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Advancing intelligent additive manufacturing: Machine learning approaches for process optimization and quality control

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Abstract

Additive manufacturing (AM) has revolutionized modern fabrication by enabling complex geometries, material efficiency, and customized production. However, process variability, material inconsistencies, and defect formation remain critical challenges, limiting scalability and industrial adoption. Machine learning (ML) has emerged as a powerful tool to address these limitations by enabling data-driven optimization, defect detection, material property prediction, and real-time process control. This review provides a comprehensive analysis of ML applications in AM, spanning polymers, metals, ceramics, and carbon-based materials, with a focus on process optimization, quality assurance, and predictive modeling. Specifically, this review examines real-time defect detection through vision-based ML techniques, printing parameter optimization using supervised and reinforcement learning, and predictive modeling of material properties–laying the groundwork for deeper exploration of key methodologies such as deep learning and physics-informed models. Key ML methodologies, including deep learning, reinforcement learning, and hybrid physics-informed models, are explored in the context of enhancing print precision, mechanical performance, and functional properties. Despite significant advancements, challenges such as data scarcity, model generalization, and real-time integration into AM workflows persist. Emerging trends, including multimodal sensor fusion, *in situ* monitoring, and cloud-based predictive analytics, are discussed as potential pathways toward fully autonomous and intelligent manufacturing. By consolidating recent developments and outlining future directions, this review provides essential insights for researchers, engineers, and industry professionals looking to harness ML in AM, facilitating advancements in process efficiency, quality control, and overall manufacturing reliability.

Keywords: Additive manufacturing; Machine learning; Process optimization; Defect detection; Quality assurance; Material property; Real-time monitoring; Data-driven manufacturing

1. Introduction

Additive manufacturing (AM), commonly known as 3D printing, has transformed modern manufacturing by enabling the production of complex geometries with high design flexibility and material efficiency. Unlike traditional subtractive manufacturing, which removes material to shape a final product, AM constructs objects layer by layer from digital models, significantly reducing material waste and enabling the fabrication of intricate structures that would be challenging or impossible to achieve through conventional methods.[1,2] Beyond material efficiency, AM eliminates many constraints associated with traditional manufacturing, such as the need for assembly and joining, and accelerates the prototyping process, reducing development time and costs.[3,4] In addition, AM facilitates the integration of multifunctional structures and multi-material designs, expanding its applicability across various industries, including aerospace, automotive, healthcare, and consumer goods.[5-11,12]

Despite these advantages, AM still faces critical challenges that hinder its scalability and widespread industrial adoption. The manufacturing process is highly sensitive to variations in processing parameters, material properties, and environmental conditions, leading to inconsistencies in part quality.[13,14] Defects such as porosity, residual stresses, warping, and poor interlayer bonding frequently occur, necessitating rigorous post-processing to ensure structural integrity.[15] Moreover, optimizing AM processes for different materials and geometries remains a complex and computationally intensive task, as each combination requires precise tuning of parameters such as laser power, scanning speed, layer thickness, and cooling rates to achieve the desired mechanical properties and surface finish.[16-19] These challenges underscore the need for advanced methodologies to enhance the reliability, efficiency, and precision of AM processes.

To address these issues, data-driven approaches leveraging machine learning (ML) have gained significant attention as a means to optimize AM workflows. ML techniques enable predictive modeling, real-time process monitoring, and adaptive control, providing a systematic approach to improving manufacturing consistency and efficiency. Early research in this field, initiated over a decade ago, demonstrated the feasibility of applying basic ML models, such as support vector machines (SVMs) and Gaussian process (GP) regression, to process AM data. For instance, GP-based surrogate models were employed to predict defect formation and porosity from process parameters in metal AM, while SVM classifiers were used to construct process maps and identify stable fabrication regimes.[20,21] Although these pioneering studies validated the potential of data-driven approaches in understanding complex process-property relationships, their impact was limited by small datasets and issues related to model generalization.[22] Subsequent developments have since advanced beyond these early efforts, leveraging more sophisticated algorithms and larger datasets to achieve robust and scalable ML solutions in AM.

Key ML applications in AM include process parameter optimization, where ML models identify optimal printing conditions to minimize defects and enhance part performance; *in situ* process monitoring and real-time feedback, which utilize sensor data to detect anomalies and adjust parameters dynamically; and quality assessment and defect prediction, allowing for early identification of suboptimal parts before post-processing.[23,24] These ML-driven strategies not only minimize reliance on empirical trial-and-error experimentation but also reduce production time, material consumption, and overall costs while improving repeatability and part quality. Moreover, ML has facilitated advancements that were previously unattainable using conventional process control methods, further demonstrating its potential to revolutionize AM.[25-27]

Given the rapid evolution of ML applications in AM, a comprehensive and up-to-date review is needed to consolidate existing knowledge and identify emerging trends. Although several related reviews have been published, many are limited in scope–often focusing on specific materials, algorithms, or AM techniques–leaving a gap in the broader understanding of ML integration across diverse AM platforms.[24,28-34] In contrast, this review offers a holistic examination of ML-driven strategies for optimizing AM processes, encompassing all major material classes, including polymers, metals, ceramics, and carbon-based composites. By analyzing recent advancements across these material systems, the review aims to provide a structured overview of how ML is being applied to enhance printing efficiency, material utilization, and product quality. Furthermore, it addresses critical challenges such as data scarcity, model generalization, and the integration of real-time control mechanisms. Emerging directions, including physics-informed ML models and multimodal *in situ* monitoring, are also highlighted to offer a forward-looking perspective. The insights presented in this work are intended to support researchers, engineers, and industry professionals in leveraging ML to advance the reliability, scalability, and intelligence of AM technologies.

2. AM and ML method

2.1. AM

Unlike conventional subtractive methods, which remove material to create a final product, this advanced manufacturing approach builds objects layer by layer from digital models, maximizing material efficiency and enabling intricate geometries. Its ability to offer exceptional design flexibility has made it a transformative technology in industries such as aerospace, healthcare, and automotive, where lightweight, customized, and functionally optimized structures are essential for innovation and performance. The ASTM standard classifies AM into seven categories, with material extrusion, vat photopolymerization, powder bed fusion (PBF), binder jetting, and directed energy deposition (DED) being the most widely adopted.[35] While AM technologies offer significant advantages over conventional manufacturing, each method presents unique processing requirements and challenges depending on the material type.

Polymer-based AM technologies, such as material extrusion and vat photopolymerization, are widely used due to their cost-effectiveness and broad material availability. Material extrusion, exemplified by fused deposition modeling (FDM) and direct ink writing (DIW), is one of the most accessible and scalable AM techniques. FDM, which utilizes thermoplastic filaments such as acrylonitrile butadiene styrene (ABS) and polylactic acid (PLA), is commonly used for rapid prototyping and functional components. However, FDM parts often suffer from anisotropic mechanical properties and limited resolution, requiring post-processing or parameter optimization to enhance quality.[36] DIW, in contrast, is particularly advantageous for soft and bioinspired materials, such as hydrogels and elastomers, but demands precise rheological control to maintain printing accuracy.[37] Vat photopolymerization, which includes stereolithography (SLA) and digital light processing (DLP), enables high-resolution fabrication with smooth surface finishes, making it particularly beneficial for biomedical applications, dental prosthetics, and microfluidic devices. However, photopolymer-based materials often exhibit brittleness and require post-curing, which may limit their mechanical performance in load-bearing applications.[38]

Metal and ceramic-based AM technologies, such as PBF, binder jetting, and DED, are essential for high-performance applications that require superior mechanical properties and thermal resistance. PBF processes, including selective laser sintering (SLS) for polymers and selective laser melting or electron beam melting for metals, utilize high-energy sources to selectively fuse powdered materials, enabling the production of complex, high-strength components. These techniques are widely used in aerospace, automotive, and medical implants, where precision and material integrity are critical. However, strict control of powder properties, high energy consumption, and extensive post-processing requirements remain key challenges.[39,40] Binder jetting, which selectively deposits a liquid binding agent onto a powder bed, offers a low-temperature alternative to PBF, making it particularly useful for ceramic and metal-based applications.[41,42] This method enables high-speed, cost-effective large-scale fabrication, but the resulting parts often require sintering or infiltration post-processing to achieve full density and mechanical strength. DED, which directly deposits molten or semi-molten material using a focused energy source such as a laser or plasma arc, is commonly used for metal repair, aerospace component restoration, and large-scale manufacturing. While DED provides greater material efficiency and repair capabilities, it typically results in lower resolution and surface quality compared to PBF, necessitating additional post-processing to improve dimensional accuracy.[43] While AM technologies continue to advance, optimizing process parameters, improving material performance, and addressing scalability challenges remain critical for industrial adoption. Recent advancements in ML have demonstrated significant potential in enhancing process efficiency, real-time monitoring, and defect prediction, as summarized in Figure 1.

2.2. ML approaches

ML techniques have become increasingly integral to AM process optimization, defect detection, and quality control. ML approaches in AM are broadly classified

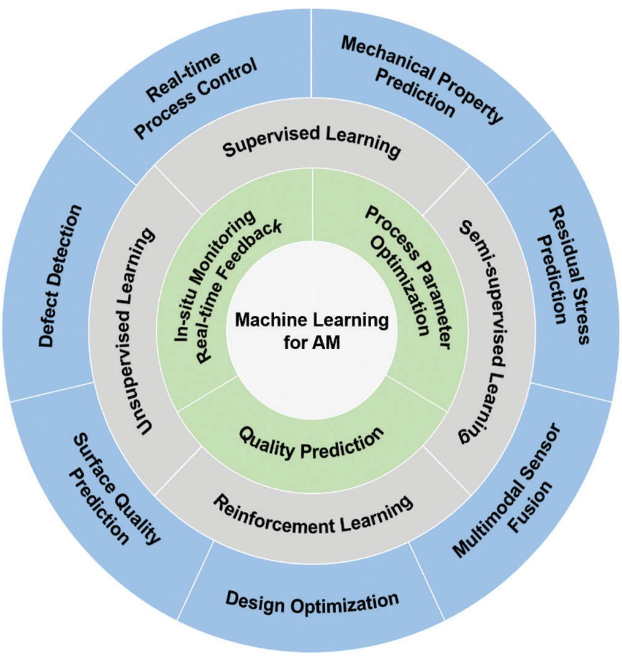

Figure 1. Overview of machine learning for additive manufacturing. Machine learning applications, learning types, and key roles in process optimization, quality prediction, and real-time monitoring.

into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, each offering distinct advantages depending on the nature of the available data and the specific manufacturing objectives. A visual summary of the major ML categories, representative models, and their applications across various AM processes and materials is provided in Figure 2, highlighting how different learning paradigms contribute to process, property, and design optimization.

Supervised learning relies on labeled datasets to establish relationships between input parameters and output quality metrics, enabling predictive modeling and automated defect classification. Commonly used algorithms such as SVM, random forests (RF), artificial neural networks (ANN), and convolutional neural networks (CNN) have been applied in AM for tasks such as predicting mechanical properties, optimizing printing parameters, and identifying defects through image-based analysis.[31,44] Unsupervised learning, which identifies patterns in unlabeled data, is particularly useful for clustering process variations and detecting anomalies. Techniques such as k-means clustering and principal component analysis have been employed to analyze sensor data and monitor inconsistencies in layer formation and material distribution.[45]

Semi-supervised learning, which leverages a combination of labeled and unlabeled data, has proven particularly advantageous in AM, where acquiring large labeled datasets for defect classification can be time-intensive and costly. Methods such as self-training and generative adversarial networks (GANs) have been explored to augment datasets, improve defect detection accuracy, and enhance model robustness.[31] Reinforcement learning, which enables an agent to learn optimal strategies through trial-and-error interactions with the environment, has been increasingly applied in AM for real-time process control and adaptive optimization. Deep Q-networks and proximal policy optimization algorithms have been utilized to dynamically adjust laser power in PBF and extrusion rates in FDM, leading to improved process stability and reduced defect formation.[16]

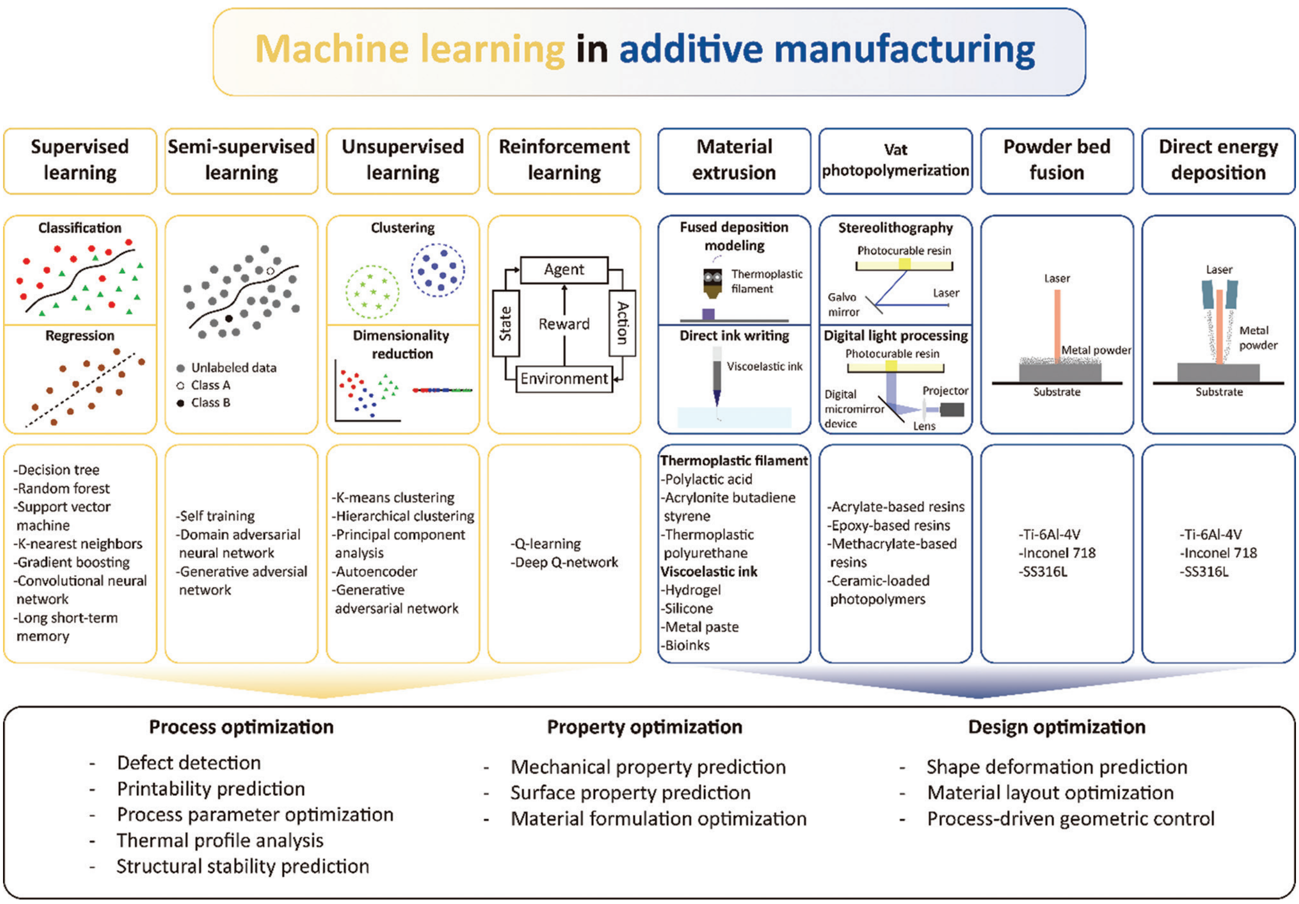

Figure 2. Summary of machine learning (ML) and additive manufacturing (AM) techniques commonly used for process optimization. ML approaches and representative models are shown on the left, while AM technologies, materials, and composites are displayed on the right. ML-driven optimization tasks in AM include process optimization, property prediction, and design optimization.

Each ML paradigm presents specific strengths and trade-offs in terms of predictive accuracy, data efficiency, and implementation complexity. Supervised learning generally achieves high accuracy when sufficient labeled data are available, but it requires extensive data collection and careful parameter tuning. In contrast, unsupervised learning offers greater data efficiency by leveraging unlabeled datasets. However, its outputs, such as clusters or anomaly scores, may lack the precision of supervised models due to the absence of ground-truth labels. Semi-supervised learning offers a compromise by combining limited labeled data with abundant unlabeled data to improve learning efficiency. For example, even a small number of labeled defect images can significantly boost detection accuracy when incorporated into a largely unlabeled dataset. Reinforcement learning is particularly suited to sequential decision-making tasks, such as real-time process control, but its application in AM remains relatively limited due to the complexity of reward design and the need for extensive experimentation. In practice, supervised CNN-based models have demonstrated over 90% accuracy in classifying FDM defects when trained with sufficient data, while unsupervised methods can still effectively flag anomalies without any labels. Reinforcement learning, although promising for adaptive control, has thus far been primarily explored in experimental setups.

In addition to purely data-driven methods, hybrid approaches that integrate physical modeling and ML–often referred to as physics-informed or physics-based ML–have gained attention for enhancing prediction reliability and reducing data requirements. For instance, physics-informed neural networks have been applied in fused filament fabrication to incorporate thermal behavior into property prediction models.[46] In addition, physics-based simulations such as finite element analysis (FEA), computational fluid dynamics, and phase-field modeling have been combined with ML to predict microstructure evolution,[47] residual stress formation,[48] and melt pool geometry in metal and ceramic AM processes.[49] These approaches ensure physical consistency in ML predictions and offer scalable solutions for complex modeling processes in AM.

The effectiveness of ML in AM largely depends on the quality and availability of training data. Data generated by AM can be categorized into process data, material data, quality data, and geometric design data, each playing a crucial role in model development and validation. Process data include sensor-based measurements such as temperature, pressure, humidity, and real-time monitoring of melt pool dynamics in metal AM processes. These data points are critical for tracking process stability, detecting deviations, and predicting potential defects.[32] Material data, encompassing parameters such as composition, viscosity, and thermal properties, influences printability, microstructure evolution, and final part performance. For instance, in vat photopolymerization, resin viscosity and photoinitiator concentration affect curing dynamics, whereas in PBF, powder morphology and packing density determine layer fusion and mechanical strength.[50,51] Quality data, such as surface roughness, porosity, and mechanical properties, are typically obtained through non-destructive evaluation techniques, including X-ray computed tomography (CT) and ultrasonic testing, providing ground truth for ML model validation. Geometric and design data derived from computer-aided design (CAD) models and G-code instructions facilitate the analysis of layer-wise deviations, part distortions, and structural integrity.[23]

Identifying which data types serve as input features versus prediction targets is essential for designing effective ML workflows in AM. In most applications, process and design data—such as machine sensor readings, processing parameters, and CAD files—serve as input features. In contrast, quality metrics (*e.g.*, porosity and mechanical strength) typically serve as the output targets for prediction or classification. Material data can play either role depending on context, for example, known properties may be used as inputs for performance prediction, or they may serve as outputs in formulation design tasks. In a defect detection task, *in situ,* sensor images and environmental data constitute the input, while defect presence or severity, verified by inspection, serves as the output. For property prediction, inputs may include process conditions and material composition, with outputs being target values such as tensile strength or elasticity. Proper alignment of input–output structure helps guide algorithm selection and ensures that the ML approach is suited to the intended application, be it predictive modeling, real-time anomaly detection, or parameter optimization.

To extract meaningful insights from these datasets, various ML-driven data analysis techniques have been adopted. Image processing and computer vision models, including CNNs and You Only Look Once (YOLO) networks, have been employed for real-time defect detection in FDM by analyzing nozzle-near images.[51] Time-series analysis models, such as long short-term memory (LSTM) networks, have been used to predict process drift in PBF by analyzing laser scan data across multiple layers.[52] Hybrid approaches that combine ML with physics-based simulations, such as FEA, have been developed to predict residual stress formation and optimize support structures in metal AM.[53] Furthermore, Bayesian optimization has been widely explored for process parameter tuning, reducing reliance on traditional empirical trial-and-error methods.[54] These ML-driven strategies significantly enhance process control, reduce production time and material waste, and improve overall manufacturing reliability.

3. ML-based 3D printing optimizations

3.1. Polymers

Polymers are macromolecules composed of covalently bonded repeating units, forming long chains that exhibit diverse rheological properties. Such chain structures endow polymers with low density, flexibility, and–in certain cases–viscoelastic behavior.[34] Their physicochemical properties can also be tuned during synthesis and processing to meet specific requirements. Owing to these adaptable characteristics, polymers are widely employed as elastomer matrices in soft robotics,[55-57] soft actuators,[58,59] and soft sensors.[8,60,61]

Because of their tunability and ease of processing, polymers are well-suited for various 3D printing techniques.[62] Material extrusion techniques like FDM typically use thermoplastic filaments such as ABS and PLA,[63] while DIW prints polymer-based materials, including hydrogels and elastomers.[37] Recent studies have leveraged ML-based approaches to optimize DIW parameters, especially for bioinks and hydrogels used in biomedical applications.[37] Key rheological behaviors–such as apparent viscosity, shear-yielding, and shear-thinning–are typically considered for DIW formulations.[8,34,64,65] A summary of recent ML applications and model types used for polymer-based 3D printing is presented in Table 1.

In addition, vat photopolymerization techniques such as SLA and DLP enable high-resolution printing for biomedical[66,67] and electronics[68,69] applications. During the printing process, photosensitive resins must maintain a low viscosity to accommodate continuous layer-by-layer fabrication and be formulated to exhibit optimal reactivity within the targeted wavelength range of the photoinitiation system. While acrylate- and epoxy-based monomers are commonly employed,[68-71] other photosensitive formulations may be used for specialized applications. For example, photocurable hydrogels are frequently considered for bioprinting.[67,71,72]

3.1.1. Process optimization

Despite the advantages of polymer-based 3D printing, process parameters can significantly influence printing quality and yield. In FDM, parameters such as nozzle temperature, layer height, printing speed, build orientation, and infill settings often affect part integrity, potentially causing interlayer delamination and uneven stress distributions.[73-77] With the rapid development of ML models, numerous studies have attempted to monitor and control defects that emerge during FDM printing. In parallel, experimental approaches based on physical sensing techniques have been used to measure process-induced deformation. For example, Kantaros and Karalekas utilized fiber Bragg grating (FBG) sensors to measure residual strains in ABS parts fabricated via FDM, offering a physics-based understanding of internal stresses through thermo-optic and strain-optic coefficients.[78]

A common approach involves *in situ* monitoring of image data.[51,77-82] For instance, capturing the top view of an FDM part printed with ABS or PLA at certain build stages and then applying image-processing techniques combined with SVM to detect the presence or absence of defects has been reported.[79] Similarly, CNN have been employed to classify defects from top-view images of partially completed prints.[80] Moreover, FDM processes are highly sensitive to environmental conditions, which may drift over time (so-called "drift" in process parameters).[81] Such domain shifts can degrade the performance of previously trained diagnostic models. To mitigate this, a deep learning-based defect detection system has been developed that utilizes top-view images of PLA-printed samples.[54] The training data were balanced using a conditional GAN (CGAN), and domain adversarial neural networks (DANN) were employed to adapt to parameter drift. This system achieved a classification accuracy of 91.01% in detecting various FDM defects. Nevertheless, relying solely on top-view images can pose challenges in detecting flaws on vertical surfaces. Complementing purely data-driven approaches, hybrid models that incorporate physics-based knowledge into ML frameworks have also been proposed. Kapusuzoglu and Mahadevan[46] demonstrated a physics-informed ML model for fused filament fabrication, which integrates thermal and mechanical principles to improve prediction accuracy and reduce the data dependency often seen in conventional ML models.

Beyond defect detection, real-time process compensation offers a more proactive strategy. One study used a CNN-based classifier to analyze nozzle-near images in real-time, detecting under-extrusion or over-extrusion and automatically adjusting extrusion flow rates.[82] By incorporating a feedback loop, the system reduced corrective action times to 8.6 s for under-extrusion and 9.8 s for over-extrusion–faster than human intervention. Another work further automated process correction by modifying G-code based on defect types.[51] Using a YOLO object detection model, under- and over-extrusions were identified in real-time, and flow rates or recent G-code commands were updated accordingly. A streamlined

Table 1. Summary of ML models for polymer-based 3D printing

Motivation	Materials	AM method	ML model	Model inputs	Remarks	References
Process optimization	ABS, PLA	FDM	SVM	Image data from semi-finished printed parts at checkpoints	Real-time defect detection using image processing and ML	84
	ABS, PLA	FDM	CNN	Top-view images from a static camera during printing	Detecting infill pattern in real-time	85
	PLA	FDM	CGAN, DANN	Top-view grayscale images of printed layers	Fault diagnosis under process parameter drift	81
	PLA	FDM	CNN (ResNet-50)	Real-time images from a nozzle-mounted camera	Autonomous *in situ* correction of under- and over- extrusion	87
	PLA	FDM	YOLOv3-Tiny, YOLOv4-Tiny, ONNX-optimized YOLO	Real-time nozzle-near images	Automated defect detection and G-code correction for *in situ* extrusion compensation	54
	ABS	FDM	Reinforcement learning	Printing speed, flow rate multiplier, cooling fan, surface quality images	Online-learning based defect mitigation	57
	PLA	FDM	XceptionTime	Temperature, humidity, air pressure, gas particle concentration	Real-time classification of FDM process states using environmental sensor data	88
	GelMA and alginate	DIW (bioprinting)	CNN (ResNeXt-50)	Layer images, interlayer continuity, uniformity metrics	Real-time anomaly detection in bioprinting	90
	16 biomaterials	DIW (bioprinting)	DT, RF, ANN	Bioink composition ratios, printability labels	Predicting the printability of bioink formulations	91
	GelMA with encapsulated cells	DLP (bioprinting)	U-Net-based master-slavee neural network	Light scattering patterns, corrected exposure masks	Generating optimized correction masks to mitigate cell-induced light scattering	97
	Epoxy acrylate resin+commercial photopolymer resin	DLP (grayscale)	RNN with LSTM layers, EA	Per-pixel grayscale values, deformed structure data	Predicting deformation and optimizing grayscale distribution for enhanced print accuracy	55
	Acrylate photopolymer resin	DLP	LSTM	Temperature data, UV exposure time, layer thickness	Optimizing DLP printing via real-time temperature prediction	99
	Three commercial photopolymer resins	DLP	U-Net, CGAN	Grayscale pixel data, boundary images	Improving printing resolution and reducing jagged edges	100
	Commercial photopolymer resin	DLP	RF with EWMA p-control chart	Strain gauge data, UV exposure levels	Real-time detection of part detachment and automatic process halting	104
	Commercial photopolymer resin	DLP	MLP	Prediction feature region, layer geometry	Predicting optimal idle time for resin drainage	107
	Photopolymer resin	SLA	CNN, Two-stream CNN	FEA-generated stress distributions, geometry data	Predicting layer-wise stress distribution to improve print reliability	56
	Commercial photopolymer resin	DLP	RF	UV exposure time, light intensity, layer thickness	Predicting print accuracy and optimizing printing parameters	106
Property optimization	PLA	FDM	RF, SVM, K-NN	Layer height, printing speed, printing temperature	Optimizing mechanical properties by predicting tensile strength	108

(Cont'd...)

Table 1. *(Continued)*

Motivation	Materials	AM method	ML model	Model inputs	Remarks	References
	ABS	FDM	LR, DT, RF, AdaBoost	Infill density, layer thickness, print orientation, raster orientation	Predicting and optimizing hardness	109
	Polydopamine-coated PLA	FDM	RF, K-NN, AdaBoost, DT, LSTM	Infill density, submersion time, shaker speed, coating solution concentration	Predicting mechanical strength (tensile and bending) of PDM-coated PLA structures	110
	PLA	FDM	LSTM	Infrared temperature, thermocouple, accelerometer, printing parameters (extruder temperature, printing speed, layer height)	Predicting tensile strength of PLA parts using process and sensor data	112
	PLA	FDM	Ensemble learning (RF, AdaBoost, CART, SVR, RR, RVFL)	Layer thickness, extruder temperature, print speed, infrared sensor, thermocouple, accelerometer data	Predicting surface roughness	113
	Acrylate photopolymer resin	DLP	GPR, BO, AL	Monomer composition ratios, Young's modulus, peak stress, ultimate strain, Shore A hardness	Optimizing photopolymer resin formulations using active learning and Bayesian optimization	117
	Acrylate photopolymer resin	DLP	Ensemble learning (K-NN, GPR, KR, RF, MLP)	Resin composition ratios, hardness, tensile strength, elongation at break	Predicting multiple mechanical properties of photopolymers	118
Design optimization	Acrylate photopolymer resin	DLP	RNN+EA	Material distribution (binary voxelized structure)	Predicting shape change and optimizing material layout for 4D printing	120
	Acrylate photopolymer resin	DLP	ResNet (CNN-based)	Voxel-level material distribution	Predicting shape deformations and optimizing material distribution	121

Abbreviations: ABS: Acrylonitrile butadiene styrene; AL: Active learning; ANN: Artificial neural network; BO: Bayesian optimization; CART: Classification and regression tree; CGAN: Conditional generative adversarial network; CNN: Convolutional neural network; DANN: Domain adversarial neural networks; DLP: Digital light processing; DT: Decision trees; EA: Evolutionary algorithm; EWMA: Exponentially weighted moving average; FDM: Fused deposition modeling; GelMA: Gelatin methacrylate; GPR: Gaussian process regression; K-NN: k-nearest neighbor; KR: Kernel ridge regression; LSTM: Long short-term memory; ML: Machine learning; MLP: Multi-layer perceptron; PLA: Polylactic acid; RF: Random forest; RNN: Recurrent neural network; RR: Ridge regression; RVFL: Random vector functional link network; SLA: Stereolithography; SVM: Support vector machine; SVR: Support vector regression UV: Ultraviolet; YOLO: You Only Look Once.

YOLOv3-Tiny model accelerated by the Open Neural Network Exchange runtime achieved 70 FPS, underscoring the viability of high-speed *in situ* defect compensation.

In addition to image-based approaches, sensor signals have also been integrated into ML frameworks to predict defects.[75,83] In one study, environmental parameters (temperature, humidity, air pressure, and gas-particle concentration) were monitored in real-time and used with an XceptionTime model to classify FDM process states automatically.[83] Air pressure emerged as the most critical feature, possibly because its relatively stable baseline made small variations highly indicative and also helped prevent model overfitting. Another work employed a dual approach combining imaging and sensor data.[75] A CNN-based model classified the severity of interlayer delamination from nozzle-near images, while signals from a strain gauge attached to the build platform predicted warping that might develop gradually (Figure 3A). The strain data were interpreted using a physics-based model, which indicated that warping was likely to occur once the strain exceeded a certain threshold.

Compared with FDM, adopting ML for DIW is relatively new, but several studies have explored ML-based optimization of DIW processes.[84-86] A study has reported

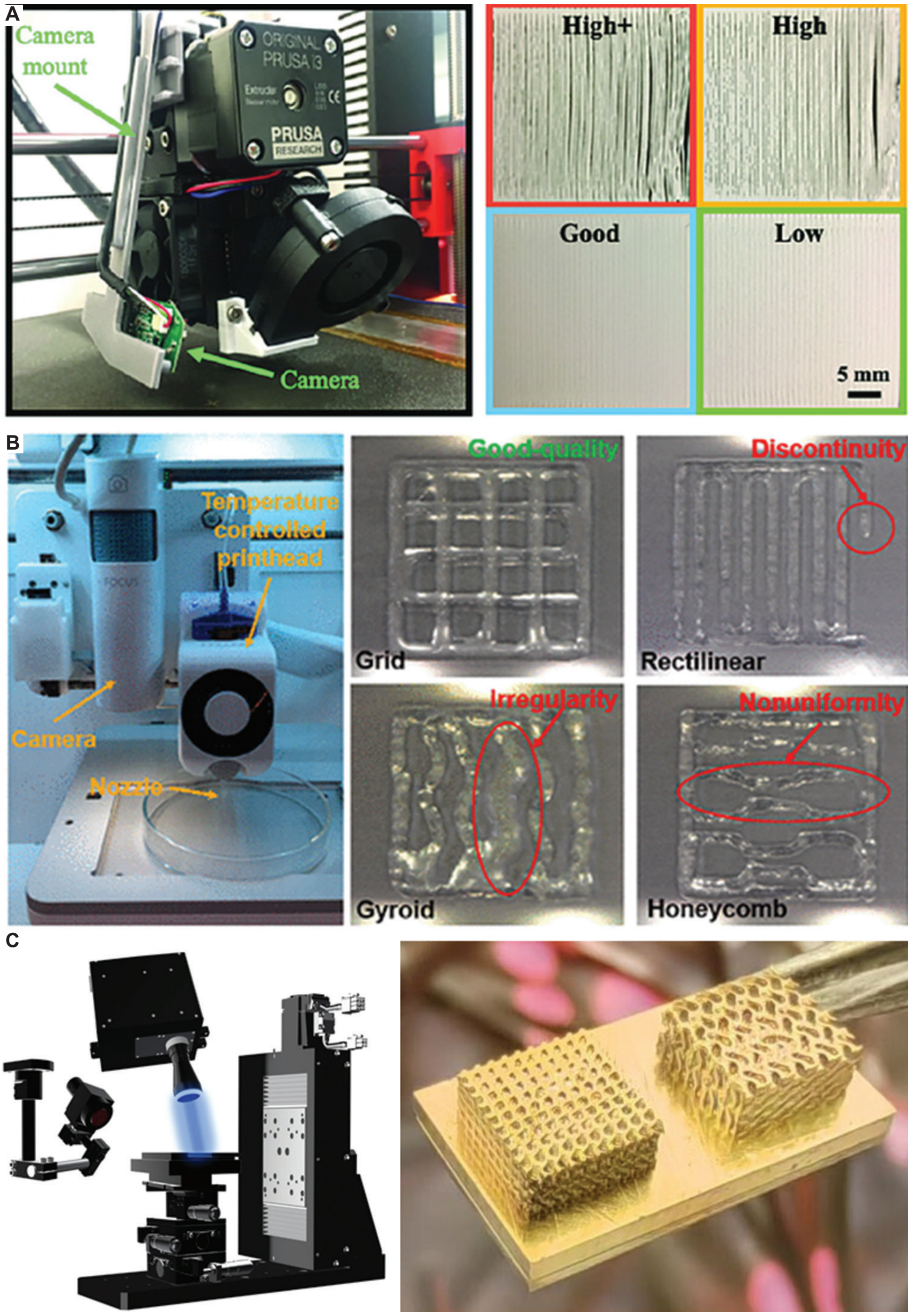

Figure 3. Process optimizations for polymer 3D printing. (A) Fused deposition modeling printer nozzle with an integrated monitoring system and corresponding images representing four nozzle height conditions. Reproduced with permission from Jin *et al.*[80] Copyright © 2020 Wiley. (B) Bioprinting platform combined with an anomaly detection system, along with representative images distinguishing normal and anomalous cases. Reproduced with permission from Jin *et al.*[90] Copyright © 2023 American Chemical Society. (C) Digital light processing printer and optimized printed structures. Reproduced with permission from Wang *et al.*[106] Copyright © 2024 Taylor & Francis.

an ML-based approach for real-time anomaly detection in bioprinting processes.[85] By employing the ResNeXt-50 CNN, the model effectively classified irregularities such as interlayer discontinuities and nonuniformities, while data augmentation techniques were implemented to enhance its generalization performance. Experimental results demonstrated a 99.03% F1-score, highlighting the high accuracy of the proposed detection method (Figure 3B). Another study leveraged ML to predict the printability of bioink formulations.[86] A total of 210 bioink compositions were experimentally constructed from 16 biomaterials, and decision trees, RF, and ANN were compared. Notably, the RF model achieved the highest precision (90.6%) and accuracy (88.1%), thus providing reliable bioink recommendations, while ANN offered better recall (87.3%) and demonstrated superior extrapolation capability. These findings illustrate how data-driven methods can overcome the limitations of purely experimental approaches, enabling rapid identification of optimal formulations.

In vat photopolymerization, process parameters–such as light intensity, exposure time, print speed, and build orientation–must be considered alongside resin properties (viscosity, photoinitiator concentration, and reactivity).[84,87-90] When printing solid-particle–filled resins in DLP, light scattering may occur as particles interact with the curing beam.[91-93] A similar phenomenon can emerge when cells are included in a hydrogel-based bioink due to refractive index differences between cells and the surrounding gel.[67,91,92] Scattering diverts light away from the intended target region, compromising pattern fidelity. Recent research used a deep learning-based correction method to mitigate cell-induced light scattering and enhance print quality in DLP-based bioprinting.[92] A master-slave neural network based on U-Net was employed to automatically generate optimized correction masks that suppress the scattering effect. This approach can significantly reduce iterative trial-and-error. Another study addressed grayscale DLP printing optimization by building a recurrent neural network (RNN) with LSTM layers to learn the relationship between per-pixel grayscale values and the final deformed structure.[52] Coupling this with finite element modeling (FEM) enabled faster and more accurate deformation prediction, while an evolutionary algorithm (EA) optimized grayscale distribution to achieve target deformation patterns. The proposed ML–EA hybrid approach significantly reduced computational time compared with conventional FEM-centric optimization, maintaining comparable precision. In a separate effort to improve geometric fidelity, boundary distortion in vat photopolymerization was mitigated using an ML-driven model that predicts and compensates for boundary shifts during layer projection.[94] More recently, ML-guided temperature prediction models have been coupled with numerical simulation to develop optimized control schemes for DLP printing, improving thermal uniformity and curing accuracy.[95]

In SLA and DLP, the printing apparatus can be arranged in either top-down or bottom-up configurations.[96-98] The top-down setup places the laser or projector above the resin, lowering the platform with each layer, which can disturb the resin surface level and expose the newly formed layer to ambient oxygen, thereby inhibiting photopolymerization. It also tends to require larger vats and more resin volume. By contrast, bottom-up printing positions the light source below the vat and raises the platform upward. While this reduces some top-down constraints, separating each cured layer from the transparent vat window can induce mechanical stress. Several ML-driven approaches have been proposed to optimize bottom-up printing.[53,99,100] One group developed a real-time monitoring system to detect part detachment during the upward movement of the build platform in DLP.[99] Using strain gauges to track platform deformation and a photodetector to measure UV exposure; they applied an RF classifier along with an exponentially weighted moving average p-control chart to detect part detachment in real time and halt the process automatically. The system achieved an F1-score of 99.03% and demonstrated robust process stability by stopping printing after repeated detections. Another study proposed an ML-driven predictive model to optimize idle times during the bottom-up approach, where the platform was raised, fresh resin flowed in, and the platform descended again.[100] Introducing the concept of a prediction feature region allowed them to estimate wait time effectively without resorting to complex fluid simulations. A multi-layer perceptron model was trained to identify geometry-specific idle times, yielding a 47% reduction in average waiting time and a 25% overall reduction in total print time compared with conventional methods. Similarly, for bottom-up SLA, a deep learning model has been employed to predict layer-wise stress distributions.[75] Training datasets built from FEA simulations fed into a basic CNN and a 2-Stream CNN architecture achieved up to a 55% reduction in prediction error compared to a conventional neural network (NN) model with high accuracy even in non-uniform geometries.

ML has also been leveraged for high-precision vat photopolymerization (Figure 3C). In one DLP study, an RF model was trained to learn the relationships between UV exposure time, light intensity, layer thickness, and final print error. This approach maintained an average printing error below 2.3 μm.[101] Moreover, it demonstrated a minimum feature size of ~20 μm in complex triply periodic minimal surface structures, highlighting the model's capacity for generalization to intricate geometries. In addition, ML-based surrogate modeling has been applied in projection two-photon lithography to optimize polymerization dynamics and improve printability, further enhancing precision in microscale fabrication.[102]

3.1.2. Property optimization

Beyond process optimization, ML has proven valuable for predicting or enhancing the mechanical and physical properties of 3D-printed parts. One study applied ML to optimize the mechanical properties of FDM-fabricated components,[103] focusing on layer height, printing speed, and printing temperature. By comparing RF, SVM, and k-nearest neighbors (K-NN) models for tensile strength prediction, the authors found that K-NN achieved the highest accuracy. They then used a sequential least squares programming-based optimization algorithm to determine optimal printing parameters. This ML-based approach enables the optimization of mechanical performance while reducing reliance on purely experimental approaches. A related study developed an ML model to predict the hardness of additively manufactured ABS, demonstrating the feasibility of using ML for estimating physical properties beyond tensile strength.[104]

A related investigation leveraged ML to predict the mechanical strength of biomedical structures printed through FDM.[105] In this case, polydopamine (PDM)-coated PLA plates were tested for mechanical performance using RF, K-NN, AdaBoost, Decision Tree, and LSTM models. Input variables included infill density, PDM coating parameters (submersion time, shaker speed), and coating solution concentration. Similarly, hierarchical ML techniques have been explored to enhance the fidelity of biopolymer-based 3D prints, addressing challenges in achieving consistent mechanical and structural integrity in biofabrication (Figure 4A).[106] Another study combined ML with sensor data to predict the mechanical properties of FDM products.[107] Employing an LSTM-based deep learning model, the authors accounted for thermal and mechanical fluctuations at the layer level. Real-time data – such as infrared readings, temperature measurements, signals from thermocouples, and accelerometer outputs – were fed into the LSTM network to analyze how nozzle temperature, print speed, and layer height influence tensile strength. Compared with traditional ML models (RF, SVR), the LSTM approach demonstrated up to a 24.3% improvement in the coefficient of determination (R^2). Furthermore, layer-wise relevance propagation revealed that layer height was the single most influential factor on tensile strength.

Similarly, ML and sensor data have been applied to predict surface quality in FDM.[108] Traditional process parameters (*e.g.*, printing speed, layer height) alone proved inadequate for capturing variability in surface roughness. To address this limitation, a combination of infrared sensors, thermocouples, and accelerometers was employed to collect real-time data, followed by an ensemble learning model combining six different ML algorithms to quantitatively forecast surface roughness. This approach underscores how sensor-based ML models can enhance predictive accuracy beyond conventional parameter-driven methods.

ML has been instrumental in optimizing the properties of functional materials such as thermoelectric composites. Recent research has employed ML-assisted 3D printing to fabricate thermoelectric materials with ultrahigh performance at room temperature, enhancing energy conversion efficiency through optimized microstructural control (Figure 4B).[109] In vat photopolymerization, ML has also been used to optimize functional polymer composites, including mechanoluminescent materials. Studies have shown that ML-based optimization in SLA and DLP printing can enhance light-emitting properties by refining resin formulations and curing parameters, contributing to advancements in smart materials for sensing and display applications.[110] Moreover, high-throughput ML approaches have been integrated into the design of photodegradable hydrogels, enabling rapid formulation screening and optimization for biomedical applications (Figure 4C).[111]

3.1.3. Design optimization

Functional polymers – often referred to as stimuli-responsive, active, smart, or intelligent polymers – can undergo shape change in response to external stimuli such as heat, electric or magnetic fields, or pH.[57,65,72,112-114] Owing to advances in sophisticated manufacturing methods, these polymers can now be designed with increasing complexity. Nevertheless, achieving specific shape transformations or functionalities often relies on labor-intensive, trial-and-error procedures, incurring substantial time and expense.

To address these challenges, recent work employed an RNN to predict deformation patterns from a given material distribution.[115] Specifically, a bi-layered active composite beam composed of two materials with differing thermal expansion coefficients was optimized by integrating ML and EA. Conventional finite element-based optimization is often prohibitively expensive for complex geometries, whereas the RNN-based approach significantly reduces computational costs. By predicting the deformation behavior of a bilayer active composite beam, the system could leverage EA to propose optimal material layouts that govern shape change via volumetric expansion mismatch. This framework achieved over 99% reduction in computational expenses compared with typical finite element workflows without sacrificing target-shape fidelity. Moreover, by coupling this pipeline with computer vision techniques, the authors demonstrated the ability to convert hand-drawn sketches into automatically generated 4D-printed structures.

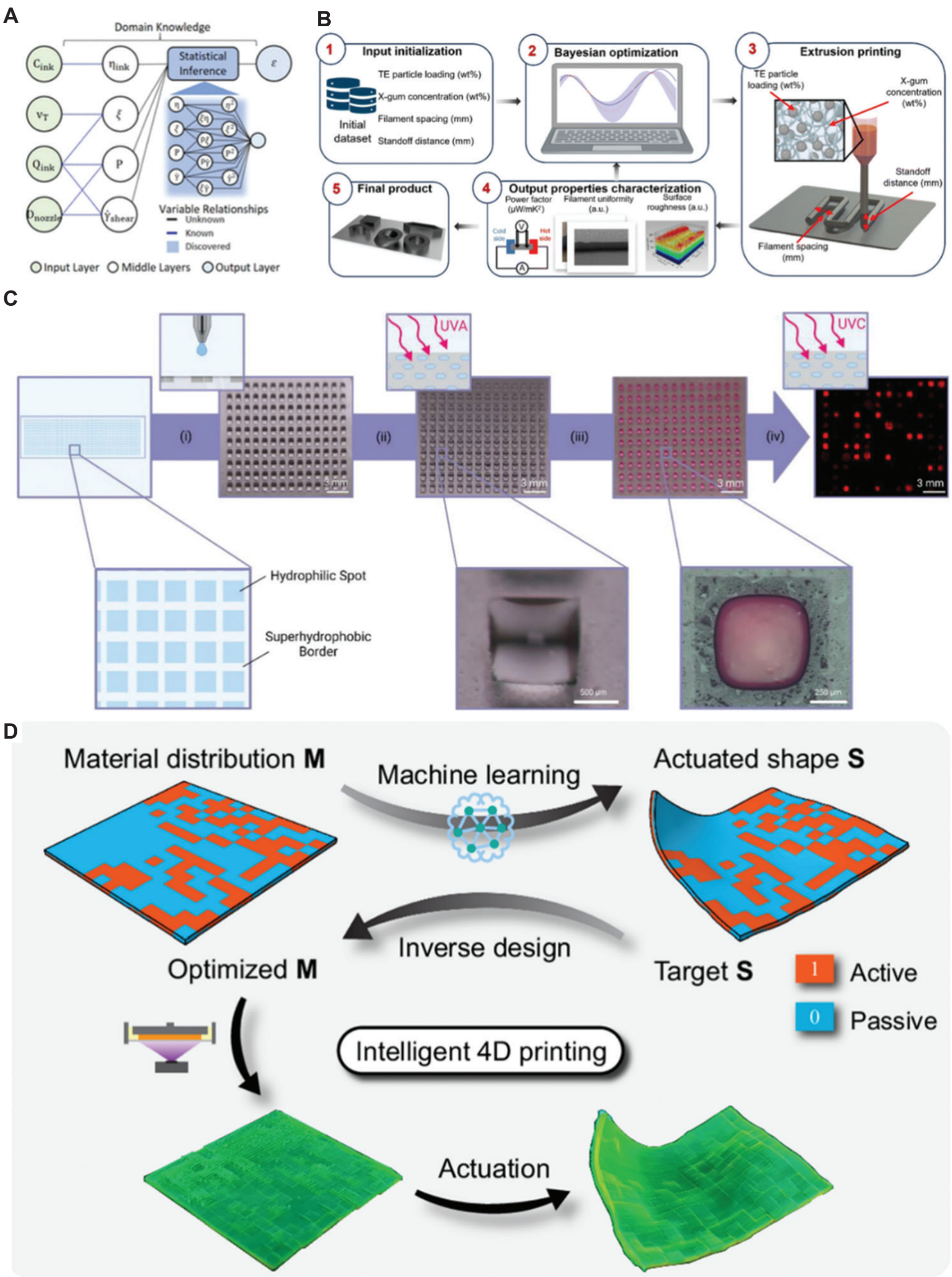

Figure 4. Property and design optimizations for polymer 3D printing. (A) Hierarchical machine learning framework integrating experimental knowledge to reduce data-driven discovery efforts. Reproduced with permission from Bone *et al.*[111] Copyright © 2020 American Chemical Society. (B) Machine learning-assisted extrusion printing workflow for thermoelectric inks with four input variables and three output properties. Reproduced with permission from Song *et al.*[114] Copyright © 2024 Royal Society of Chemistry. (C) Experimental workflow for synthesizing and screening sub-microliter-scale photodegradable hydrogels. Reproduced with permission from Seifermann *et al.*[116] Copyright © 2023 Wiley. (D) Overview of voxel-level inverse design of 4D-printed active composite plates enabled by machine learning. Reproduced with permission from Rodriguez and Goodman.[122] Copyright © 2024 Springer Nature.

In their subsequent study, the same authors extended this approach to active composite plates.[116] While plate architectures offer higher design freedom and enable more intricate shape transformations than beam structures, they also present a combinatorial explosion of possible design variables. To handle this complexity, the authors combined ML with gradient descent (GD) and EA for the inverse design of active plates. A ResNet-based ML model was developed as a forward prediction tool to precisely forecast shape deformation from a given material distribution; this was then coupled with GD and EA to form an inverse design loop. By optimizing the voxel-level material layout, the proposed method effectively controlled 3D shape transformations in more complex configurations. The results highlight how ML-driven strategies can replace or augment high-cost finite element simulations, significantly accelerating the design of 4D-printable smart polymer structures (Figure 4D).

3.2. Metals

Metals exhibit a regular atomic lattice structure held together by robust metallic bonds, which impart notable physical properties such as high density, strength, and electrical/thermal conductivity.[117,118] Moreover, techniques such as heat treatment, alloying, and post-processing enable the tailored adjustment of these physical and chemical properties, facilitating their application as essential materials in aerospace, medical, and automotive industries.[119-123] Recently, to achieve complex geometries and weight reduction, the integration of metal materials with 3D printing technology has garnered significant attention, with two principal AM processes widely employed.

For enhanced geometric complexity and reduced weight, metals are increasingly used in 3D printing technologies.[124-127] A representative metal 3D printing method, PBF, selectively melts and solidifies the powder using a high-energy source.[128-130] Typically, fine metal powders (10–60 µm) such as aluminum, stainless steel, nickel, or titanium are used, enabling the production of high-precision parts. Another method, DED, deposits metal powder (or wire) by melting it with a high-power laser or a plasma arc.[43,131-133] While the alloys commonly utilized in PBF can also be employed in DED, the powder used in DED is generally larger (around 50 – 150 µm). Compared to PBF, the DED process may have lower dimensional accuracy but fewer constraints on part size and faster production speeds, making it highly attractive for industrial applications. A summary of representative ML models and their applications in metal-based 3D printing is provided in Table 2.

3.2.1. Process optimization

Various defects can arise in metal AM (both PBF and DED), such as excessive porosity, balling, lack of fusion, spattering, and warping. These defects occur due to the complex interplay among multiple process parameters, including laser power, scanning speed, and powder feed rate.[122,134,135] Conventional optimization typically relies on trial and error, which can be time-intensive, costly, and potentially misaligned with experimental results. To address these challenges, ML approaches have gained prominence. ML models can learn intricate correlations among variables, predict optimal parameters, minimize defects, and enhance print quality.

An augmented ML framework integrating mechanistic modeling and domain knowledge has also been proposed to mitigate the lack of fusion in laser PBF (LPBF) processes (Figure 5A).[136] By computing five dimensionless variables from process parameters and material properties and applying decision tree and linear regression models, lack of fusion defects were predicted with over 90% accuracy. The resulting index and process maps facilitate quantitative defect prediction and alloy-specific parameter optimization.

While many ML applications focus on real-time monitoring and control during printing, model-driven approaches for pre-print process parameter optimization are also gaining traction. A representative example is the integration of high-throughput LPBF experiments with ensemble ML models to optimize process parameters for 316L stainless steel (Figure 5B).[137] By simultaneously fabricating 54 samples under varied laser power and scanning speed, and training ML models on porosity, hardness, and corrosion data, researchers successfully predicted optimal parameters that significantly reduced porosity (<0.1%) while enhancing tensile strength and corrosion resistance. The trained model also demonstrated transferability to AlSi7Mg, indicating the framework's potential for cross-material optimization and accelerated process design.

Mitigating defects that arise during printing is crucial for ensuring the reliability and performance of the final parts, and research has been actively conducted to address issues related to thermal fluctuations. In particular, deep reinforcement learning has been applied to PBF processes to regulate laser speed and power in real time, thereby maintaining a stable melt pool shape and preventing overheating.[138,139] Such methods effectively reduce defects and improve print quality. Meanwhile, for DED processes, ML-based thermal characteristic prediction has been investigated. Using XGBoost and LSTM algorithms, researchers developed a model that analyzes the relationships between process parameters and temperature, thereby predicting temperature distributions.[140] This strategy effectively controls temperature variations, leading to improved microstructure formation and mechanical properties.

Furthermore, a vision-based real-time defect detection technique was introduced using an autoencoder-based ConvLSTM model.[141] This model autonomously detects

Table 2. Summary of ML models for metal-based 3D printing

Motivation	Material	AM method	ML model	Model inputs	Remarks	References
Process optimization	SS316L, Ti-6Al-4V	PBF	Deep reinforcement learning	Heat distribution, melt pool depth	Control process parameters such as laser velocity and power in real time	138
	Metal powder	PBF	Multi-input neural network	Thermal images, process parameters (scan vector length, heat trace length, heat transfer distance, cumulative scan time)	Feedback control based on multi-input data to achieve the desired thermal history	139
	CarTech® 718 superalloy	DED	XGBoost, LSTM	Laser power, scan speed, layer index, time index, average height, average width	Real-time melt pool temperature prediction	140
	Ti-6Al-4V	DED	ConvLSTM Autoencoder	Video frames of melt pool dynamics	Detect melt pool anomalies (wire dripping, arcing, oscillation, stubbing) for quality control	141
	Inconel 625	PBF	C-RNN	Melt pool video frames	Improve defect detection using spatiotemporal analysis of melt pool videos	142
	SS316L, Ti-6Al-4V, Inconel 718	PBF	Vision transformer	High-speed imaging of melt pool dynamics	Improve process development and defect detection in 3D printing of new metal alloys through *in situ* process mapping	143
	SS316L	DED	CNN	Coaxial camera images of melt pool	Improve fault detection by monitoring nozzle clogging and abnormalities in the powder stream	144
	Inconel 718	DED	Bayesian LSTM, BOTSPO	Temperature history, laser power profile, spatial location	Develop a digital twin framework for real-time predictive control, enhancing process stability and efficiency	150
Property optimization	SS316L	PBF	DT (CART), RF, XGBoost	Build location, post-chamber pressure drop, powder properties, gas flow characteristics	Quality prediction based on the combination of build location and post-chamber pressure drop	148
	Ti-6Al-4V	PBF	GPR, BO	Laser power, scan speed, hatch spacing, porosity data	Discovered an expanded processing window that optimizes mechanical properties and density	149
	Inconel 625	DED	CNN, YOLOv8	Melt pool video frames, bead geometry data	Predict geometric characteristics and analyze their correlation with process parameters and bead geometry for real-time process control	150
	Ti-6Al-4V	DED	CGAN	Laser power, powder feed rate, scan speed	Predict and optimize surface morphology to improve surface quality and reduce cost	151
Design optimization	ER70S-6 steel	DED	SVR, NSGA-II	Laser power, travel speed, wire feed rate	Optimize process parameters for achieving desired layer geometry	152

Abbreviations: BO: Bayesian optimization; BOTSPO: Bayesian optimization for time series process optimization; C-RNN: Convolutional recurrent neural network; CART: Classification and regression tree; CGAN: Conditional generative adversarial network; CNN: Convolution neural network; ConvLSTM: Convolutional long short-term memory; DED: Directed energy deposition; DT: Decision tree; GPR: Gaussian process regression; LSTM: Long short-term memory; ML: Machine learning; NSGA-II: Non-dominated sorting genetic algorithm-II; PBF: Powder bed fusion; RF: Random forest; SVR: Support vector regression; XGBoost: Extreme gradient boosting; YOLO: You Only Look Once.

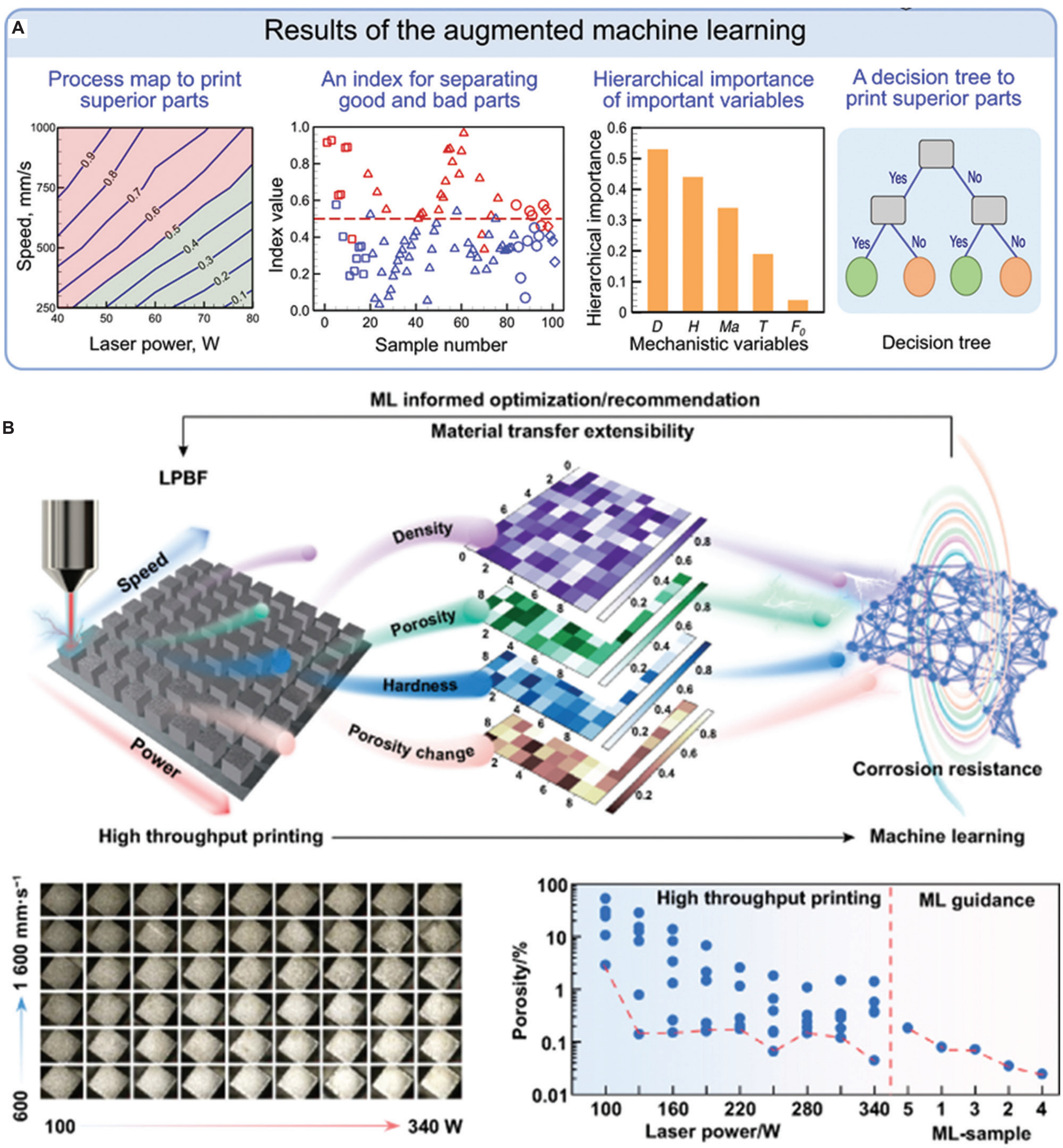

Figure 5. Process optimization for metal 3D printing. (A) Outputs of the augmented machine learning framework. Reproduced with permission from Seifermann *et al.*[116] Copyright © 2022 Springer Nature. (B) Schematic of high-throughput experimentation and machine learning-guided process optimization in laser powder bed fusion. Reproduced from Jain *et al.*[117] Copyright © 2025 IOP Publishing. Abbreviations: LPBF: Laser powder bed fusion; ML: Machine learning.

abnormal melt pool fluctuations, effectively identifying critical defects and consequently improving process stability and quality assurance. In ddition, ML-based strategies have attracted attention for real-time monitoring and quality control in metal 3D printing. Existing CNN-based analyses have been limited to spatial features, but combining CNNs with RNNs allows simultaneous analysis of spatial and temporal characteristics.[142] This integrated approach enables real-time detection of surface quality degradation in PBF and more accurate layer-by-layer surface finish monitoring. Moreover, employing high-speed imaging data to generate process maps and variability maps for various alloys can further improve the reliability and quality stability of metal 3D printing. Notably, the use of vision transformers enables real-time analysis of dynamic melt pool changes, significantly enhancing process control efficiency (Figure 6A).[143] In DED processes, a vision-based real-time powder stream defect detection technique has also been introduced.[144,145] By analyzing melt pool images acquired through a coaxial camera to classify normal versus abnormal states and identifying defective nozzles during deposition, researchers have demonstrated improvements in the precision of in-process quality monitoring. Ultimately, such real-time monitoring and ML-based analytical methods are critical for automating and advancing metal 3D printing processes, and they form indispensable components for establishing stable mass-production systems.

3.2.2. Property optimization

Optimizing the mechanical, thermal, and functional properties in metal AM is paramount for simultaneously ensuring the performance of the final product and the stability of the manufacturing process. In particular, combining microstructure analyses (*e.g.*, electron backscatter diffraction, X-ray CT) with deep learning is an active area of research aimed at quantifying correlations among material properties.[146,147]

For PBF processes, ML techniques have been used to improve repeatable quality by analyzing how part location and chamber pressure variations impact mechanical properties, and by optimizing process control strategies accordingly.[148] Furthermore, by employing Bayesian optimization and GP regression, researchers have explored expanded process windows to optimize the mechanical properties and density of Ti-6Al-4V alloys.[149] This approach has demonstrated the effective mitigation of balling instabilities in newly discovered high-density process regions.

In DED processes, a CNN-based real-time monitoring and melt pool segmentation approach has been introduced for process stability and optimization.[150] A YOLO-based model was employed to predict geometric features of the melt pool, such as area, height, and width, and to analyze the correlations between process parameters and bead geometry, thereby facilitating real-time process control (Figure 6B). An artificial intelligence (AI)-based method using conditional GAN was also proposed to generate virtual surface morphologies of Ti-6Al-4V parts.[151] When provided with process parameters, this model offers a visual prediction of the expected surface roughness, showing high alignment with experimental observations and underscoring its utility for improving mechanical properties.

In addition, ultrasound-assisted DED (UADED) has been explored as a method to improve melt pool stability and reduce process defects. An unsupervised learning model has been applied for *in situ* monitoring of melt pool dynamics, spatters, and plume formation in UADED.[152] The model effectively classifies process variations by extracting and reconstructing features from high-speed imaging data, enabling real-time detection of anomalies and enhancing the overall stability of the deposition process.

3.2.3. Design optimization

To meet the dual demands of complex geometries and requisite performance in metal components, effective approaches must be adopted at the design stage, in addition to process optimization. Traditional simulation-based optimizations can require prohibitively large amounts of iterative computation. However, ML, particularly reinforcement learning, allows for the rapid and accurate exploration of additively manufactured shapes and structures. Combining reinforcement learning with multi-objective optimization algorithms can effectively address diverse objectives, such as topology optimization, weight reduction, and structural integrity. For instance, a study integrating support vector regression with non-dominated sorting genetic algorithm-II (NSGA-II) demonstrated the precise prediction of a component's final height and width, which was then leveraged to refine process control strategies.[153] By enhancing geometric accuracy and optimizing the interplay between design and manufacturing processes, metal 3D printing can be extended to a far broader range of applications.

3.3. Ceramic

Ceramic AM has gained significant attention due to its ability to fabricate complex geometries with high thermal, chemical, and mechanical stability. Unlike traditional ceramic manufacturing methods that require extensive post-processing, such as sintering and machining, AM techniques such as DIW, SLA, and powder-based extrusion offer a more flexible and efficient approach to producing ceramic components. However, challenges such as viscosity control, printability optimization, defect detection, and microstructural consistency remain critical obstacles in achieving high-quality ceramic prints. To address these issues, ML has been integrated into various stages of the ceramic AM process, including material formulation, process parameter optimization, defect detection, and quality assurance.

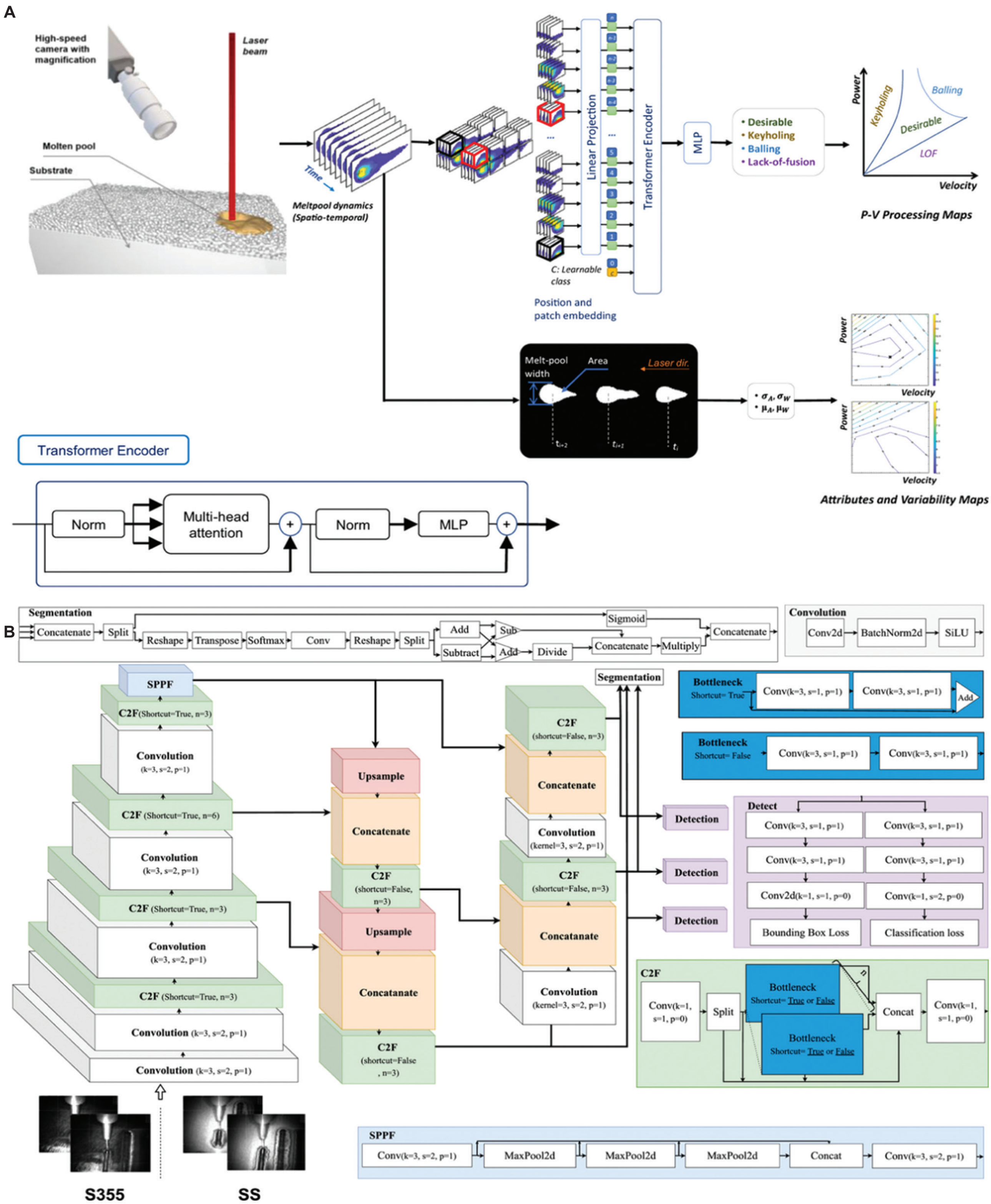

Figure 6. Process monitoring for melt pool detection. (A) *In situ* process development pipeline using high-speed imaging to capture molten pool dynamics, classify defects, and generate variability maps for process stability assessment. Reproduced with permission from Guirguis *et al.*[148] Copyright © 2024 Springer Nature. (B) You Only Look Once (YOLO) architecture integrating an additional segmentation branch for simultaneous object detection and segmentation. Reproduced with permission from Asadi *et al.*[155] Copyright © 2024 Elsevier.

One of the key applications of ML in ceramic AM is the prediction of viscoelastic and printability properties of ceramic pastes, particularly in binder-free DIW systems. Since the rheological behavior of ceramic pastes strongly influences their printability and structural integrity, researchers have utilized ML models to correlate formulation parameters with viscoelastic properties. Recent studies have demonstrated that ML-driven predictive models can effectively optimize ceramic ink compositions, ensuring improved extrusion stability and defect-free printing.[154]

Beyond material formulation, ML has played a crucial role in enhancing defect detection and surface quality evaluation in 3D-printed ceramic components. Due to the inherent brittleness of ceramics, even minor surface imperfections can lead to mechanical failure, making precise defect detection essential. Deep learning-based image processing techniques have been employed to identify surface defects in ceramic AM, mitigating interference from background noise and improving detection accuracy.[155] Furthermore, low-contrast defects, particularly in curved ceramic surfaces, pose significant challenges for conventional inspection methods. Deep learning models trained on high-resolution imaging datasets have demonstrated superior performance in identifying and classifying such defects, improving the reliability of ceramic AM processes.[156]

Another major challenge in ceramic AM is process stability and consistency across deposition lines in extrusion-based printing techniques. Variability in extrusion pressure, layer adhesion, and drying-induced deformations can compromise final part quality. To address these issues, ML-based quality optimization frameworks have been developed to analyze real-time process data and adjust deposition parameters dynamically. These models enable adaptive control of layer deposition, reducing print failures and enhancing mechanical uniformity in ceramic structures.[157]

In addition to process control, ML has facilitated the material development and optimization of lithography-based ceramic AM, particularly for porous alumina ceramics. The microstructure of porous ceramics is highly dependent on photopolymerization kinetics, resin composition, and post-processing conditions. By leveraging ML algorithms to predict porosity, shrinkage behavior, and mechanical performance, researchers have improved the material design process for high-performance ceramic components.[158]

Beyond material design and process monitoring, another critical application of ML in ceramic AM is the prediction of microstructural evolution during post-processing steps such as sintering. Supervised learning models have been trained to correlate process parameters and binder content with sintering outcomes–including shrinkage, densification, and grain coarsening–enabling optimization of thermal profiles to minimize residual stress and improve final part integrity.[159] Other studies have applied ML techniques to tailor ceramic microstructures by predicting grain growth and porosity as functions of printing conditions and sintering temperature profiles.[160] However, modeling ceramic microstructures remains particularly challenging due to the complex multiscale phenomena involved, including powder packing, binder removal, and thermally driven phase transitions.[157] Progress in ML for ceramic AM is further constrained by the scarcity of high-quality datasets, as experimental studies are limited and involve high variability across materials and processes.[154] Moreover, the brittle nature of ceramics demands extremely high prediction accuracy since minor defects or heterogeneities can lead to catastrophic failure.[160] These factors highlight the need for specialized ML strategies and interdisciplinary domain knowledge tailored to the unique challenges of ceramic AM.[161]

Overall, the integration of ML into ceramic AM has significantly enhanced material formulation, process optimization, defect detection, and quality control. By leveraging advanced ML models, researchers and manufacturers can overcome the limitations of conventional ceramic printing techniques, paving the way for improved mechanical performance, reduced production costs, and increased industrial adoption. However, challenges such as data scarcity, model generalization across different ceramic materials, and real-time implementation of ML algorithms in AM workflows remain key areas for future research. Continued advancements in ML-driven ceramic AM optimization will further strengthen the role of AI in next-generation AM.

3.4. Carbon-based materials

Carbon-based materials have garnered significant interest in AM due to their exceptional mechanical, electrical, and thermal properties. Carbon fiber-reinforced polymers, carbon nanotube composites, and graphene-based materials exhibit high strength-to-weight ratios, electrical conductivity, and flexibility, making them ideal for applications in aerospace, energy storage, structural reinforcements, and wearable electronics.

One of the most critical applications of ML in carbon AM is the optimization of mechanical properties in continuous carbon fiber-reinforced composites. The mechanical behavior of these materials is influenced by fiber alignment, resin infiltration, and interfacial bonding.[162] Deep learning models such as CNNs and multi-objective optimization techniques like NSGA-II have been employed to fine-tune printing parameters, ensuring improved tensile strength, flexural performance, and reduced void formation.[163] In addition, ML-based predictive modeling has been applied to estimate the flexural strength of additively manufactured carbon fiber composites, aiding in material selection and process design.[164]

In this review, continuous fiber-reinforced composites and nano-carbon composites–including those utilizing carbon nanotubes and graphene–are collectively discussed under the category of carbon-based materials, as they share common goals such as enhancing mechanical strength, electrical conductivity, and structural performance through carbon-based reinforcements. Despite this shared objective, these materials differ significantly in terms of scale, structure, and manufacturing challenges. Continuous carbon fibers provide macroscopic reinforcement and often induce anisotropic mechanical behavior in printed parts, requiring ML models that can account for fiber orientation, continuity, and alignment during process monitoring or property prediction. In contrast, nano-carbon composites employ dispersed carbon nanotubes or graphene as nanoscale fillers that influence rheological behavior, filler dispersion, and electrical percolation networks. Accordingly, ML approaches in nano-carbon systems tend to focus on optimizing material formulations and predicting bulk properties – such as strength, elasticity, or conductivity – based on composition and processing conditions.

While both material systems rely on carbon reinforcements, their distinct physical characteristics demand tailored ML strategies. Continuous fiber-based composites benefit from spatially aware models capable of capturing fiber trajectories and interfacial features, whereas nano-carbon systems often utilize ML to uncover correlations between nano-filler morphology, distribution uniformity, and macroscopic functional properties. This distinction highlights the necessity of material-specific ML pipelines, even within a unified classification of carbon-based materials in AM.

Beyond mechanical optimization, ML has been leveraged to enhance the dimensional accuracy of 3D-printed carbon-based structures. Variability in the curing process, thermal expansion, and shrinkage can lead to deviations from intended geometries, particularly in polydimethylsiloxane-carbon nanotube (PDMS-CNT) composites. ML-driven models have been used to predict and correct dimensional inaccuracies, improving precision in printed components.[165]

In energy storage applications, ML-guided optimization has played a crucial role in tuning the architecture and performance of carbon microlattices for supercapacitors. The intricate microstructure of these lattices directly affects their electrochemical properties, including charge storage capacity and ion transport efficiency. ML models have enabled the design of 3D-printed carbon microlattices with tailored properties, enhancing supercapacitor performance for next-generation energy storage solutions.[166]

Strain sensing and structural health monitoring represent another important area where ML has advanced carbon-based AM. 3D-printed carbon nanotube/polypyrrole/UV-curable composites have been studied for their strain-sensing capabilities, with ML models facilitating accurate prediction of electromechanical responses and real-time sensor calibration.[167] Similarly, graphene-based self-powered strain sensors for smart tires in autonomous vehicles have been developed, utilizing ML for real-time performance optimization and fault detection.[168]

Graphene-based materials have also found applications in gas sensing, Internet of Things (IoT)-enabled energy harvesting, and biocompatible electronic interfaces. ML has been employed to enhance the sensitivity and selectivity of textile-based graphene gas sensors, improving their performance in energy harvesting-assisted IoT applications.[169] In addition, graphene-based nanomembrane bioelectronics have been optimized using ML to achieve multimodal human-machine interfaces with improved flexibility and durability (Figure 7A).[170]

Furthermore, ML has contributed to the development of conformal, wearable carbon-based sensors for health monitoring. 3D-printed graphene-based humidity and strain sensors have been designed for human motion prediction, leveraging ML to refine sensor calibration and response accuracy (Figure 7B).[171]

In summary, the integration of ML into carbon-based AM has significantly advanced the fabrication, optimization, and application of these materials. By harnessing ML-driven insights, researchers have improved mechanical properties, enhanced structural accuracy, optimized energy storage devices, and enabled next-generation sensor technologies. However, challenges such as real-time ML implementation, multi-material process optimization, and the generalization of predictive models across different carbon-based materials remain key areas for further investigation. Continued advancements in ML-driven optimization will expand the capabilities of carbon-based AM, driving innovations in high-performance materials for industrial and biomedical applications.

4. Conclusions and future perspectives

The integration of ML with AM has demonstrated significant potential in optimizing 3D printing processes, improving

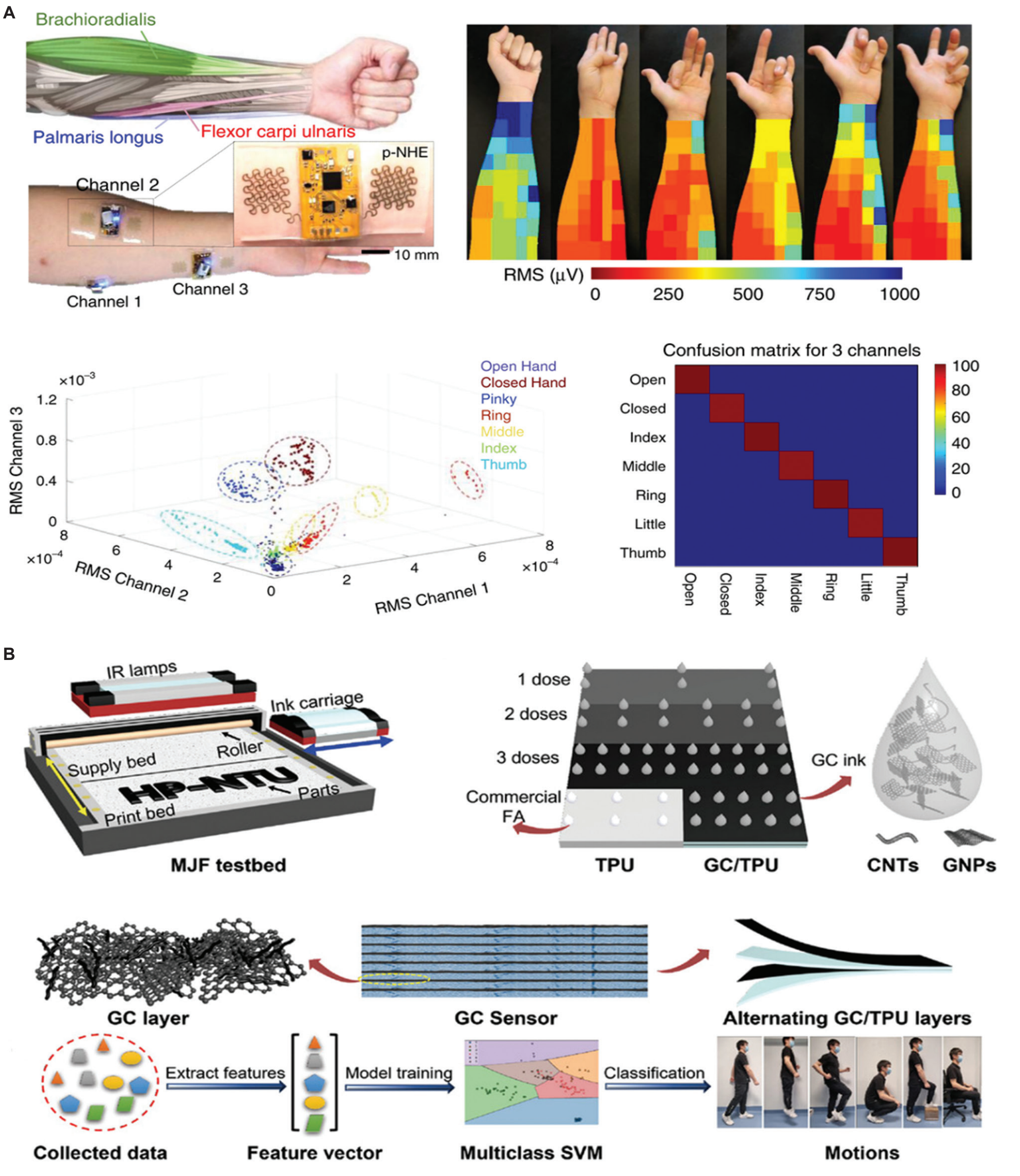

Figure 7. Machine learning applications for materials processing and biomechanical sensing. (A) Deep learning-based selection of three channels for classifying seven finger movement classes. Reproduced with permission from Kwon *et al.*[170] Copyright © 2020 Springer Nature. (B) Human motion prediction using a support vector machine model trained on variation data from graphene nanoplate-carbon nanotube sensors. Reproduced with permission from Hou *et al.*[171] Copyright © 2023 Wiley. Abbreviations: CNT: Carbon nanotube; GC: Graphene nanoplate-carbon nanotube; GNP: Graphene nanoplate; IR: Infrared; MJF: Multi jet fusion; RMS: Root mean square; SVM: Support vector machine; TPU: Thermoplastic polyurethane.

quality control, and enabling real-time monitoring. As AM continues to evolve into a key technology for next-generation manufacturing, the demand for higher precision, material efficiency, and scalable production methods has intensified. The application of ML in AM has addressed many of these challenges by providing data-driven solutions for process parameter optimization, defect detection, and mechanical property prediction, thereby reducing reliance on empirical trial-and-error methods.

This review explores the role of ML in optimizing 3D printing, highlighting advancements in process monitoring, defect mitigation, material property prediction, and design optimization. In polymer-based AM, ML techniques have significantly enhanced printability assessment, process stability, and surface quality prediction. Studies on FDM, DIW, and vat photopolymerization (SLA/DLP) have demonstrated how ML models, particularly CNNs, GANs, and time-series models, can improve printing accuracy by compensating for environmental variations, detecting defects in real time, and optimizing material formulations. Similarly, in metal-based AM, ML applications in PBF and DED have contributed to thermal control, melt pool monitoring, and mechanical property enhancement. Reinforcement learning and hybrid physics-informed ML models have facilitated adaptive process control, leading to improved consistency in microstructural integrity and mechanical performance.

Despite these advancements, persistent technical challenges remain in realizing the full potential of ML in AM. Data scarcity and variability continue to impede model training, as high-quality labeled datasets are often limited in AM contexts. Models also struggle to generalize across different machines, materials, and process settings, meaning an ML model tuned for one scenario may perform poorly when applied elsewhere. Moreover, many advanced ML models function as "black boxes," raising interpretability concerns and limiting user trust in critical manufacturing decisions. Achieving real-time, closed-loop process control via ML is another hurdle due to computational constraints, and current implementations still face latency and integration issues. Finally, there is a need to better integrate fundamental physics with data-driven approaches to generate emerging physics-informed ML techniques that aim to improve prediction accuracy and reliability while reducing reliance on massive training data. Addressing these unresolved issues will be crucial for transitioning from promising prototypes to robust, industrial-grade intelligent AM systems.

In the future, the convergence of ML with advanced sensing technologies, *in situ* monitoring systems, and cloud-based manufacturing platforms will drive further innovation in AM. Multi-modal data fusion techniques, incorporating thermal imaging, X-ray CT, and acoustic sensors, will refine defect detection accuracy and improve process stability. Moreover, the development of self-learning AI-driven AM systems, capable of autonomously optimizing print parameters and material compositions, will enable fully automated, intelligent manufacturing workflows.

Ultimately, the synergy between ML and AM is poised to revolutionize manufacturing by enabling higher precision, faster production cycles, and more sustainable fabrication processes. As interdisciplinary collaborations between materials science, computational modeling, and AI engineering continue to grow, the vision of fully functional, AI-optimized 3D printing for industrial-scale applications is becoming increasingly tangible. Continued research efforts in scalable ML architectures, real-time adaptive control, and robust AM process simulations will be essential for advancing next-generation intelligent manufacturing ecosystems.

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Conflict of interest

Im Doo Jung is an Editorial Board Member of this journal, but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. Separately, other authors declared that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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