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Review

AI-Driven Innovations in 3D Printing: Optimization, Automation, and Intelligent Control

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Abstract

By greatly increasing automation, accuracy, and flexibility at every step of the additive manufacturing process, from design and production to quality assurance, artificial intelligence (AI) is revolutionizing the 3D printing industry. The integration of AI algorithms into 3D printing systems enables real-time optimization of print parameters, accurate prediction of material behavior, and early defect detection using computer vision and sensor data. Machine learning (ML) techniques further streamline the design-to-production pipeline by generating complex geometries, automating slicing processes, and enabling adaptive, self-correcting control during printing—functions that align directly with the principles of Industry 4.0/5.0, where cyber-physical integration, autonomous decision-making, and human–machine collaboration drive intelligent manufacturing systems. Along with improving operational effectiveness and product uniformity, this potent combination of AI and 3D printing also propels the creation of intelligent manufacturing systems that are capable of self-learning. This confluence has the potential to completely transform sectors including consumer products, healthcare, construction, and aerospace as it develops. This comprehensive review explores how AI enhances the capabilities of 3D printing, with a focus on process optimization, defect detection, and intelligent control mechanisms. Moreover, unresolved challenges are highlighted—including data scarcity, limited generalizability across printers and materials, certification barriers in safety-critical domains, computational costs, and the need for explainable AI.

Keywords: artificial intelligence (AI); machine learning (ML); 3D printing; optimization; defect detection

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1. Introduction

This review intends to identify relevant journal and conference publications and to extract useful information to provide valuable insights to researchers and enthusiasts in AI and additive manufacturing (AM) field. To adopt a transparent approach to assess and collect literature about the incorporation of AI in additive manufacturing, research database platforms like ScienceDirect, IEEE Xplore, Scopus, and Google Scholar were explored from 2015 to 2025 using keywords like AI in additive, machine learning in 3D printing, intelligent control WAAM, defect detection, and real-time monitoring. The scholarly criteria were narrowed down to peer-reviewed journals and conference proceedings focused on factual validations and practical implementation of AI-assisted additive manufacturing [1–3].

3D printing—what was once fictional—has now become the governing technology of the 21st century, spanning every manufacturing industry, from kids' toys to concrete structures. Also known as additive manufacturing, it works by executing a digital design file, known as a computer-aided design (CAD) file, by adding the required material layer by layer, minimizing waste, whereas its counterpart, traditional manufacturing, works by subtracting material. The layer-by-layer addition of material enables the fabrication of complex geometries which are impossible to achieve by conventional manufacturing. Three-dimensional printing, which began as a prototyping tool in the 1980s [4–6], is now one of the most powerful innovative engines, spanning industries from aerospace, automotive, and construction to fashion [7,8].

With the ongoing evolution of 3D printing comes the challenge of navigating countless parameters, real-time decision-making, and geometric intricacies. These limitations give great scope to AI to incorporate intelligence in additive manufacturing. AI aims to create building machines that can impersonate and sometimes exceed human cognitive abilities like reasoning, learning, and decision-making. It is a collection of powerful systems across various industries, like automating the automotive industry and disease prediction in the medical industry. The combination of AI and 3D printing technologies marks the beginning of a new era of intelligent manufacturing. When it comes to 3D printing, AI refines the process from being static and preprogrammed to a robust and adaptable one by optimizing print paths, detecting defects mid-build, and even generating digital blueprints for entirely new structural designs by learning from past prints.

This powerful coordination is supported by several key motivations, such as the ability of AI to perform complex permutations simultaneously, as it can explore several thousand of them, compared to traditional design solutions, which often include human assumptions. In addition to that, AI can monitor and control the process in real-time with various sensors to detect manufacturing defects, assuring quality. This enables reduced human intervention, which in turn makes 3D printing accessible to non-experts [2,3]. Economically, AI's design optimization by identifying sustainable design strategies will allow the conservative use of material, reducing wastage and cost [9], as demonstrated by Srivastava et al. [10].

The process of 3D printing generates a large amount of data because it is susceptible to many variables like flow rate, printing inconsistencies, temperature fluctuations, and geometric deviations, as it progresses layer-by-layer, which requires continuous monitoring. This data can be analyzed and interpreted by AI, and machine learning algorithms can be trained to recognize patterns and predict outcomes. In recent times, real-time defect detection technology based on deep learning has been introduced by G. Wang et al. to produce 3D microelectronics by training and introducing a new algorithm, YOLOv8 [11]. This real-time detection also contributes to predictive maintenance to minimize downtime. Furthermore, AI-enabled 3D printers are self-learning, adapting to real-time materials and geometries on the go [12]. As manufacturing industries are shifting towards 3D printing, the combination of AI and 3D printing is laying the groundwork for automation in manufacturing plants, enhancing accuracy, sustainability, and customizability.

The urgency of integrating AI into additive manufacturing is particularly evident at this stage of technological and industrial development. As AM transitions from a prototyping tool to fully industrialized production, the demand for higher reliability, repeatability, and scalability has never been greater. Conventional process control approaches are insufficient to handle the large volume of variables and real-time adaptability required in industrial environments. AI transforms AM into a data-driven, intelligent, and autonomous manufacturing paradigm, which is essential for industries operating under the principles of Industry 4.0 and moving toward Industry 5.0, where human–machine collaboration and sustainability play a central role.

Therefore, the objective of this paper is to explore the integration of AI in 3D printing and its impact on industry. Specifically, this review aims to: (i) critically examine the methods and technologies through which AI enhances AM processes such as design, monitoring, optimization, and quality assurance; (ii) contextualize these advancements within Industry 4.0/5.0 and highlight their transformative impact on manufacturing ecosystems; and (iii) identify unresolved challenges, research gaps, and future directions that must be addressed for AI-driven AM to achieve industrial maturity. By clarifying both the motivation and objectives, this paper provides a structured roadmap for researchers and practitioners working at the intersection of AI and AM.

This review uniquely integrates AI-driven optimization, automation, and intelligent control in 3D printing, framing their role in Industry 4.0/5.0 and outlining both the transformative potential and unresolved challenges that have not been consolidated in prior literature.

2. Challenges of Additive Manufacturing

Mechanical Anisotropy and Quality: In techniques where production is carried out layer by layer, it is seen that the efficiency of strength in the materials decreases depending on the build direction. This shows that the bond between the layers changes in efficiency based on the production direction direction [13,14].

Material Limitations: The range of materials in additive manufacturing is not as extensive as in traditional methods. For example, photopolymer resins are brittle and are not suitable for every production method; high-performance polymers (e.g., PEEK, PEI) require working with high-cost equipment. The reason for this is the necessity of producing at the desired standards with additive manufacturing [15]. Non-Newtonian material behavior in extrusion-based 3D printing presents particular challenges that AI systems must address. Materials exhibiting shear-thinning or thixotropic behavior require sophisticated understanding of rheological properties that current AI models may inadequately capture [16]. Bioactive ink optimization represents a missed opportunity to demonstrate AI adaptability across material categories. Recent research in bioprinting shows how machine learning algorithms can optimize complex bioink formulations through Bayesian optimization approaches [17]. These applications demonstrate AI's potential for handling materials with unique challenges, including cell viability requirements and complex rheological behaviors. Multi-material 3D printing applications present additional complexity that the manuscript should address more thoroughly. Co-sintering challenges in ceramic printing require careful material pairing and shrinkage behavior adaptation. AI systems must understand these material interactions to optimize printing parameters effectively, yet current research shows limited success in handling such complexity [17]. Cross-material knowledge transfer represents both an opportunity and a challenge for AI systems. While transfer learning approaches show promise for adapting models across similar materials, substantial gaps remain when transitioning between material categories [18]. Temperature-dependent material behaviors add another layer of complexity that AI systems must address. High-performance polymers and metal powders exhibit different thermal responses that affect printing outcomes [19]. Current AI models may struggle to generalize across these thermal regimes without extensive retraining.

Speed and Scale: Additive manufacturing methods are generally slow methods and are not suitable for mass production of large-scale objects because they take hours or even days [20,21].

Cost: One major drawback of additive manufacturing is the high price of not only the machines but also the raw materials, such as metal powders and resins. The advanced setup that can perform high-tech alloy or polymer processes will need a very large amount of money, which is usually far more than that of traditional manufacturing machines.

In addition, the production of high-purity metal powders involves complex atomization and quality control processes, which further raise material prices. Compared to traditional methods, the cost challenge becomes clearer. For example, high-speed machining of a titanium alloy block also incurs significant expenses due to tool wear, energy consumption, and material waste.

Nevertheless, the slow build rates in additive manufacturing and the resulting limited economies of scale have made additive manufacturing even more expensive [21]. While machining is often criticized for material wastage through subtractive processes, the faster cycle times and well-developed infrastructure make it more cost-effective in large-volume production.

Eventually, the question of whether additive manufacturing is economically feasible comes down to the extent that it can offset the high costs with its characteristic advantages, namely design freedom, lightweighting, and assembly reduction. The machine efficiency, material production, and process scalability that come with technology growth are the factors that are expected to help close the cost gap with conventional manufacturing.

Post-Processing: After production is completed, post-processes such as removal of supports, heat treatment, and surface finishing increase the cost [22].

Standardization and Quality Control: In fields such as aviation and medicine, the formation of quality and safety standards is still not completed. The reason for this is that additive manufacturing is still developing. Recently, quality control systems systems have been developed using AI, but in AM methods, the detection of defects is more complex compared to other methods. Because of this situation, detection is difficult [23].

Cyber-Physical Security Vulnerabilities: The integration of digital design files, AI-driven process control, and internet-connected hardware creates a complex cyber-physical system with an expanded attack surface. Malicious actors can target multiple points in the AM workflow, with motivations ranging from intellectual property theft to outright sabotage. One of the most egregious risks is tampering with digital files to subtly—and often invisibly—inject flaws into a finished part. Attackers may find ways by which they could change the CAD file or G-code that resulted from an AI-driven slicer, adding in small internal voids not originally present or changing geometric tolerances of some critical part (e.g., an aircraft turbine blade or a load-bearing implant) [24]. These defects, which were meant to fail only under certain operational pressures, could have disastrous effects. The AI control system could be a target of attack itself; if the machine learning model were compromised, the model could be modified to converge to a set of printing parameters that overall decrease part quality for the entire production run.

As smart factories become more reliant on interconnected, AI-managed systems, they also become vulnerable to denial-of-service or ransomware attacks. A malicious actor could compromise the central AI controller, halting production across an entire facility and holding the operation hostage until a ransom is paid [25]. This represents a significant threat to supply chain stability and manufacturing resilience.

Environmental and Intellectual Property Issues: The amount of energy consumed in the AM method, material recycling, and the easy duplication of digital files are still being debated. Because of this, it is concluded that there are still gaps in the AM method, and this situation provides a large research area [20].

Many studies are being carried out to overcome these challenges. For example, in the FDM method, the use of fiber-reinforced filaments and the optimization of printing parameters can result in increased efficiency [26,27]. It is seen that production systems such as metallic glasses, biodegradable resins, and hybrid manufacturing expand the production range of AM and address more fields. The use of AI in production and the development of large-volume machines are among the efforts aimed at increasing efficiency [23].

In general, with developments in AM processes, materials, and software, many of the current disadvantages will turn into advantages. The design flexibility, customization, and low waste offered by AM help overcome disadvantages such as cost and speed and enable the development of applications.

3. AI-Driven Innovations in 3D Printing: The Role of AI and Its Benefits

The integration of AI into 3D printing has led to groundbreaking advancements in optimization, automation, and intelligent control. AI enhances 3D printing by improving design accuracy, predicting failures, automating processes, and enabling real-time adjustments [28]. By analyzing vast amounts of data, AI-driven systems can make informed decisions that enhance print quality, minimize waste, and expedite production times. The following section is an explanation of AI concepts and key types relevant to 3D printing innovations.

3.1. AI in Manufacturing: Types of AI Used in 3D Printing

3.1.1. Machine Learning (ML)

Machine learning (ML) involves algorithms that learn from data to improve performance without explicit programming. In 3D printing, ML plays a crucial role in predictive maintenance, where it detects potential machine failures before they occur. It also optimizes printing processes by adjusting parameters such as speed, temperature, and material flow in real time. Additionally, ML enables generative design, where AI suggests optimal structures based on load requirements, leading to lighter and stronger components [29].

3D micro-printing is a highly detailed extreme AM method that allows the creation of small and tiny structures on the scale of micrometers or even nanometers with very high accuracy. The main applications of this technology are in areas such as biomedical devices, microelectronics, and photonics, in which small and complicated shapes are necessary. One of the most established methods is two-photon polymerization (2PP), which uses focused femtosecond lasers to solidify photosensitive resins at extremely fine resolutions [30]. One example of where ML is applied is in Bayesian parameter optimization. Johnson et al. applied an active-learning framework (Bayesian optimization) to 3D micro-printing. They used a Gaussian-process surrogate to predict optimal printing parameters for projection multiphoton lithography iteratively. With only a few hundred training points, the model reduced print errors to within measurement tolerance in just four iterations [31]. This ML-driven approach replaces exhaustive trial-and-error with a digital twin that guides process settings for new designs.

Another application of AI in 3D printing is the tuning of fused deposition modeling (FDM) for multiple objectives. Panico et al. combined the design of experiments with machine learning to optimize fused filament prints [32]. They trained a Random Forest regressor on tensile test data, boosting predictive accuracy (test R^2) by over 40%. A genetic algorithm (NSGA-II) then searched for parameter sets (layer height, extrusion temp, speed, infill pattern) that maximize strength and stiffness. Figure 1 shows 3D printing factors and their effect on ultimate tensile strength (UTS), elastic modulus (E), and strain at maximum stress (ε_d). UTS and E are primarily influenced by the infill pattern factor, while the layer thickness primarily affects ε_d, although minor differences are observed among all factors for this response. The ML-optimized settings (e.g., a lines infill pattern) yielded specimens with higher tensile strength and modulus than standard settings, confirming the model's predictions [32].

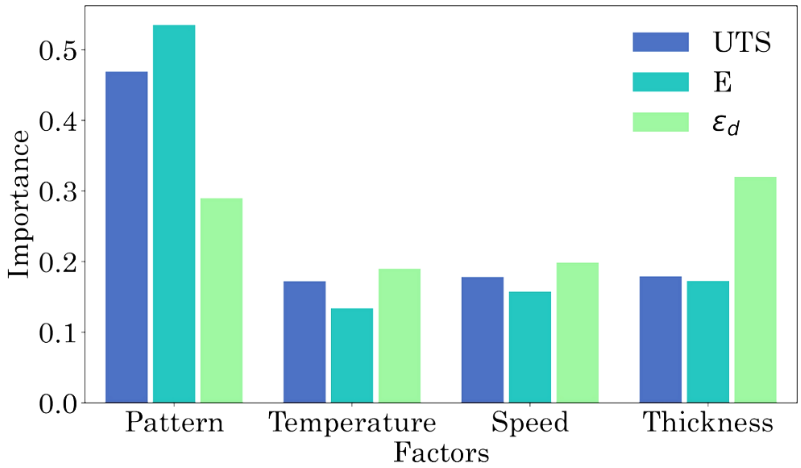

Figure 1. Effect of 3D printing parameters on mechanical properties [32].

The outcome of Panico et al. is summarized in in Figure 2a,c,e which shows that the RF model predictions closely align with the target values ($R^2 > 0.80$ for all cases), indicating strong predictive performance and over 40% improvement compared to the RSM method. To compare the RSM and RF methods, the average of four experimental observations per run was used as the target. Figure 2b,d,f shows the residuals (as percentages), revealing that the RF model consistently has the lowest residuals, confirming its superior accuracy [32].

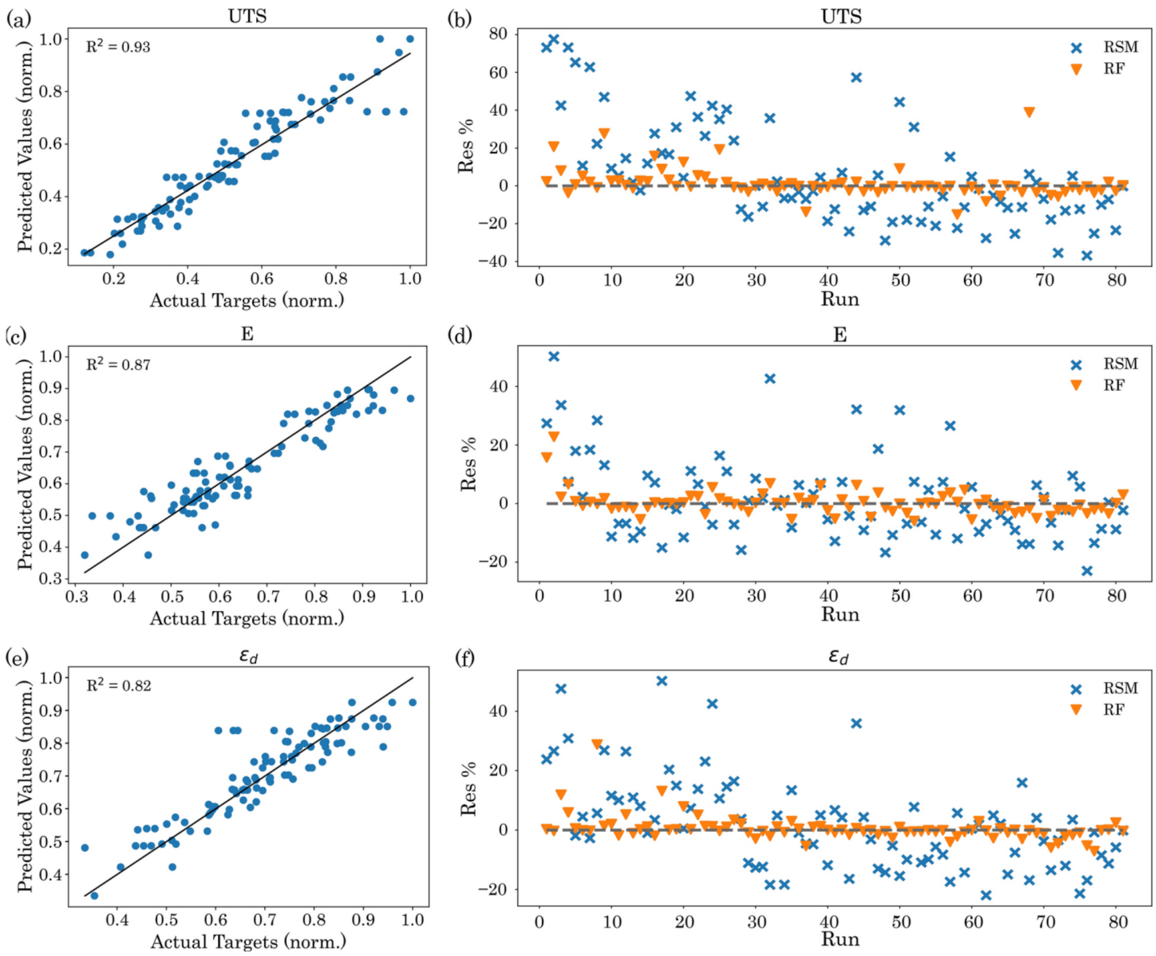

Figure 2. Evaluation of the performance of the RF model on the test dataset (left) and in comparison with the RSM method (right). (**a**,**c**,**e**) Predicted vs. target values showing strong agreement and over 40% improvement for RF. (**b**,**d**,**f**) Residuals confirming lower errors and higher accuracy of the RF model [32].

Another example is real-time defect detection. Wang et al. built a deep-learning vision system to monitor extrusion-based 3D printing layer by layer [11]. They trained an enhanced YOLOv8 convolutional network to recognize four defect types (scratches, holes, over-extrusion, and impurities) in real-time. The model achieved a mean average precision of 91.7% at ~72 frames per second [23], enabling on-the-fly quality control. It is highly important to note that these findings in terms of performance measures were curated from an in-house dataset under controlled laboratory conditions. The model's robustness against variations in material, ambient lighting, and different printer kinematics remains an open question for industrial deployment. In practice, this enables the printer to flag or halt operations upon detecting anomalies, significantly automating the inspection process.

Closed-loop reinforcement learning (RL) control is also utilized in 3D printing. M. Piovarci et al. demonstrated a reinforcement-learning controller for direct ink writing (DIW). Trained in simulation, the RL agent learned to adjust nozzle speed and deposition path based on in situ feedback. When deployed on real hardware, the learned policy outperformed fixed (open-loop) controls, correcting material flow errors in real-time and producing more accurate single-layer prints [33]. This demonstrates that ML can enable printers to self-correct, adapting process parameters in real-time.

ML can perform integrated error prediction and local tuning. K.A Hunt et al., developed a system that couples defect detection with local parameter optimization. The tool captures layer images and predicts the likelihood of defects at each location; it then computes locally optimal printing settings to avoid those flaws. In effect, the printer self-optimizes by adjusting parameters for each area of the part to maximize overall quality. As described in the NASA report, a tool was developed that can predict and implement locally optimized printing parameters consisting of elements to detect errors, predict flaw probability at each point, and select the optimal local parameters [34].

Garboczi et al. used ML and sensors to predict wear in metal AM parts. They instrumented laser-fused maraging-steel specimens with strain gauges and eddy-current probes to monitor fatigue. By correlating the signals with damage, the system functions like an odometer for part life, where increases in sensor readings indicate accumulating damage. This enabled forecasting part failure before it happens. As *Lab Manager* reports, the study showed the Army could detect and monitor the wear and tear of 3D-printed maraging steel through sensor measurement, using those signals to predict when parts will degrade or fail [35].

Industry is also using AI for printer maintenance scheduling. For example, startup SAMGEN's Prediction software, launched in 2025, continuously collects data from key printer components (heated bed, fans, motors, etc.) and uses ML algorithms to predict remaining useful life (RUL). By analyzing patterns in historical and live sensor data, the software alerts users when a part is likely to wear out. According to *3DNatives*, Prediction can help accurately predict the maintenance needs of 3D printers, optimize operations, avoid unnecessary downtime, and eliminate excessive use of spare parts [36].

Researchers advocate creating AI-enabled digital twins of 3D printers that mirror the physical machines in software, enabling end-to-end automation. These twins use real-time sensor data and ML models to simulate and control the print process. A recent review notes that integrating ML into digital twins can convert offline simulation into a real-time, closed-loop production system, where the twin autonomously adjusts parameters and predicts failures [37]. Such end-to-end automation (from design through print to maintenance) promises fully self-monitoring, self-optimizing 3D printing workflows under Industry 4.0/5.0 paradigms.

3.1.2. Deep Learning (DL)

Deep learning (DL) is a subset of ML that uses neural networks to analyze complex patterns. In 3D printing, DL is beneficial for defect detection, where convolutional neural networks (CNNs) analyze layer-by-layer print quality to identify imperfections. DL also advances material science by predicting how new materials will behave under 3D printing conditions, allowing for the development of innovative composites and alloys.

Deep learning facilitates optimization through parameter tuning and predictive modeling of outcomes. The following examples illustrate this.

Recent work has shown that DL models can learn the complex mapping from printer settings to part quality and then be used to find the best settings. For example, K. A. Hunt et al. envisioned a system where a network views a part geometry and predicts locally optimal printing parameters. They built a tool that predicts and implements locally optimized printing parameters in 3D printing, selecting the best speed, temperature, etc., at each point to maximize part quality [34]. Similarly, Kadauw trained multiple artificial neural networks (ANN) on SLA (stereolithography) process data to predict key mechanical outcomes (tensile/yield strength, hardness, surface roughness) from print parameters. Their ANN models achieved very high accuracy (correlation R ≈ 0.99 between predictions and measurements) for all properties [38], and they then used multi-objective optimization on the trained models to find the printer settings that maximize strength and minimize roughness. Zhang et al. adopted a vision-based approach, building a convolutional neural network (CNN) (called MPR-Net) that utilizes metallography images of LPBF-printed 316L stainless steel to predict tensile strength and hardness. The network achieved $R^2 \approx$ values of approximately 0.96 (tensile) and 0.91 (hardness) on test parts and was used to identify the laser power and scan speed that yielded nearly full-density parts (~99.97% dense) with a tensile strength of approximately 763 MPa [39]. These examples illustrate how deep nets serve as accurate surrogate models of the print outcome, enabling automated tuning of process parameters for optimal part performance.

Real-time defect detection and quality inspections using deep vision in automation are now feasible. Deep convolutional networks have been applied to monitor builds and catch defects as they form. Hespeler et al. demonstrated a CNN-based quality monitor in a laser-directed deposition process. By classifying each printed layer as either acceptable or porous, the network achieved approximately 90% accuracy in distinguishing layers with significant internal defects [40]. In extrusion-based printing, Zhou et al. developed an improved YOLOv8 object-detection CNN to identify four common defects (cracks, holes, etc.) in 3D-printed microelectronics. Their model ran at ~72 fps and achieved a mean average precision (mAP50) of 91.7% on live printing images [21], demonstrating real-time deep learning defect detection.

The collaborative autonomous extrusion network (CAXTON) is an end-to-end monitoring/control system for FDM printers. A network of webcams captures the nozzle tip, while a single multi-headed CNN processes the images. CAXTON automatically labels deviations from optimal settings and simultaneously detects and corrects multiple error modalities in real time [41]. In other words, the CNN not only classifies the current error (e.g., under-extrusion, layer shift) but also feeds back adjustments to the printer. These and similar systems (often using CNN variants or one-stage detectors) provide automated in situ quality inspection and process monitoring, flagging surface flaws or internal voids as they arise and even trigger corrective actions without human intervention.

Intelligent control is achieved through machine-learning-driven closed-loop adaptive printing systems. Researchers have used deep learning in feedback loops to adapt print parameters on the fly. Mieszczanek et al. demonstrated this for melt-electrowriting (a fine polymer fiber printing). By imaging the polymer jet during printing and feeding that into a feed-forward neural network with a feedback loop, the system actively adjusts flow rate and speed to stabilize fiber deposition. Their results showed that this AI-enabled closed-loop control greatly improved reproducibility of a highly nonlinear printing process [42]. Reinforcement learning (RL) has also been applied to 3D printing control. M. Piovarci et al. trained an RL agent (in simulation) to modulate a direct-ink-write print head. The learned closed-loop policy, when deployed on actual hardware, outperformed traditional controllers and had a minimal sim-to-real gap [33]. In effect, the RL controller learned how to adjust extrusion parameters in real time based on sensor feedback, correcting for disturbances. On a larger scale, B. Felbrich et al. used model-free deep RL (TD3 and SAC) in a robotic fabrication framework: a DRL-trained robot learned to plan and execute structures (e.g., concrete 3D printing) with on-board sensing. Their two case studies (block stacking and sensor-adaptive 3D printing) showed that deep RL can autonomously handle complex constraints and adapt on the fly, effectively bringing closed-loop adaptivity to architectural-scale AM [43]. These works illustrate the trend toward intelligent closed-loop systems in AM, where deep networks or RL agents continuously adjust print parameters (temperature, speed, flow, etc.) based on live data, rather than relying on fixed pre-set values [33].

3.1.3. Computer Vision

Computer vision refers to AI systems that interpret visual data from cameras or sensors. In 3D printing, computer vision enables real-time monitoring by detecting issues like layer misalignment, warping, or cracks as they happen. It also ensures quality control by comparing printed objects with their digital models, ensuring precision and consistency across production runs. Examples of optimization, automation, and intelligent control in computer vision for 3D printing are shown below.

One example of visual feedback optimization is an automated calibration system for FDM printers. G. S. Ganitano et al. developed a system that prints a known calibration object and utilizes a camera to compare the actual print with its 3D model. A computer-vision metric (comparing the image to the CAD model) is combined with a metaheuristic algorithm to adjust print parameters iteratively. This closed-loop vision-based calibration achieved sub-millimeter geometric accuracy, with an average deviation of 0.047 mm, thereby improving print quality beyond the printer's nominal tolerance [44].

For automated defect detection, W. Wang et al. integrated a camera and deep learning into an extrusion 3D printer to identify print errors in real time. As the printer builds each layer, a high-resolution camera captures the surface and feeds the images into an enhanced YOLOv8 convolutional network, which is trained on common FDM defects (e.g., scratches, over extrusion, voids). The system achieved 91.7% mean average precision (mAP) at ~71.9 frames per second, enabling on-the-fly identification of failures [23]. By classifying defects as they occur, the printer can halt or correct the print, automating quality control during manufacturing.

A recent demonstration of vision-guided adaptive control comes from melt electrowriting (MEW) 3D printing. P. Mieszczanek et al. used a camera to image the fine polymer jet during printing and applied a neural-network control in a feedback loop. In real time, the computer vision system measures the jet angle and Taylor-cone area, and a feedforward neural network plus optimizer adjusts process parameters (voltage, flow rate, etc.) to achieve the target fiber diameter. This closed-loop, vision-based control ensured reproducible part geometry by continuously modifying the printer's behavior based on the live image feedback [42]. A key limitation of vision-based systems is their sensitivity to environmental conditions. Variations in ambient lighting, camera angle, and reflective material surfaces can drastically reduce model accuracy. This necessitates highly controlled environments or more robust, multi-modal sensing approaches to be viable for industrial shop floors.

3.1.4. Reinforcement Learning (RL)

Reinforcement learning (RL) is a type of AI that learns through trial-and-error, using rewards and penalties to refine its actions. In 3D printing, RL is applied to create self-correcting printers that adjust settings mid-print to avoid failures. It also optimizes robotic control in multi-axis 3D printing, enabling more complex and efficient manufacturing processes. Here are some examples of how RL is used in innovations related to 3D printing.

RL is increasingly used to improve 3D printing by tuning process parameters, automating decision-making, and enabling closed-loop control. For example, Ali et al. proposed a digital-twin RL framework for robotic AM that integrates multiple functions. Their system uses a vision-based monitor and a Soft Actor-Critic agent to adjust print parameters in real time continuously [3]. By synchronizing a Unity simulation with a physical robot arm, the agent learns to correct printing errors in real-time, resulting in rapid policy convergence and robust print execution. This combined approach integrates parameter tuning, quality monitoring, and adaptive control within one RL pipeline, achieving stable adjustments of flow rate and temperature and consistent print quality [45].

S. Dharmadhikari et al. demonstrated RL for parameter optimization in metal AM. They cast laser power and scan velocity selection as an RL problem: a Q-learning agent explores the (power, speed) space to maximize rewards for steady melt-pool depth In simulation, the agent learns a Q-table where the state (power, speed) with the highest Q-value corresponds to the optimal settings. For instance, targeting a 1 mm melt-pool depth in SS316L steel, the trained RL agent predicted an optimal setting (888.9 W, 566.7 mm/min) that matched experimental results within 50 µm. This example shows how RL can automatically tune printing speed, layer energy, and other parameters to optimize print quality and consistency [46].

M. Sun et al. applied RL to automate job scheduling in an AM factory. They modeled the dynamic scheduling of printers (with random order arrivals and machine constraints) as a Markov decision process and train a dueling deep Q-network (O3-DDQN) to assign jobs adaptively. The RL scheduler outperforms single scheduling rules, random rules, and a classic DQN, reducing overall tardiness by about 13% compared to heuristic baselines. In other words, the learned policy automatically prioritizes and sequences print jobs (possibly out of order) to improve throughput and on-time delivery. This illustrates how RL can automate complex planning tasks, continuously optimizing job allocation without human intervention [47].

M. Piovarci et al. provided a clear case of closed-loop RL control in 3D printing. They trained an agent in simulation to adjust deposition parameters during direct ink writing. The resulting policy was then deployed on a real printer to compensate for material and process variability. As reported, they demonstrated the feasibility of learning a closed-loop control policy for AM using reinforcement learning, and the policy outperformed baseline controllers when applied to a single-layer print. In practice, the RL agent observes the ongoing print and continuously tweaks nozzle speed and material feed to prevent defects. This on-the-fly adjustment exemplifies an intelligent control loop, where RL enables real-time corrections and improves print reliability [33]. The implementation of RL in manufacturing processes has been largely a success. Despite these successes, a significant hurdle for RL in AM is the 'sim-to-real' gap, where policies trained in simulation often fail when deployed on physical hardware due to unmodeled physics and system noise. Furthermore, the sample inefficiency of many RL algorithms makes training directly on physical printers prohibitively slow and expensive.

3.1.5. Natural Language Processing (NLP) and AI Assistants

Natural language processing (NLP) allows AI to understand and generate human language. In 3D printing, NLP enables voice or text-based control, allowing users to command printers using AI assistants (e.g., optimizing this part for strength). It also automates documentation by generating reports on print performance, reducing manual effort and improving traceability. NLP and AI assistants are helping to improve 3D printing. Here are some examples that explain more.

AI Build's AiSync is a unified 3D printing AI platform that uses a GPT-4-based assistant to manage the entire workflow [48]. AiSync acts as both a slicer and a process controller: it controls the entire 3D printing process, including monitoring, control, measurement, and optimization. Users simply type high-level commands (e.g., optimize for strength), and the AI copilot generates optimized toolpaths and print settings accordingly [48]. By combining design interpretation, parameter tuning, and machine integration into a single interface, AiSync automates setup, slicing, and adaptive adjustments across the print job with minimal expert input.

In terms of optimization, NLP-driven tuning is possible. Tools like Style2Fab enable users to describe their design goals in plain language and automatically refine the 3D model for printing. For instance, Style2Fab takes a prompt such as "make it pink and rough" and adds those esthetic changes without breaking the part's function. The system uses deep learning to segment the model into functional vs. nonfunctional parts, then applies the requested stylizations only to the esthetic regions. In this way, design requirements expressed in natural language are converted into an optimized 3D model that is ready for printing, even by users with little CAD experience [49].

Conversational AI can automate printing steps like G-code generation and job initiation. For example, a recent student project built an NLP pipeline where a user simply dictates what they want to be able to print, and the software parses the English description to generate the corresponding G-code instructions [50]. Likewise, the PrintAssist chatbot lets users control a 3D printer by text: novices use chat commands to search for a model, slice it, and start a print. Participants noted that using the chatbot was faster than the traditional SD-card method [51]. These systems effectively translate voice or text commands into automated slicer actions and build commands, reducing manual setup effort.

Large language model (LLM)-based assistants can also interpret live print data and adjust parameters on the flight. In a recent experiment, researchers fed layer-by-layer camera images and print metrics into a GPT-4 agent after each layer [52]. The LLM analyzed the visual diagnostics to identify defects (e.g., under-extrusion or warping) and then immediately adjusted printer settings, such as speed, flow rate, or temperature, for the next layers. This feedback loop significantly improved results by dynamically adjusting print parameters based on real-time analysis, thereby enhancing print quality and reducing material waste. In short, the assistant acts as a 3D printing expert that reads the current state (images, logs) and makes intelligent parameter adjustments to optimize the ongoing print [52].

4. Applications of AI in 3D Printing

While reviewing the literature gives many case-specific studies, relevant insights are gained when these are normalized and systematically analyzed across AM processes. Table 1 summarizes the case studies by methodology, functionality, applications, and outcomes. When it comes to real-time process optimization, both reinforcement learning and Gaussian-process active learning have consistently shown their ability to minimize process defects and reduce material waste, as demonstrated by Dharmadhikari et al. and Lee et al. [46,53]. In material behavior prediction, data-driven models consistently outperform statistical approaches as evidenced by Akbari et al. [45]. In defect detection, Herzog et al. and Yin et al. highlighted that CNNs, along with YOLO models, achieve detection accuracies exceeding 90% [54,55]. Automating design processes using generative AI has minimized design cycles while exhibiting significant structural innovation, as demonstrated by Dritsas et al. and Koul [56,57]. Continuous melt-pool tracking with adaptive feedback and predictive analysis enabled by vision- based monitoring helped balance surface roughness vs. energy efficiency, as demonstrated by Khan et al. [58]. While AI tools are highly effective, their specific advantages greatly vary by process. For example, ANN excels in defect detection, regression models in FDM material prediction, and reinforcement learning in DED/WAAM adaptive control.

Table 1. AM case studies by AI methodology, functionality, applications, and outcomes.

Application Area	AI Methods/Models	Key References	Purpose/Functionality	Benefits/Outcomes
Real-Time Process Optimization	Reinforcement learning (RL), feed-forward ANN, and Gaussian-process active learning	Dharmadhikari et al., Lee et al., and Rojek et al. [37,46,53]	Dynamically adjust laser power, scan speed, layer thickness, and extrusion rates during printing	Minimizes defects, reduces material waste, improves part quality, and enhances process efficiency
Material Behavior Prediction	ANN, SVM, Random Forest, CNN, MechProNet, Hybrid Mechanistic-Data Driven Models	Akbari et al., Xie et al., and Ziadia et al. [45,59,60]	Predict mechanical, thermal, and flow properties of metals and polymers	Speeds up material selection, reduces trial-and-error, improves accuracy and reproducibility, and optimizes mechanical performance
Defect Detection and Quality Assurance	CNNs (ResNet, EfficientNet), YOLOv5, and SVM	Yin et al., Herzog et al., and Alldredge et al. [54,55,61]	Detect porosity, cracks, delamination, and warping in real time	Early fault detection, minimizes scrap, improves reliability, and enables certification-critical applications
Automation in Design and Workflow	Generative design algorithms, GANs (DA-GAN), GPT-like models, and ANN	Koul, Yuan, and Moghaddam, Dritsas and Trigka [56,57,62]	Automate topology optimization, slicing, and design generation; create innovative structures	Reduces design time, improves structural performance, and enables highly customized and complex designs
Vision-Based Monitoring	CNNs, deep learning, and YOLO	Kwon et al. and Yin et al [55,63]	Real-time image analysis for melt-pool or powder bed monitoring	Accurate defect localization, continuous process monitoring, and adaptive feedback control
Predictive Analytics and Parameter Optimization	ANN, SVM, k-NN, and gradient boosting	Khan et al. and Rojek et al. [37,58]	Predict process outcomes such as surface roughness, tensile strength, and energy consumption	Optimizes process parameters, improves part quality, and balances multiple production objectives
AI Model Selection Guidelines	CNN for vision-based tasks, ANN/SVM for prediction, and hybrid ML models	Multiple studies	Select AI model depending on data availability and task type	Enhances precision, reduces waste, and accelerates design-to-product timelines

4.1. Real-Time Process Optimization

Real-time process optimization in AM utilizes AI to dynamically modify critical printing parameters, such as laser power, printing speed, extrusion rates, and layer thickness. These modifications guarantee that the production process reliably yields high-quality components, markedly improving efficiency and dependability [64]. AI-driven adaptive control systems leverage data from many sensors, including infrared cameras, temperature sensors, and acoustic monitoring devices, facilitating accurate, real-time feedback for process regulation [65]. Machine learning and reinforcement learning techniques enable AM systems to learn from prior prints, facilitating iterative enhancement and reducing dependence on human involvement [66]. These feedback loops have proven efficient in minimizing errors, material waste, and manufacturing time, providing significant economic benefits in industrial environments [67]

Dharmadhikari et al. developed a novel reinforcement learning (RL)-based approach to optimize AM process parameters, formulating laser power and scan speed adjustments as interactive learning tasks within a simulated environment; through iterative trial-and-error interactions, the RL agent autonomously identified parameter combinations that enhanced part quality and minimized defects and residual stresses, underscoring the potential of RL algorithms in developing self-correcting, adaptive 3D printing systems [46].

Lee et al. presented an innovative Pareto-active learning framework leveraging Gaussian-process surrogate modeling for efficient, simultaneous optimization of conflicting mechanical properties—specifically strength and ductility—in additively manufactured Ti-6Al-4V alloys; through intelligent selection of experimental points from a candidate pool, their iterative strategy successfully pinpointed optimal laser powder bed fusion and post-processing parameters, significantly enhancing the material's tensile strength (1190 MPa) and elongation (16.5%), demonstrating active learning's capacity to streamline targeted exploration of complex parameter spaces [53].

Rojek et al. employed feed-forward ANNs coupled with optimization algorithms to refine extrusion-based fused deposition modeling (FDM) process parameters, explicitly targeting improvements in sustainability, energy efficiency, and print quality; their ANN-based surrogate models effectively predicted part surface finish and energy consumption, facilitating parameter adjustments that reduced material waste and optimized overall manufacturing performance, thereby exemplifying a robust approach to balancing multiple, often competing, production objectives through machine learning [37].

Process optimization plays a vital role in direct energy deposition (DED) AM process, as the quality of fabricated parts is dependent on various parameters. Relative importance index for process parameters like power, speed, feed rate of the laser, and layer thickness were concluded using MultiLayer Perceptron (MLP) by Narayana et al. [68]. Weld process parameter optimization to obtain a minimum heat affected zone (HAZ) width in gas metal arc welding (GMAW) was proposed by Mezaache et al. [69]. The particle swarm optimization algorithm was used to optimize parameters like welding speed, nozzle-to-plate distance, voltage speed or wire feed speed to achieve minimum HAZ.

In summary, AI-driven optimization in AM encompasses supervised learning (rapid surrogate models for parameter selection) and reinforcement learning (adaptive control that learns from the printing process itself). These strategies are resulting in more intelligent machines that can dynamically adapt to sustain optimal printing conditions and part quality.

4.2. Material Behavior Prediction

Understanding and accurately predicting material properties and behaviors in 3D printing is crucial for achieving consistent and reliable results. AI models—especially machine learning and deep learning algorithms—can predict various mechanical, thermal, and flow properties of materials [45]. Machine learning models such as ANNs, support vector machines, and random forest models can efficiently work with large and complex datasets derived from experimental tests and simulation results to produce consistent predictions [59]. These advanced predictions help fine-tune material selection and process parameters, thereby reducing optimization costs and accelerating the integration of novel materials into manufacturing processes [70]. Additionally, AI-driven predictions minimize reliance on empirical trial-and-error methods, thereby speeding up the overall production process.

In a detailed benchmarking study, Akbari et. al. [45] proposed *MechProNet*, a machine learning-based framework specifically designed to predict mechanical properties of metal additively manufactured components, leveraging a curated dataset extracted from over

90 published sources encompassing diverse process parameters, material properties, and experimental outcomes; notably, the authors integrate physics-aware feature engineering and explainable AI techniques, such as SHAP analysis, to enhance interpretability and demonstrate accurate, cost-effective predictions of critical mechanical attributes, including yield strength, tensile strength, and hardness, thereby significantly significantly reducing reliance on extensive empirical testing.

Xie et al. introduced a hybrid mechanistic–data-driven methodology that integrates wavelet transformations with convolutional neural networks (CNNs) to predict location-specific mechanical properties in metal AM; by systematically analyzing thermal history data captured during the printing process, their model effectively mapped localized thermal signatures to spatial variations in mechanical attributes, such as tensile strength, thereby achieving high predictive accuracy despite limited experimental data and illustrating the efficacy of domain-specific deep learning in revealing intricate process–structure–property relationships [59].

A. Ziadia et al. employed ensemble machine learning models to accurately predict critical mechanical properties—such as ultimate tensile strength, Young's modulus, and strain at break—for polymer-based fused filament fabrication (FFF) components made from PLA and carbon-fiber reinforced PLA, using input parameters like printing temperature, speed, and layer thickness. The authors further combined their predictive framework with a genetic algorithm for multi-objective optimization, successfully identifying optimal print settings (e.g., 222 °C printing temperature, 0.26 mm layer thickness) that improved ultimate tensile strength significantly (~41 MPa). This study highlights the effectiveness of integrating machine learning and evolutionary algorithms to concurrently model, predict, and optimize the mechanical performance of additively manufactured polymer composites [60].

A neural network (NN) model was used by Kats et al. to predict grain structure characteristics in DED [71]. Machine learning networks like XGBoost and LSTM were used by Zhang et al. to predict melt pool temperature in DED [72]. When it comes to wire arc additive manufacturing (WAAM), Lv et al. developed a prediction model using ANN [73]. They specifically had a backpropagation artificial neural network (BPANN) model, which predicted welding penetration. Using this model, they then proposed BPANN-piecewise (BPANN-PW) controller for real-time control. A multi-input multi-output (MIMO) model predictive control (MPC) based on linear autoregressive (ARX) modeling was proposed by Mu et al. for predictive control of bead geometry in WAAM [74]. Real time updates on weld parameters between successive layers by the MPC controller in addition to measuring the deposited bead geometry by laser scanner acted as inputs to the ARX model, which in turn made future bead geometry predictions, enabling real-time control. This methodology showed a reduction in part height by 400%, in addition to improving fluctuations in bead width by 50%.

4.3. Defect Detection and Quality Assurance

The involvement of AI in defect detection and quality control has enhanced the reliability of AM. Advanced computer vision and sensor fusion techniques are capable of detecting defects such as porosity, warping, delamination, cracks, and lack of fusion [61]. Studies have demonstrated that deep learning methods—particularly convolutional neural networks (CNNs)—are highly effective in real-time image processing and defect detection [75]. Moreover, AI systems are continuously evolving, enhancing their defect detection capabilities and thereby increasing the adoption of AM in certification-critical industries such as aerospace and medical [54]. These real-time defect management systems significantly reduce the risk of part rejection due to defects or faulty parts reaching the assembly stage, thus lowering both time and cost.

AI-driven quality control emphasizes the utilization of computer vision and sensor data to autonomously identify flaws in the printing process Yin et al. [55] created an AI-based monitoring system for metal powder bed fusion that analyzes layer-wise images using deep learning. A fresh annotated dataset was constructed, and various CNN architectures were evaluated for fault recognition. Their findings indicated that ResNet-50 and EfficientNet models could categorize powder bed images (normal versus defect) with an accuracy over 99%, while the YOLOv5 network was more adept at identifying defect spots (e.g., spatter, incomplete fusion) compared to the conventional Faster R-CNN method (Figure 3) [54]. This validates the potential of deep learning in real-time anomaly detection, facilitating prompt modifications to prevent print failures.

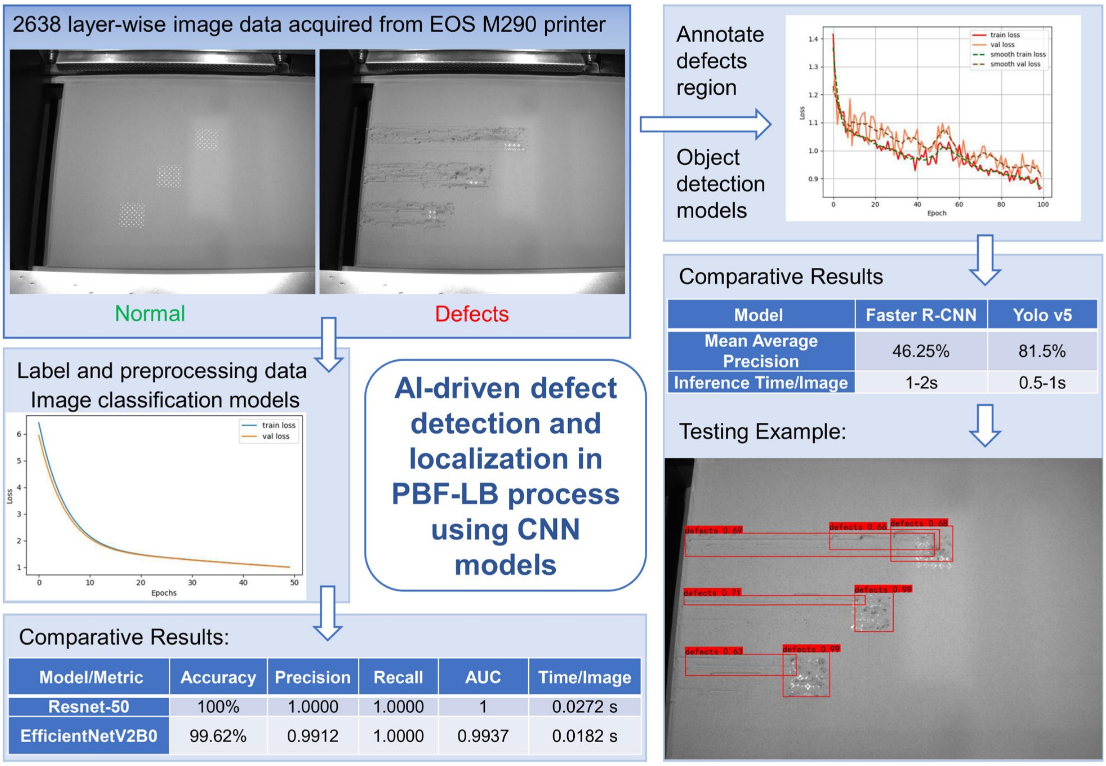

Figure 3. Example of an AI-driven defect detection system for metal laser powder bed fusion. Layer images are analyzed by classification and object detection models to identify anomalies. In one study, ResNet-50 and EfficientNet-V2 achieved ~99–100% accuracy in classifying normal vs. defective layers, while a YOLOv5 detector localized defects with higher mean average precision (81.5%) than a Faster R-CNN model (46.3%) [55].

In a comprehensive and insightful review, Djenouri et al. critically analyzed recent advancements in the application of AI, particularly machine learning and computer vision methodologies, for defect detection in AM; they systematically examined prevalent evaluation metrics, publicly accessible datasets along with their inherent limitations, and emphasized key unresolved issues, including data scarcity and challenges associated with real-time defect inspection [76].

Fu et al. conducted a comprehensive review of machine learning algorithms for defect detection in laser-based AM. They reported that techniques ranging from support vector machines to neural networks have been used to recognize defects like porosity, lack of fusion, and surface anomalies. The consensus is that integrating in situ monitoring with ML models can significantly improve quality assurance by catching defects early and reducing scrap [77].

DED is prone to defects because of its geometry, pores and cracks, and incomplete fusion. DED-assisted parts often have a poor surface finish due to incomplete melting and sputtering, and surface anomaly prediction is gaining traction. A machine learning-based KNN model with in situ cloud processing was developed by Chen et al., achieving 93.15% accuracy [67]. An self-organizing map with a clustering algorithm was used to group melt-pool thermal distributions based on similarity for porosity prediction with 96% accuracy by Chowdhury et al. in DED [78]. Parameters of multipass GMAW by robotic arms were monitored and datasets were generated for different topologies. Using this data, four characteristic deviations of welding parameters were acquired and a neural network was trained to detect defects in a multipass GMAW process by Nele et al. [79]. A new transfer learning model was proposed by Pan et al. [80], in deep learning, where they used a non-welding defect dataset, ImageNet, to train a MobileNet model and migrated the MobileNet model to detect welding defects. The resultant TL-MobileNet model accomplished 96.88% accuracy.

4.4. Automation in Design and AM Workflow

AI significantly enhances automation capabilities in AM design and slicing software. Optimal structures that meet functional, structural, and esthetic criteria can be created using AI-supported generative design algorithms [57]. This approach makes structural designs lighter, more durable, and more material efficient than traditional methods. AI-supported slicing software can significantly reduce production times and improve part quality by making complex decisions such as optimal layer thickness, support structure orientation, and tool path [81]. AI-supported generative design and advanced slicing algorithms can not only accelerate production processes but also deliver more innovative designs and improved mechanical strength for parts [82].

In a comprehensive review, Koul [57] examines the integration of AI and machine learning with generative design methodologies, including topology optimization and automated shape generation, emphasizing how AI-driven strategies vastly expand the exploration of design solutions, uncovering innovative, non-intuitive structuresstructures. Notably, the study highlights the transformative potential of ML-enabled generative approaches for rapid, scalable customization and iterative design refinement, significantly accelerating innovation cycles within AM.

Yuan and Moghaddam, demonstrated the applicability of generative adversarial networks (GANs) for attribute-aware design generation by developing a specialized model termed “Design-Attribute GAN (DA-GAN),” capable of autonomously synthesizing and manipulating product shapes based on targeted visual and functional attributes; their experiments illustrate the versatility of GANs in creating diverse design variants and systematically modifying existing designs, underscoring the substantial potential for deep generative models to enhance AM workflows by automating the generation of tailored structures, such as lattice configurations or advanced metamaterials [62].

Dritsas and Trigka, in a forward-looking perspective, explore the emergent roles of generative AI technologies—particularly GPT-like and diffusion-based models—in AM, envisioning a future in which textual descriptions seamlessly translate into fully realized printable models; their analysis indicates nascent but growing adoption of generative AI tools capable of autonomously proposing and optimizing complex AM designs, including automated generation of support structures and real-time adjustments during fabrication, marking a profound evolution toward a highly automated, creativity-driven 3D printing pipeline [56].

Convolutional neural networks (CNNs) have emerged as powerful tools in AM, particularly for real-time defect detection and quality control through advanced image analysis. Notable examples include the work of Kwon et al., who employed a deep CNN to classify melt-pool images from metal printing, accurately identifying distinct melt-pool states directly from camera feeds [63]. Likewise, Yin et al. leveraged CNN architectures such as ResNet and EfficientNet to achieve near-perfect accuracy in identifying powder bed defects, while implementing the YOLOv5 object detection model to precisely localize anomalies during the printing process, illustrating CNNs' unique ability to autonomously extract and interpret visual and thermal signatures for continuous monitoring and feedback-driven process correction [55].

Support vector machines (SVMs) and other classical machine learning classifiers such as decision trees, k-nearest neighbors (k-NN), and ensemble techniques have shown considerable utility in AM applications characterized by smaller datasets or when interpretability is critical. For example, Khan et al. combined an ensemble of machine learners—including SVM, k-NN, and gradient boosting—to predict the flexural strength of carbon fiber–reinforced printed parts, achieving a notably high coefficient of determination ($R^2 \approx 0.97$) [58]. Additionally, SVMs have demonstrated robustness in classifying defects and equipment health signals, particularly excelling when working with structured or limited datasets, thereby underscoring the value of hybridized and interpretable ML approaches within AM processes.

ANNs, including multi-layer perceptrons, have demonstrated their broad applicability and effectiveness across AM tasks involving regression, optimization, and surrogate modeling. For instance, Rojek et al. successfully utilized a feed-forward ANN to predict surface roughness and tensile strength in fused deposition modeling (FDM), subsequently employing this predictive model to optimize printing parameters for improved component quality [37]. Furthermore, deep ANN architectures have effectively modeled and predicted complex surface properties in metal additive processes, outperforming traditional empirical models, highlighting ANNs' versatility and potential as predictive, adaptive, and surrogate models in scenarios where the underlying process–structure–property relationships are highly nonlinear and difficult to capture through conventional methods.

The selection of an AI model is contingent upon the particular difficulty in AM. Vision-based challenges, such as defect identification, favor convolutional neural networks (CNNs) and deep learning, whereas predictive analytics for process parameters may employ simpler machine learning models or ANNs in scenarios of insufficient data. These AI technologies are enhancing 3D printing by increasing precision, minimizing waste, and expediting design-to-product timelines.

5. Smart Manufacturing Systems

Production intelligence towards the era of Industry 4.0 indicates a paradigm shift: a technology-based, environmental responsive interconnected revolution involving intelligent manufacturing, including AI and IoT (Internet of Things) as an integrated digital twin application [83,84]. In continuation of the fourth Industrial Revolution, this transdisciplinary feature of Industry 4.0 has been coined "smart manufacturing", in which technology convergence is redefining traditional manufacturing paradigms to create smart manufacturing systems that can learn autonomously, optimize processes and take corrective action [85–87]. Consequently, manufacturing operations have reached limits of efficiency, quality and operational flexibility that lead to dynamic responses to changing market demand and operating conditions [88,89]. Such intelligent systems use real-time data acquisition and analytics for informed decisions at all production stages [90–93]. The integration of machines, sensors and enterprise systems through IoT not only enriches the visibility on the shop floor but also empowers predictive maintenance and process self-optimization, which in turn minimizes downtime and leads to higher yield.

5.1. Development of Self-Learning, Self-Correcting Systems

At the heart of smart manufacturing are self-learning and self-correcting systems. By using AI algorithms (especially machine learning (ML) and deep learning (DL)), these systems grow better and better over time. Such self-learning systems mine large databases of data—including sensors, machines, and others—to identify patterns, detect anomalies, and make predictive decisions [94,95]. For example, a 3D printing system that can learn to optimize its process parameters based on big data analysis is able to improve print quality and reduce defect rates [96,97]. Furthermore, expert systems have been embedded with capacities for self-learning, self-correcting, and expansion, enabling them to easily adjust to ever-changing industrial environments without the need for updates from knowledge engineers [98]. These enhancements ensure that manufacturing systems maximize productivity and reliability with minimal oversight [99]. Kumar and Mishra proposed a self-correcting architectural system capable of generating an excellent manufacturing plan that reduces the supply chain and production cost In the multi-agent framework, the corporate memory agent serves as a central knowledge hub, storing all critical information necessary for the effective execution of manufacturing processes. The manufacturing agent approaches the task of generating production plans with a portfolio of algorithms and adapts to shifting market conditions, using a self-reacting capability modeled after the human immune system. The forecasting agent automatically selects the most appropriate forecasting method (judgmental or quantitative) based on input data complexity. Meanwhile, the supplier selection agent identifies the most appropriate supplier by balancing trade-offs among factors such as cost, availability, quality, geographical proximity, and reliability.

Henke et al. [100] imparted a novel, infrastructure-free way of implementing automated guided vehicle (AGV) use. The authors noted that this new structure of logistics eliminates the need for significant investment in traditional infrastructure, such as universal warehouses (Figure 4). Rather, they endorsed modular and adaptive systems deployable in a plug-and-play manner [100,101]. Utilizing these advanced AGVs will enable warehouses to load, without the need to expand their physical footprint. The vehicles can then calculate new in-driving logistics routes automatically if there are changes with information about the load carrier or storage location [102]. The flexibility and intelligence of AGVs allow them to recursively optimize their paths and operations, making it possible for material flow within the warehouse to remain smooth and efficient. Thus, innovative AGVs make the implementation of infrastructure-less logistics advantageous in many ways. Firstly, it eliminates the need to invest in capital expenditure to establish and maintain traditional warehouse infrastructure. Secondly, modularity contributes to flexibility and scalability, meaning warehouses can be expanded or adapted quickly to meet new demands [103]. Thirdly, AGVs operate autonomously with minimal human intervention, increasing production line efficiency and reducing labor costs.

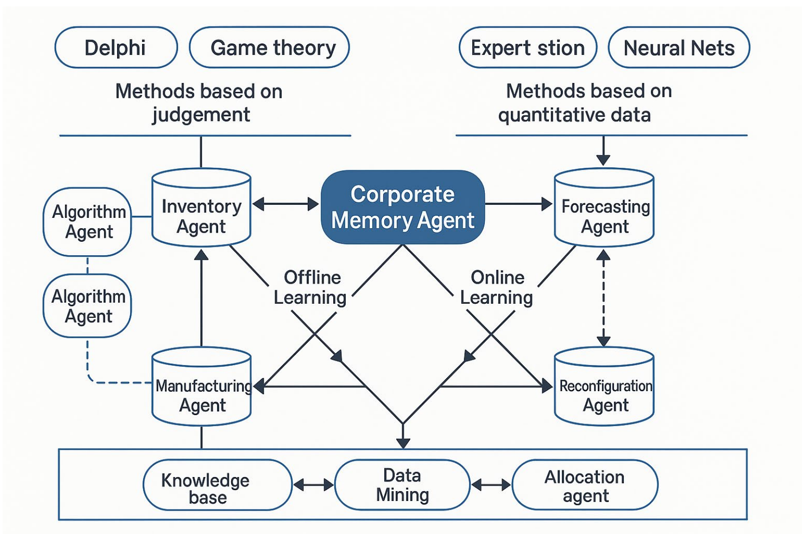

Figure 4. The proposed multi-agent architectural model with self-correcting capabilities [99].

Most self-recovering 3D printing systems are closed-loop in architecture and often combine feedback of multiple types. They monitor process variables continuously and alter printing parameters automatically to maintain optimal quality. Lu et al. [104] showed a reinforcement learning method in which their system learned from past printing experiences to achieve a 37% reduction in defect rates compared with open-loop controls. A novel framework that blends advanced deep learning architectures with robot-based AM systems was presented in a typical study (Figure 3). The robotic hardware setup shown in Figure 5a consists of the IRC5 controller, which coordinates the working module of the robot, and the important parts in the extrusion systems are the fan, motor, heater, print head, and temperature sensors, responsible for cooling, driving thermoplastic filament, material feeding, and showing print temperature, respectively (Figure 5b).

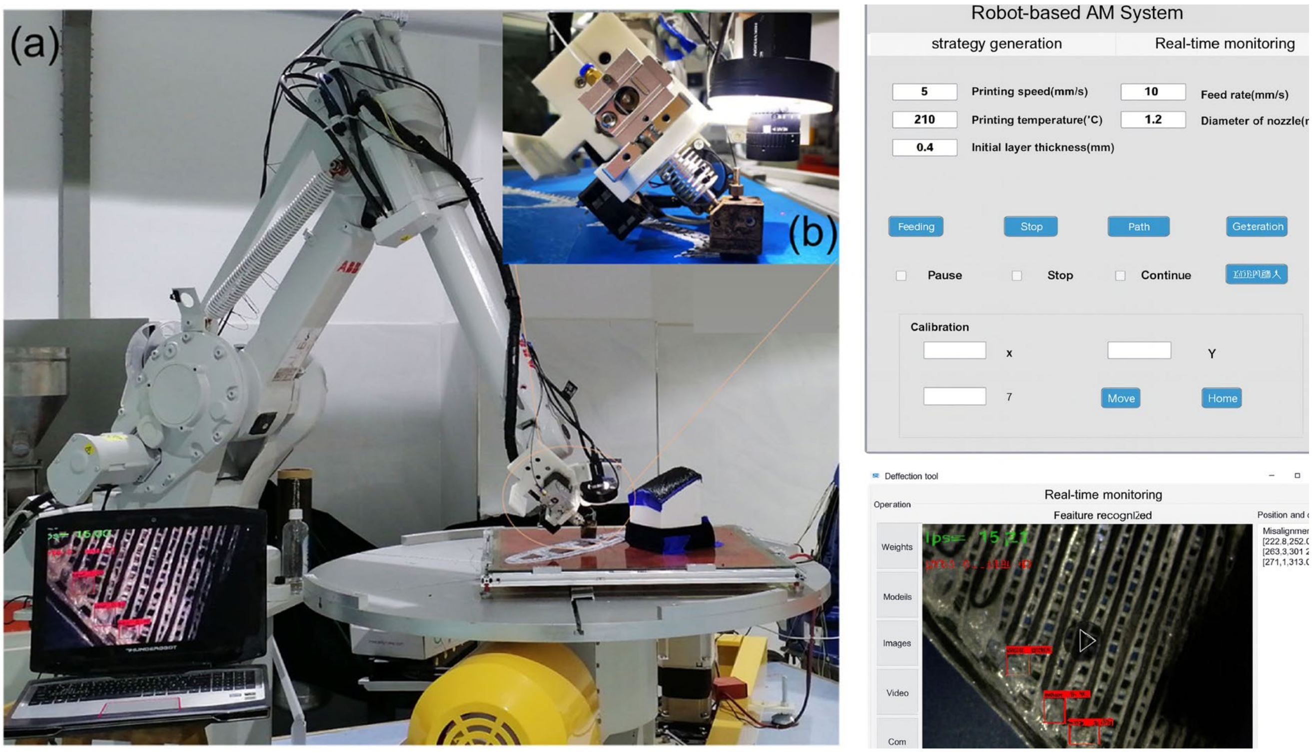

Figure 5. The overall hardware setup. (**a**) robot-based AM system; (**b**) extrusion interface [104].

Furthermore, the developed methodology allows for real-time defect identification in CFRP manufacturing, which substantially improves printing accuracy through automatic process parameter adjustment within a closed-loop control system. The proposed system exhibits strong performance in detecting and classifying two important CFRP defect families: fiber misalignment (FM) and surface abrasion. Subsequently, quantitative relationships were reported between the designs of different toolpaths and process parameter settings and specific defect types, based on thorough experimental inspection. Moreover, the framework adopts a hybrid analytical strategy by synthesizing CNN classifications with geometric analysis algorithms to quantify the degree of misalignment and accurately identify what kind of compensatory actions should be applied. This integrated approach provides a foundation for autonomous quality control in composite AM systems.

Figure 6 illustrates a novel proprietary software architecture for robot-based AM. It connects serial and ethernet-based interfaces through temperature control, video monitoring, extrusion parts, and robotic elements. To enhance strategy generation and an in-flight real-time detection, four modular functions run concurrently. The workflow includes: on-the-fly path planning with parameterization (hatch size, infill type, contour lines, speed control, and temperature); synchronized feed rate propagation to the motion controller; and sending path coordinates to the robot controller. This visual CFRP defect identification is used to automatically regulate the process parameters, and thereby a closed-loop manufacturing system is more responsive, self-correcting during printing to maintain defect-free print quality.

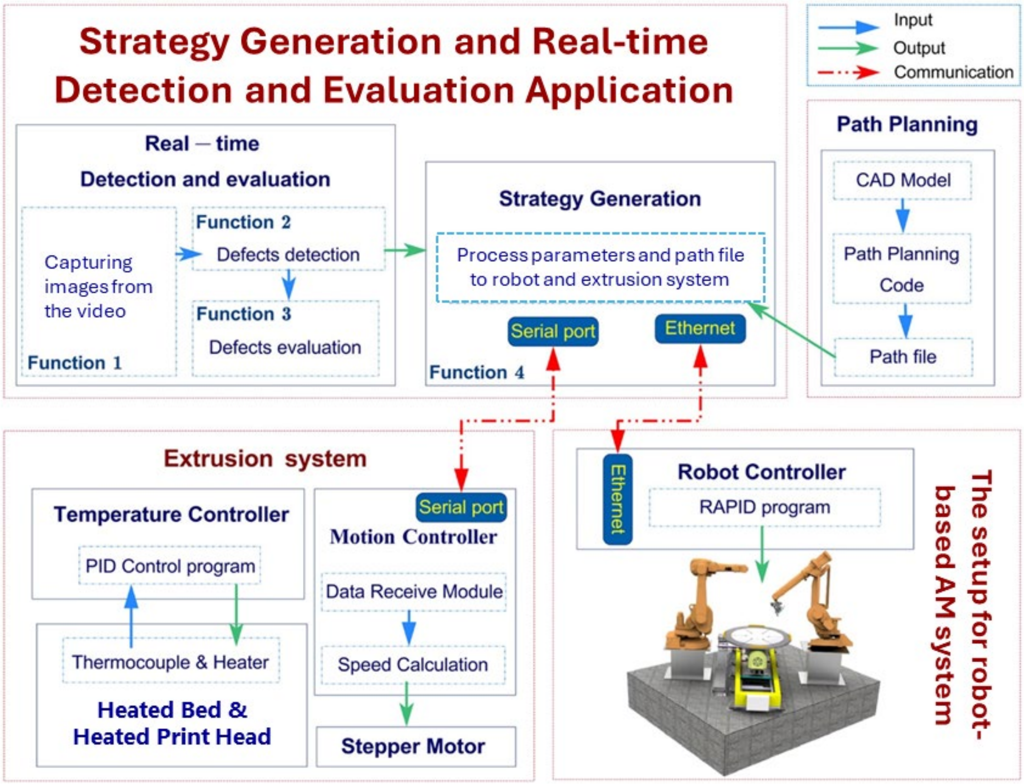

Figure 6. Software architecture of the robot-based AM system [104].

The term "cognitive manufacturing" refers to systems that are able to interpret comprehensive sensor data patterns that manual diagnosis are likely to neglect based on typical statistical methods, compared with the ability of neural networks, similar to multi-sensor arrays used by [105,106]. Using an experimental apparatus including thermal, acoustic and optical sensors, they were able to accurately predict and compensate for dimensional deviations in 94.2% of instances. Apparently, in self-learning models transfer learning has come as a savior. For new materials and components, rather than training (almost) from scratch for every new part to be printed, they are able to generalize what they learned from prior printing examples. Several studies have made assumptions to characterize the performance of transfer learning in predicting part quality when changing from one HP polymer material to another, and have shown that calibration time is 78% faster with comparable part quality [107–109].

5.2. Integration of AI with IoT and Digital Twins

Smart manufacturing systems also depend on AI integrated with IoT technologies. Sensors, actuators, and connected machines (IoT devices) provides real-time data acquisition and communication throughout the manufacturing ecosystem [110]. AI-based algorithms can subsequently analyze this data to learn about machine performance, product quality, and supply chain efficiency. For example, real-time 3D printing under IoT with AI can monitor the health of 3D printers and predict maintenance to avoid unexpected failures [111,112]. The empirical examination offers quantitative results on the transformative role of IoT-AI integration in Industry 5.0 manufacturing. Rigorous data analysis demonstrates a statistically significant production efficiency improvement of 1.52%, correlated with post-implementation environmental modifications, specifically temperature elevations of 36.2 °C and humidity reductions of 44.8% [113]. Quality metrics exhibited marked enhancement, with fault occurrences decreasing by two instances, corresponding to a 0.76% elevation in quality assessment scores (93.1). Maintenance time decreased by 2.3 h, while the impact of unplanned downtime on overall throughput by 52 mi. These data verify the benefits to operations of IoT–AI symbiosis and thus represent this technological convergence as a cornerstone in the Industry 5.0 era, with visible improvements in productivity, quality control, and maintenance efficiency.

Smart manufacturing systems also rely on digital twins, virtual replicas of physical objects or processes. Manufacturers can use this 3D printing digital twin to simulate and optimize the entire production cycle before producing the object in real life [110]. Digital twins may be used to apply AI algorithms to material behavior predictions, issue identification and design parameter optimization. Physical prototyping then saves time and resources, this in turns improves the overall quality of the product [114,115]. The major applications of AI in material systems are summarized in Figure 7, which is divided into four main fields: material design, process simulation, defect detection and property prediction. AI in material design also stresses molecular modeling, predictive algorithms and new material compositions. AI can visualize stress–strain behavior, fluid flow dynamics, and process parameters optimization by using AI-assisted techniques for process simulation like finite element modeling (FEM) and computational fluid dynamics (CFD). For defect detection, anomaly detection and automatic inspection systems powered by AI are used to detect microstructural defects that improve quality control. These processes characterize the residue via condition monitoring and plant diagnostic methods, followed by application of AI-based property prediction to approximate mechanical and thermal properties, correlate properties on a macroscopic scale, and automate material evaluation procedures. Overall, AI integration makes the development of material a lot easier as it helps to improve design, simulation, prediction, and defect detection processes.

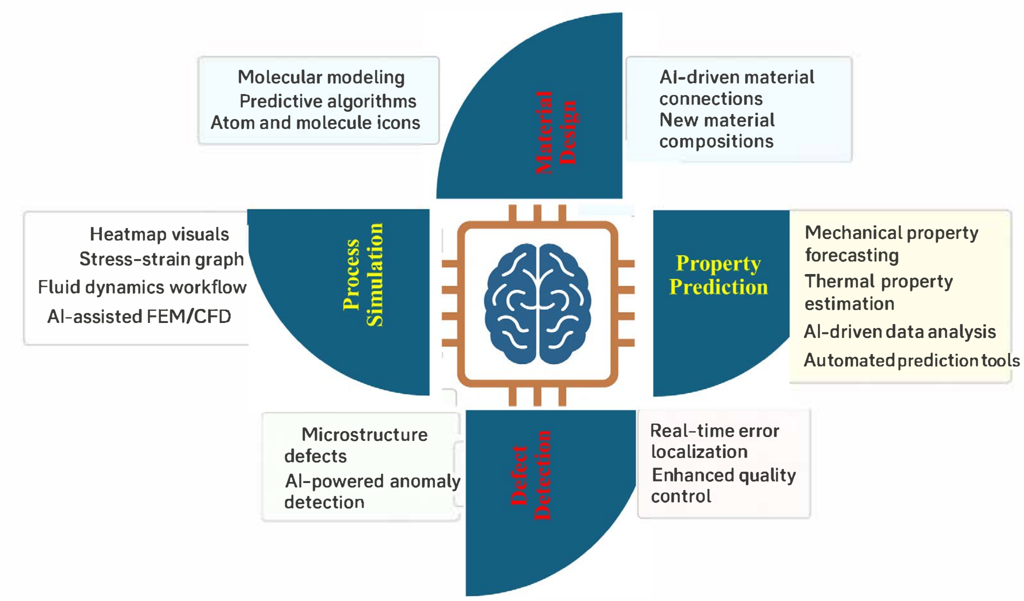

Figure 7. AI implementation in the material printing system [116].

Gu et al. [117] proposed a new type of distributed physical architecture for smart factories, named DPASF-IA, using intelligent agents. The architecture is straightforwardly divided into four functional units named: processing, transportation, storage, and decision-making. These heterogeneous units are seamlessly integrated by intelligent agents. To improve scheduling efficiency in the smart factory, they propose a data-driven reinforcement-learning based scheduling algorithm. This enables effective management and optimized scheduling performance. Figure 8 illustrates the physical architecture of the smart factory, where IoT using a local area network (LAN) interconnects different types of units with cloud for transmitting and exchanging information continuously. The architecture consists of several functional units: the processing unit (including components such as machine tools, buffers, and manipulators), the transportation unit (e.g., automated guided vehicle (AGV) trolleys), the storage unit (such as automatic storage and retrieval systems), the decision-making unit (supervisory control), and the cloud infrastructure.

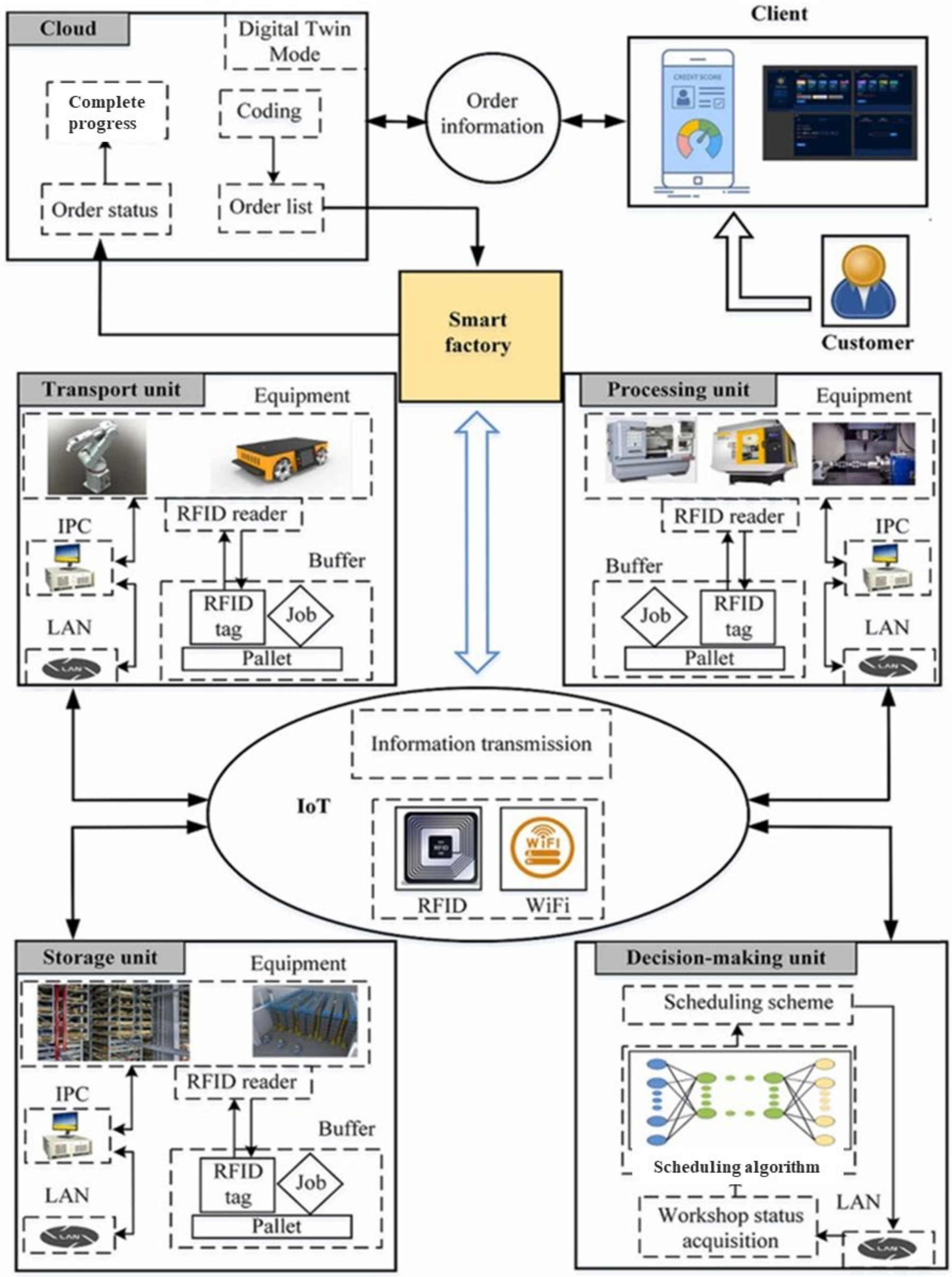

Figure 8. A proposed physical architecture of a smart factory based on intelligent agent [117].

Under the surface, these various modules conceal a single structural design with an industrial PC (IPC) inside every system to centralize control and data processing. This buffer associated with the processing units also serves as a buffer at the transportation destination within the processing unit—thus illustrating an integrated resource management concept. Similarly, Wang and colleagues present a smart factory architecture by combining through industrial networks and the cloud with supervisory control terminals as well as intelligent shop-floor elements supported among machines, conveyors, and products [118]. This framework classifies these smart objects as different types of agents and then sets up a coordinator in the cloud. The combination of planning flexibility and operation flexibility (Figure 9) comes from the working level where agents make their own decisions and locally cooperate as a network. Moreover, this self-organizing system needs external feedback and control from a central coordinator for optimum efficiency. The processes and agents are represented as different agent types, and the system can ensure that these diverse tasks are managed efficiently, thereby enabling each category of smart object able to participate in achieving the overall operational goals. The central coordinator is responsible for coordinating interactions across all these agents, making sure that they can operate independently but together to accomplish goals.

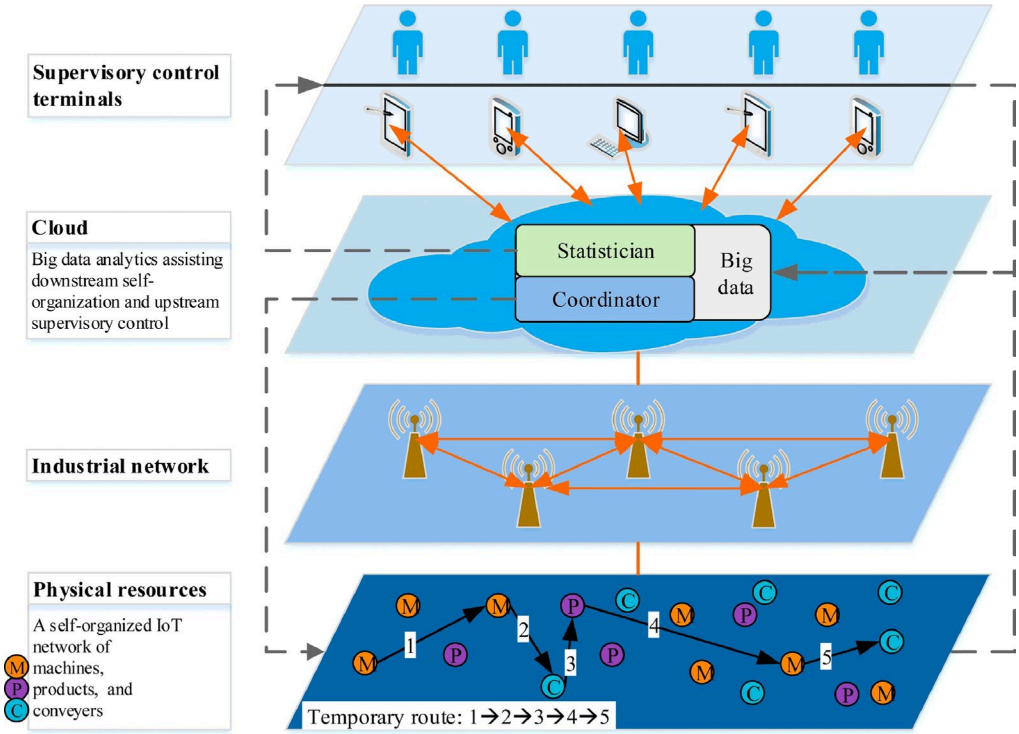

Figure 9. Framework for the proposed smart factory of Industry 4.0 [118].

Zhou et al. [21] proposed multi-agent system (MAS) architecture for smart factories that enhances the learning and scheduling efficiency of multiple AI schedulers, allowing them to effectively manage low-volume-high-mix orders and adapt to real-time changes in production conditions, such as rush orders and machine failure. These approaches pave a new way for cyber-physical integration in smart manufacturing leveraging IoT technologies to enable seamless communication between manufacturing units (Figure 10). The solution uses RFID tags to efficiently store and share machining operation details so that they can be incorporated into a distributed architecture, which substantially improves the efficiency and reliability of scheduling procedures [93,119]. This near-real-time scheduling uses these state-of-the-art neural networks built for each individual factory and forms a core component of the approach. These are real-time AI-enabled schedulers that can make decisions based on dynamic operations and sensor data to ensure optimal resource utilization without bottlenecking production [120]. It leverages the collective experience of one smart AI scheduler learning from another scheduling approach, as well as from collaboratively learning capabilities, promoting its common sense in a way that contributes to the overall improvement of performance measures [87,121].

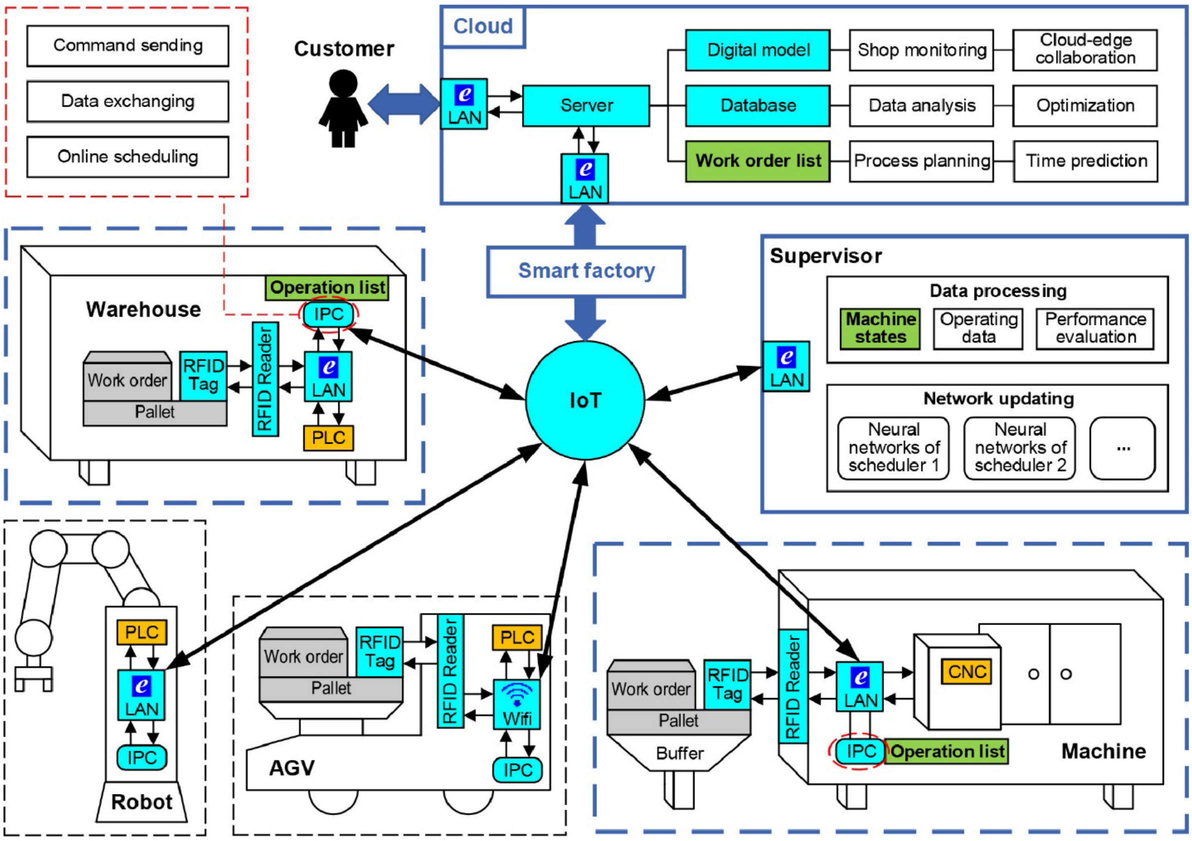

Figure 10. A Cyber-physical system integrated into a smart factory architecture.

5.3. Case Studies and Current Implementations

AI-driven smart manufacturing systems appear to have transformative potential, as seen from several well-known case studies in which they revolutionized production processes and were the next big step of Industry 4.0 or even 5.0. However, a study conducted by Dmitrieva et al. [113] revealed that IoT and AI incorporation in smart manufacturing lines had a substantial impact on production efficiency, quality control, and maintenance practices. Manufacturers were able to optimize their operations, reduce downtime, and improve performance through real-time data collected from IoT sensors processed with AI algorithms for predictive analytics and decision-making. Smart factories, as the automotive industry has certainly seen, offer huge advantages. Table 2 shows an overview of implementations of self-learning and AI integrated with digital twins. A comprehensive study by Sjödin et al. [122] showcased the positive impact of implementing smart manufacturing systems in automotive production lines.

The improvements in processed productivity, quality and sustainability were significant based on the results. For example, new automotive products started to adopt AI-driven optimization techniques to reduce product flaws and waste via IoT-powered real-time surveillance, which means that low-cost competition becomes a significant factor, although only in price rather than technical means [123].

In another, self-learning factory mechanisms were shown to reduce energy consumption and improve customer satisfaction by predicting process plans in advance, with a success case study carried out in the metal-cutting industry. By incorporating AI algorithms and IoT sensors, advanced intelligent systems were enabled to self-regulate cutting parameters and tool paths through real-time data analysis. Over the long term, these self-sufficient factories managed to predict and adapt to changing machining conditions, leading to a dramatic decrease in energy use while preserving product quality and productivity [124].

Table 2. Overview of smart manufacturing systems and real-world implementation.

Aspect	Self-Learning Systems	AI with IoT and Digital Twins	Case Studies
Capabilities	Predictive modeling, autonomous optimization, and energy reduction	Real-time monitoring, predictive maintenance, quality control, and resource optimization	Improved efficiency, quality control, and sustainability
Technologies Used	Hybrid learning, machine learning, and transfer learning	AI algorithms, IoT devices, and digital twins	IoT, AI, digital twins
Benefits	Enhanced adaptability, reduced energy consumption, and improved machine tool selection	Reduced downtime, proactive maintenance, and increased productivity	Increased production efficiency, effective maintenance practices, and higher quality
Challenges	Data integration, ensuring data quality, and managing complex systems	Data security, compatibility concerns, and managing heterogeneous sensor networks	Large-scale transformation, high initial costs, and interoperability issues
Examples	Self-learning factory mechanism in metal cutting industries [123]	Concerns like AI-driven digital twins for predictive maintenance and quality control [110,112]	Smart factory implementation in automotive manufacturing [122]

6. Industrial Impact and Future Potential

AI-driven 3D printing has enabled great customization, optimization, and efficiency than before, resulting in shorter production times and reduced costs. These systems minimized waste by 30% in fused deposition modeling (FDM) printers, according to [125]. AI-driven 3D printers are equipped with sensors that offer predictive maintenance, reducing downtime, according to Additive manufacturing standards. Recently, it has expanded into many fields like Aerospace, healthcare, construction, and consumer products, to name a few. Some of the recent developments of 3D printed manufacturing backed by AI are highlighted in this section.

6.1. Aerospace

3D printing driven by AI is revolutionizing aerospace production by enabling the production of complex, lightweight parts that significantly enhance efficiency. A prototype of a rocket engine made using both 3D printing and AI was revealed by Munich-based Hyperganic in 2020. After making a lot of progress, they were able to create the world's largest 3D-printed rocket engine in partnership with AMCM, an EOS sister company [126]. In another instance, GE Aviation 3D-printed a fuel nozzle for the LEAP engine, which is 25% lighter. They were able to consolidate 20 parts into a single component, which is a landmark achievement [127]. While GE Aviation's consolidation of 20 parts into a single, lighter fuel nozzle is a landmark achievement, publicly available and detailed ROI analyses remain scarce. However, if put in proper perspective, the reduction in aircraft weight translates into reduced fuel consumption and costs. This lack of transparent economic data is a broader challenge in the industry, making it difficult for other companies to build a business case for similar AI-driven adoption.

6.2. Healthcare

AI-driven 3D printing in healthcare has enabled early disease prediction, personalized implants and prosthetics, bio-printed tissues, and dental implants, among other applications. For example, Materialize offers a wide variety of services involving AI-enabled 3D-printed implants based on CT scan data [128]. Additionally, drug toxicity was assessed on 3D printed liver tissue by Organovo [129]. Three-dimensional printing platforms and AI-assisted design software also help in the production of personalized dental implants at Carbon [130].

6.3. Construction

3D printing in construction is undergoing a significant transformation because of the smart contributions of AI, by automating complex tasks, enabling real-time problem solving and decision-making, and improving the quality and print design. An AI-driven mobile robotic printer was used by Apis Cor to construct a home.; they 3D-printed an entire house in just 24 h in Russia [131]. Three-dimensional printable building models were generated using AI through NASA's Mars Habitat Challenge, in which AI optimized models by analyzing environmental factors [132].

6.4. Consumer Products

Intelligent manufacturing is altering the consumer product landscape by mass personalization, rapid prototyping, and on-demand production. Its analytical tools include behavioral prediction, forecasting demand, and sensors, to name a few. Personalized ergonomic gaming accessories were made by IKEA in collaboration with UNYQ using AI and 3D printing [133]. AI algorithms at Gilette streamline the design to 3D print handles for their razors [134].

The incorporation of AI in 3D printing has transformed product development, from design optimization to real-time control, enhancing productivity and reducing costs. The era of intelligent manufacturing is in its beginning stages, but fast progress is giving way for a future where AM becomes faster and smarter. The days of print farms being cloud-connected, allowing thousands of machines to work simultaneously, are not too far away. AI-supported life cycle analysis (LCA) will help make better material and geometry choices. New user interfaces might emerge with the help of AI, making 3D printing more accessible. With ongoing research and development, AI will transform the initial 3D printing into a fully integrated, intelligent system.

7. Data Governance, Adaptability, and Standards

As AI-driven AM gains popularity and widespread use, we will face challenges beyond performance and control, including data governance, adaptability, and regulatory compliance. AI models are trained using previous datasets, such as process logs, feed data, and design data. Sharing these datasets might raise concerns about intellectual property, privacy, and cyber security. Another barrier at the industry level is that a model may not be automatically generalizable beyond the data it was trained on. A model trained to detect wear on one machine may not be able to do the same on a different machine, because of the variations between machines. In addition to these, AI-enabled AM must comply with regulatory standards like ISO/ASTM 52904 [135]. When using AI in AM in highly regulated fields like medical or aviation, the builds must meet FDA and FAA requirements. Without meeting these criteria, AI might be confined to experimental applications. Transparent data policies, transferability in learning strategies, and compliance with global standards will accelerate the use of AI in AM.

8. Conclusions

AI is transforming 3D printing through smart automation, defect detection, and optimized production. Technologies like machine learning, deep learning, and computer vision are making 3D printing faster, more accurate, and more adaptable. However, significant challenges still exist. The 'black-box' nature of many deep learning models limits their use in safety-critical applications where explainability is essential. Data scarcity, particularly for rare defect types, reduces the ability of predictive models to generalize across different machines and materials. Additionally, the high computational and financial costs of deploying advanced AI systems create a major obstacle to widespread industry adoption. Future research should focus on developing physics-informed AI, establishing standardized validation datasets, and advancing explainable AI to build the trust and reliability necessary for mission-critical manufacturing.

However, despite these advances, several challenges remain, including data scarcity, limited generalizability across printers and materials, certification barriers in safety-critical industries, computational costs for real-time deployment, and the need for explainable AI.

Addressing these challenges presents significant opportunities for future research. Developing standardized datasets, physics-informed AI models, efficient algorithms, and human-in-the-loop systems will be essential to fully realize the potential of AI in AM. Indeed, when these solutions reach maturity, there is a potential for additive manufacturing with AI to be not only a supplementary tool but the heart of innovative production systems. Such a transition would, besides benefiting the company with increased effectiveness and dependability, also allow for design possibilities and sustainability initiatives that are beyond the capability of traditional methods. By overcoming these hurdles, AI can transform AM into a more reliable, sustainable, and intelligent production paradigm, unlocking new possibilities in design, production, and quality assurance, and accelerating the adoption of Industry 4.0/5.0 principles across manufacturing sectors.

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