images. Authors may format formulas in either in-line or display style.

3.4 ML for Quality Inspection and Defect Identification in AM

Quality inspection and defect identification are core components of the AM quality assurance system. ML technology can automatically identify and classify various defect types, achieve rapid and accurate quality assessment, and reduce the workload of manual inspection. Karabiyik [45] conducted innovative research in this field in 2025. They used RF, reinforcement learning, ML and other ML algorithms, which provided an important methodological foundation for subsequent research. Subsequently, as shown in Fig. 7 and Table 5, Abdolahi et al. [46] further explored process capability analysis of AM process: a ML-based predictive. The RF, ML and NN methods used in the study showed good performance in processing complex data. On this basis, Chen et al. [47] conducted in-depth research on a physics-informed machine learning approach for temperature-field prediction in metallic additive manufacturing. This work used RF and ML techniques, which provided new ideas for solving key problems in this field. Kumar et al. [48] compared the performance of RF, SVM, and Decision Tree models for predicting melting efficiency and bead geometry in wire arc AM, and reported meaningful results for process prediction. Ye [49] focused on digital technology according to specific needs. They achieved significant results by applying ML and NN methods. In addition, many other scholars have made important contributions in this direction. Kazmi et al. [50] studied the estimation of deposition rate in robotic-controlled wire arc AM using the RF method: implementation; Cevik et al. [51] proposed support for precision machining of am aluminum alloys; Choi et al. [52] developed structures with multi-functionalities; accelerates simulations; Tridello et al. [53] studied the assessment of the critical defect in AM components through ML; Anidjar et al. [54] proposed phase of productivity in the field; involves initially segmenting out areas without initiation point; Headley et al. [55] developed the development of an augmented ML approach; Wu et al. [56] studied a more uniform strain field in complex anatomical and physiological condition; opportunities and fle; Chernyavsky et al. [57] proposed enablings to systematically improve ml-driven am processes; Korzeniowski et al. [58] developed an application of machine vision.

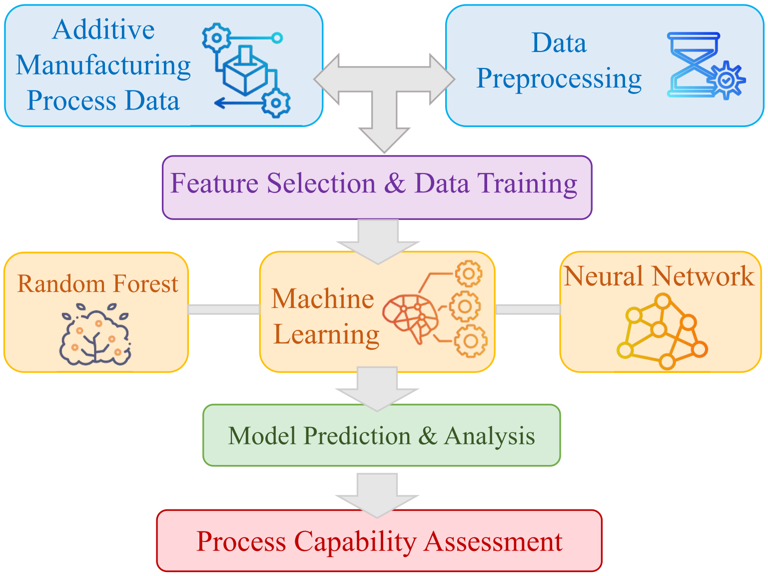

Figure 7: A ML-based predictive.

Table 5: Representative studies on ML for quality inspection and defect identification in AM.

Author	Year	ML Algorithm	Core Innovation
Karabiyik et al. [45]	2025	RF, reinforcement learning, LLM-assisted fault analysis framework	Which leverages strategies such as zero-shot prompting; is the prompt evaluation framework
Abdolahi et al. [46]	2025	RF, ML-based predictive framework, NN process capability analysis of AM	Process: a ML-based predictive m
Chen et al. [47]	2025	Physics-informed ML, RF-assisted prediction	A physics-in
Kumar et al. [48]	2025	RF, SVM, decision tree	Comparison of ML per
Ye [49]	2025	Neural-network-based and ML-assisted material-development framework	Digital technology according to specific needs
Kazmi et al. [50]	2025	RF, state-of-the-art ML algorithms	Estimation of deposition rate in robotic-controlled wire arc AM: implementation
Cevik et al. [51]	2025	ML-driven optimization framework	Supports precision machining of am aluminum alloys
Choi et al. [52]	2023	AI/ML-assisted design framework	Structures with multi functionalities; accelerates simulations
Tridello et al. [53]	2023	ML-based defect assessment framework	Assessment of the critical defect in AM components through ML algo
Anidjar et al. [54]	2024	Segmentation-based ML framework	Phase of productivity in the field; involves initially segmenting out areas without initiation points
Headley et al. [55]	2024	Augmented ML approach	The development of an augmented ML approach
Wu et al. [56]	2023	ML-assisted strain-field analysis framework	A more uniform strain field in complex anatomical and physiological condition; opportunities and flexibility for fabricating 3d complex lattice struct
Chernyavsky et al. [57]	2023	ML-driven process-improvement framework	Enables to improve ml-driven am processes
Korzeniowski et al. [58]	2023	Machine vision	Application of machine vision

Although ML-enabled AM research has demonstrated promising advances in process prediction, defect detection, and intelligent decision-making, most studies remain at the stage of supervised prediction or algorithm benchmarking, without realizing full closed-loop control or cross-machine generalization.

4 Discussion and Perspectives

4.1 *Summary of Key Findings*

This systematic review of ML applications in AM reveals significant progress across multiple domains, yet exposes critical limitations that must be addressed to realize the full potential of intelligent AM systems. Our analysis of recent literature demonstrates that ML techniques have successfully transitioned from laboratory demonstrations to practical implementations in real-time monitoring, parameter optimization, material property prediction, and quality assurance. In the domain of real-time process monitoring and control, ML algorithms, particularly RF and NN, have demonstrated robust performance in detecting process anomalies and classifying defect types. Studies have achieved classification accuracies exceeding 85% in identifying instability onset during the manufacturing process. The integration of multi-sensor fusion techniques—combining thermal imaging, acoustic signals, and visual inspection—has enabled comprehensive monitoring of melt pool dynamics, temperature field evolution, and powder bed morphology. However, these systems predominantly operate in a reactive mode, identifying defects after they occur rather than preventing their formation through predictive control. Process parameter optimization represents another area where ML has made substantial contributions. Ensemble learning methods and SVMs have successfully mapped complex nonlinear relationships between process variables (laser power, scanning speed, layer thickness) and product quality metrics. These models can reduce experimental trials and accelerate process development cycles. Nevertheless, the majority of optimization frameworks remain offline tools that require human interpretation and manual parameter adjustment, falling short of the autonomous optimization capabilities needed for adaptive manufacturing.

Material property prediction has benefited significantly from ML approaches, with RF and physics-informed NN demonstrating capability in predicting mechanical properties, microstructural characteristics, and performance metrics. Yet, most models exhibit limited generalizability across different material systems, requiring retraining when applied to new alloys or material compositions. This material-specific nature constrains the practical deployment of these models in multi-material manufacturing environments.

Quality inspection and defect identification have witnessed perhaps the most mature ML applications, with deep learning models achieving near-human accuracy in detecting porosity, cracks, and surface irregularities. Convolutional NN excel at processing high-resolution imaging data and identifying subtle defect signatures. However, these models often function as black boxes, providing limited insight into the underlying physical mechanisms of defect formation, which hinders root cause analysis and process improvement.

4.2 *Critical Limitations and Challenges*

Despite these achievements, our analysis identifies several fundamental limitations that constrain the transformative impact of ML in AM: First, the lack of closed-loop control systems represents a significant gap. Most current ML applications operate in open-loop configurations, providing predictions or classifications without directly influencing process parameters. True autonomous manufacturing requires closed-loop systems that continuously monitor process state, predict potential defects, and automatically adjust parameters in real-time to prevent quality degradation. Current research has made limited progress toward this goal, with few demonstrations of reinforcement learning-based adaptive control systems. Second, cross-domain generalization remains a major challenge. Supervised learning remains dominant in AM largely because it is the most practical framework for current AM tasks, but this dominance reflects data and validation constraints more than methodological superiority. In practice, many existing models are trained on small, material-specific datasets and therefore learn local correlations rather than transferable process–structure–property relationships. This limitation is further reinforced by the lack of shared multi-material datasets and benchmark protocols, which restricts rigorous validation of transfer learning and domain adaptation methods. As a result, broader adoption of semi-supervised, unsupervised, and transferable learning frameworks will depend on improved data sharing, more reliable benchmarks, and physics-informed representations that remain meaningful across materials and manufacturing conditions. A further limitation is that high-value labels in AM are often expensive and difficult to obtain, since reliable supervision may require destructive testing, microstructural characterization, or expert annotation of rare defects. This makes supervised models practical for many current tasks, but also limits dataset scale and class balance. By contrast, unsupervised and semi-supervised methods are attractive for exploiting large volumes of unlabeled process data, yet their wider use is constrained by difficulties in physical validation, domain shift, and stable pseudo-label generation. Reinforcement learning is similarly promising for adaptive control, but it remains largely exploratory in AM because of reward-design complexity, safety concerns, and low sample efficiency. ML models trained on specific materials, machines, or process conditions typically fail to transfer to new scenarios without extensive retraining. This brittleness severely limits the scalability and practical utility of these approaches. Transfer learning techniques that could enable knowledge sharing across materials and platforms remain underexplored in the AM domain. Third, data scarcity and quality issues plague many ML implementations. A further challenge lies in the limited comparability of existing AM datasets. Because many studies rely on small, task-specific datasets collected under different machines, sensing setups, preprocessing pipelines, and reporting standards, their results are often difficult to reproduce or compare fairly across studies. Therefore, future progress will depend not only on better models, but also on shared benchmark datasets, standardized reporting protocols, and reproducibility-oriented evaluation frameworks. While modern AM systems generate vast quantities of sensor data, labeled datasets for supervised learning—particularly for rare defect types—remain limited. This apparent contradiction reflects the fact that AM is a Big Data problem in terms of raw sensor volume, but a Small Data problem in terms of labeled, high-quality failure cases that can support reliable supervised learning and comparative evaluation. Moreover, data heterogeneity across different machines, sensors, and environmental conditions complicates model training and validation. The field lacks standardized data collection protocols and benchmark datasets that would facilitate comparative evaluation and reproducible research. Fourth, model interpretability presents both a scientific and practical concern. Physics-agnostic black-box models, while often achieving high predictive accuracy, provide limited understanding of the underlying mechanisms governing AM processes. This opacity hinders scientific knowledge discovery, limits user trust, and complicates regulatory approval for safety-critical applications. The integration of physics-based knowledge into ML frameworks—through physics-informed NN or hybrid models—represents a promising but underdeveloped research direction. Fifth, computational efficiency and real-time capability remain constraints for many advanced ML approaches. For high-speed processes such as L-PBF, the practical requirement for real-time correction is determined by the latency budget of the full sensing-to-actuation loop rather than by prediction accuracy alone. This implies that real-time ML deployment in AM depends not only on model design, but also on high-speed sensing, reduced preprocessing overhead, and hardware platforms such as edge GPUs or other accelerated edge-computing systems capable of near-machine. Deep learning models, particularly those processing high-resolution imaging or three-dimensional thermal field data, may require computational resources incompatible with real-time process control requirements. Edge computing solutions and model compression techniques are needed to bridge this gap.

A major barrier to deploying ML models in true closed-loop AM control is that the key challenge lies in end-to-end latency, not prediction accuracy alone. In real-time AM, control decisions must be made while the melt pool, deposited bead, or thermal field is still evolving. However, high-speed optical, thermal, acoustic, and multimodal sensor data often require denoising, synchronization, segmentation, feature extraction, and sometimes multimodal fusion before inference can occur. As a result, total delay includes sensing, data transfer, preprocessing, inference, and actuation; if this latency approaches the time scale of defect initiation or process drift, the response becomes too late for effective correction. This problem is especially severe for deep learning models using high-resolution images or three-dimensional thermal data, which demand substantial computational resources near the machine. Therefore, the current gap in real-time AM feedback control reflects not only algorithmic limitations, but also the mismatch among sensing bandwidth, inference speed, and edge hardware capability. Progress will require lightweight models, streamlined sensor pipelines, hardware-accelerated edge deployment, and control architectures designed around latency budgets.

4.3 Future Research Directions

Based on these identified limitations, we propose several critical research directions that could advance the field toward truly intelligent AM:

Integration of Physics-Informed ML

Physics-informed ML in AM can be realized through several practical strategies. These include physics-guided feature construction using descriptors such as heat input, cooling rate, melt-pool geometry, and thermal gradients [59]; physics-constrained learning, where governing principles are embedded into loss functions or regularization terms; and hybrid mechanistic–data-driven models, in which ML is used to correct or refine coarse predictions from physical models. In addition, physics-informed surrogate models can approximate expensive thermo-mechanical or multi-physics simulations while preserving consistency with known process behavior. Compared with purely data-driven approaches, these frameworks can improve generalization, provide more reliable extrapolation beyond the training domain, and enhance interpretability by linking predictions to physically meaningful process variables and mechanisms. Recent studies cited in this manuscript, including physics-based prediction of melt-pool depth and dendritic arm spacing and physics-informed temperature-field modeling in metallic AM, support this direction.

Development of Closed-Loop Autonomous Control

The field must transition from passive monitoring to active control. Reinforcement learning frameworks that learn optimal control policies through interaction with the manufacturing environment represent a promising pathway. These systems should demonstrate the ability to detect process drift, predict impending defects, and automatically adjust multiple process parameters in coordinated fashion to maintain quality. Key challenges include defining appropriate reward functions, ensuring safety during exploration, and achieving sample-efficient learning.

Advancement of Transfer Learning and Meta-Learning

To overcome the limitation of material-specific models, research should focus on transfer learning architectures that can leverage knowledge from well-characterized materials to accelerate learning for new systems. Meta-learning approaches that learn to learn—developing models that can rapidly adapt to new materials or machines with minimal additional training—could dramatically improve the practical scalability of ML in AM.

Multi-Scale and Multi-Physics Modeling

Future ML systems should integrate information across spatial scales—from microscopic melt pool dynamics to macroscopic part geometry—and across physical phenomena—including thermal, mechanical, and metallurgical processes. Graph NN, which can naturally represent multi-scale hierarchical structures, and attention mechanisms, which can selectively focus on relevant information, offer promising architectural foundations for such integration.

Human-AI Collaboration and Explainable AI

Methods such as SHAP and LIME could further strengthen explainability in AM by quantifying how process parameters, sensor-derived features, or image characteristics influence model predictions. This would improve transparency, root-cause analysis, and decision support in tasks such as defect detection, process optimization, and material-property prediction. Rather than seeking complete automation, research should explore collaborative frameworks where ML systems provide decision support to human operators. Explainable AI techniques—including attention visualization, feature importance analysis, and counterfactual explanations—can help operators understand model predictions, identify failure modes, and build appropriate trust. This is particularly critical for safety-critical applications where human oversight remains essential.

5 Conclusion

This comprehensive review examined the application of ML in AM, analyzing recent advances across four critical domains: real-time monitoring and control, process parameter optimization, material property prediction, and quality inspection. The analysis reveals that ML techniques, particularly RF, NN, and SVMs, have demonstrated significant success in establishing complex mappings between process parameters and product quality, achieving high accuracy in defect detection and classification tasks. However, the review also identifies fundamental limitations that must be addressed to realize the transformative potential of intelligent AM. Most current research remains at the supervised learning and offline prediction stage, lacking the closed-loop control capabilities, cross-material generalizability, and model interpretability required for autonomous manufacturing systems. The field faces critical challenges in data scarcity for rare defect types, computational efficiency for real-time applications, and integration of physics-based knowledge with data-driven approaches. Future progress toward truly intelligent AM requires a paradigm shift from passive monitoring to active control, from material-specific models to transferable knowledge frameworks, and from black-box predictions to explainable, physics-informed systems. The development of standardized benchmarks, hybrid modeling approaches combining domain knowledge with ML, and reinforcement learning-based adaptive control systems represents critical research priorities. Success in these areas will enable the evolution of AM from an experience-driven technology to a data-driven, autonomous manufacturing paradigm capable of consistently producing high-quality components across diverse materials and applications.

A practical pathway toward intelligent, autonomous, and high-reliability AM should be understood as a staged progression rather than an immediate end state. In the near term, the priority is to improve data quality, benchmarking, and model trustworthiness; in the medium term, the focus should shift toward low-latency sensing, edge-deployable models, and human-supervised adaptive control; and in the longer term, fully autonomous AM will depend on robust cross-material generalization, validated physics-informed digital representations, safe adaptive control strategies, and qualification frameworks capable of verifying the reliability of autonomous decisions. In this sense, high reliability must be treated as a measurable capability supported by reproducibility, generalization, and validated closed-loop performance, rather than as a purely conceptual goal. Ultimately, the integration of ML into AM is not merely a technical enhancement but a fundamental transformation in how we approach design, production, and quality assurance. As ML capabilities mature and research addresses current limitations, intelligent AM systems promise to unlock new possibilities in customized manufacturing, reduce production costs, and accelerate innovation across aerospace, medical, automotive, and other critical industries.

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