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REVIEW PAPER

Real-Time Monitoring and Adaptive Control in 3D Printing: Trends, Challenges, and Opportunities

Mr. Himanshu Barhaiya
Department of Computer Science and Engineering,
Lakshmi Narain College of Technology
Bhopal
himanshub@lnct.ac.in

***Abstract*—Additive manufacturing (3D printing) has emerged as a transformative technology for producing complex and customized components across aerospace, biomedical, automotive, energy, and other industrial sectors. Despite its advantages, maintaining consistent print quality remains a critical challenge due to process instability, material variability, and defect formation during fabrication. This paper presents a comprehensive review of 3D printing fundamentals, real-time monitoring techniques, adaptive control strategies, and recent advancements in intelligent manufacturing systems. It systematically analyzes vision-based, sensor-driven, and multimodal monitoring approaches, along with emerging technologies for process optimization. Furthermore, current trends in adaptive and autonomous control systems are discussed, highlighting their role in improving accuracy, stability, and defect reduction. A comparative analysis of recent studies is also presented to identify key advantages, limitations, and research gaps. The findings reveal that existing approaches are limited by scalability issues, computational complexity, and lack of real-world validation. Finally, the paper outlines future opportunities toward fully autonomous, real-time, and self-correcting 3D printing systems enabled by AI-driven closed-loop control and multimodal sensor fusion.**

***Keywords*—Additive Manufacturing, 3D Printing, Real-Time Monitoring, Adaptive Control, Digital Twin, Intelligent Manufacturing.**

I. INTRODUCTION

As 3D printing becomes a critical technology across industry, healthcare, and research, challenges related to quality control and process stability persist. This study investigates the application of advanced technologies such as image analysis and machine learning—for real-time detection of printing defects, which has the potential to enhance both production efficiency and product quality. Its overarching aim is to contribute to the optimisation of 3D printing in industrial contexts by improving automation and reliability monitoring. The field of 3D printing is more diverse than it might initially appear[1][2]. It has found significant applications in sectors such as construction and automotive manufacturing[3]. The most well-known technique associated with 3D printing involves the use of filament that is heated and extruded through a nozzle to build the desired shape on a print platform via a layer-by-layer process[4].

The term "3D printing" encompasses several distinct methods, each utilising different machines and materials. This technology allows for the fabrication of a wide array of objects—from simple flowerpots to rocket engines. While the manufacturing techniques vary considerably, all fall under the umbrella of additive manufacturing[5]. Substantial progress has been made in improving the quality and performance of printed components, particularly through ongoing advancements in Fused Deposition Modelling (FDM), the most widely used technique in 3D printing[6]. As industries transition into the era of the Fourth Industrial Revolution, the integration of intelligent manufacturing systems has highlighted the pivotal role of additive manufacturing in enhancing efficiency, reducing waste, and enabling rapid prototyping. This technology not only facilitates the production of complex geometries but also promotes sustainability through its economic and environmental benefits [7]. Consequently, assessing the quality of 3D printing requires consideration of both its technical capabilities and its broader implications for future manufacturing paradigms [8].

A. *Structure of Paper*

The structure of this paper is organized as follows: Section II presents the fundamentals of 3D printing. Section III discusses real-time monitoring techniques in 3D printing along with major challenges. Section IV reviews current trends. Section V provides a detailed literature review followed by a discussion of research gaps. Finally, the paper concludes by future research.

II. FUNDAMENTALS OF 3D PRINTING

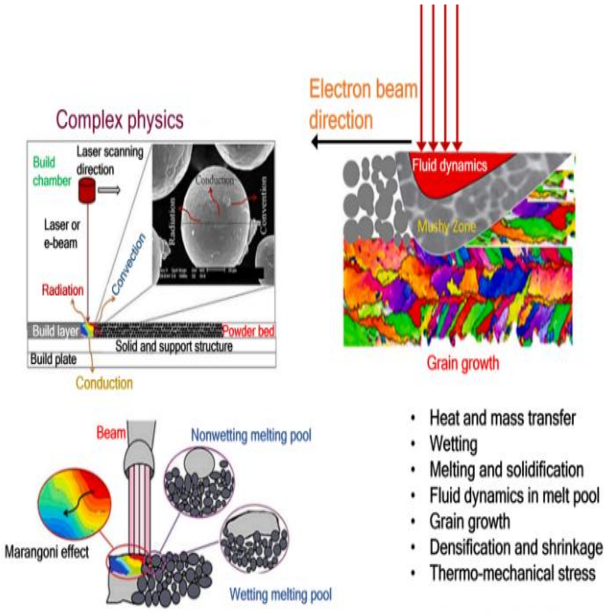

Fig. 1. The multiscale nature of the powder-bed metal AM process, showing various properties and interactions across different length and time scales [9].

Additive Manufacturing (AM), also known as 3D printing, produces three-dimensional objects from a digital file by incrementally layering material. Unlike traditional methods, which usually remove material from a larger block, AM constructs objects directly from a digital design. This approach enables the creation of intricate geometries that are challenging or impossible to achieve with conventional techniques. AM can work with a variety of materials, such as plastics, metals, and ceramics [10][11]. Typically, the digital design is created using Computer-Aided Design (CAD) software, which is then sliced into thin layers for the AM machine to read and construct sequentially [12]. Figure 1 illustrates an example of the AM process in a powder bed metal scenario.

There are several types of AM technologies, each with its unique process and applications (as shown in Figure 2). The most common types include:

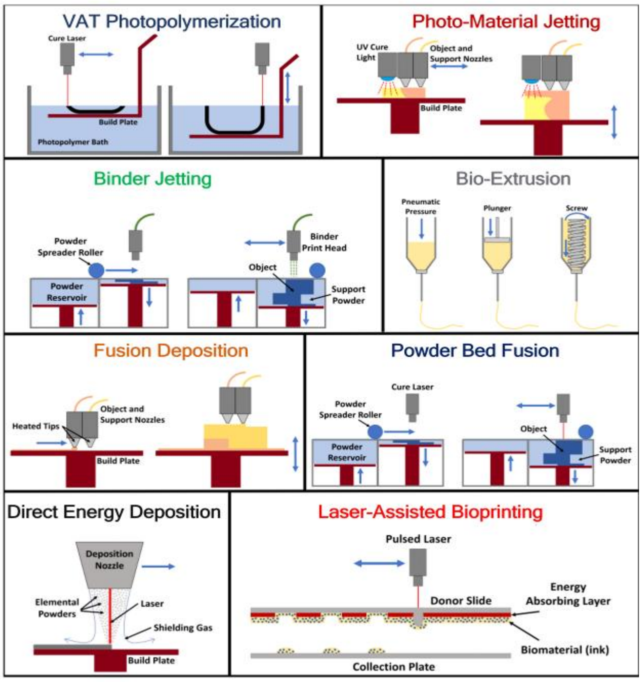

Fig. 2. Different types of AM techniques

- **Stereolithography (SLA)**: SLA employs a laser to cure liquid resin into hardened plastic through a layerby-layer process. This method is renowned for creating parts with high resolution and smooth surface finishes.
- **Fused Deposition Modeling (FDM):** FDM extrudes thermoplastic filament through a heated nozzle, which is deposited layer by layer to create a part. It is widely used due to its simplicity and cost-effectiveness.
- **Selective Laser Sintering (SLS):** SLS uses a laser to sinter powdered material, typically nylon or other polymers, into a solid structure. This method is known for its ability to create strong and durable parts without the need for support structures.
- **Digital Light Processing (DLP):** This method is similar to SLA but uses a digital light projector to cure photopolymer resin. It can quickly produce high-resolution parts [13].
- **Binder Jetting:** In this process, a liquid binding agent is deposited over a powder bed to bond the material and form a solid part. It's suitable for metals, ceramics, and even sand.
- **Material Jetting:** This technique involves depositing droplets of build material layer by layer, which are then cured by UV light. It allows for high precision and can print multiple materials at once [14].
- **Powder Bed Fusion (PBF):** PBF includes technologies like Selective Laser Melting (SLM) and Electron Beam Melting (EBM). These use a laser or electron beam to melt and fuse powder particles together.
- **Direct Energy Deposition (DED):** DED uses thermal energy, such as a laser or electron beam, to fuse materials by melting them as they are deposited. This method is used for repairing and adding material to existing components [15].
- **Sheet Lamination:** This method involves stacking and bonding sheets of material, which are then cut to shape using a laser or another cutting tool. It is known for its speed and ability to use a wide range of materials.

A. Classification of monitoring technologies

The core objective of 3D printing monitoring technology is to capture abnormal signals during the printing process in real time, such as geometric deviations, material defects, and temperature fluctuations[16]. The collected data is then analyzed to provide a basis for quality control. Existing monitoring technologies can be broadly categorized into three groups based on data acquisition modalities and operational principles: (a) In-situ computer vision-assisted anomaly identification, (b) sensor data-driven monitoring approaches, and (c) new type monitoring paradigms, including digital twin-enabled monitoring and self-sensing material-integrated systems [17][18].

1) In-situ computer vision-assisted anomaly identification

In-situ computer vision-assisted anomaly identification has become the mainstream method in 3D printing monitoring due to its non-contact and high-resolution characteristics. The core methodology involves capturing visual data of the printing process through imaging devices (e.g., cameras, laser scanners), integrating image processing algorithms with deep learning models to achieve defect detection and localization[19].

2) Sensor data-driven monitoring approaches

Data sources for identifying 3D printing process anomalies can be categorized into two primary modalities: imaging data and sensor-derived measurements. Sensor-based monitoring technologies provide foundational support for anomaly detection and control feedback through real-time quantification of critical physical parameters during printing operations. Commonly deployed sensors include accelerometers, thermal cameras, thermocouples, ultrasonic transducers, and current/pressure sensors [20].

3) New type of monitoring

Exclusive reliance on machine vision, infrared sensors, or acoustic monitoring systems results in monochromatic data streams, inherently compromising comprehensive defect prediction capabilities essential for industrial-scale production. No singular sensing modality can holistically monitor product quality or pre-emptively mitigate defects across the entire manufacturing lifecycle[21]. To address this critical limitation, multimodal sensor fusion architectures have emerged as a transformative solution.

4) 3D Printing Applications

To date, 3D printing has been used in a variety of applications, ranging from consumer products to complex industrial components. Some of the major applications of 3D printing are presented in Figure 3.

Fig. 3. Major applications of 3D printing

5) Aerospace and Defense

The application of 3D printing technology in the aerospace and automotive industries has been widely recognized. When compared to traditional manufacturing methods, AM creates stronger and lighter products with excellent mechanical properties. This technology has also been applied in the automotive sector, enabling the production of lighter car parts, components, and prototypes with faster turnaround times. Furthermore, 3D printing can also manufacture replacement and spare parts more efficiently

6) Energy

Using 3D printing to produce energy conversion technologies could be a major shift. It could be a low-cost strategy that allows for the manufacturing of complicated designs and improved performance per unit of mass and volume. It can be used to create intricate and customized components for renewable energy systems, such as wind turbines and solar panels. Additionally, it is possible to reduce waste and improve efficiency in energy production by enabling the creation of precise and optimized components [22].

7) Biomedical and Healthcare

From the creation of custom prosthetics and implants to the printing of surgical guides and organs, 3D printing technology has an enormous number of applications in the healthcare industry. Organ 3D printing has demonstrated significant progress in both animal and human models, paving the way for potential developments in transplantation and regenerative medicine. The technology has also been used to produce personalized medicine, such as customized pills with specific dosages and active ingredients. With the ability to create precise and intricate structures, it has the potential to transform the way the medical industry operates [23].

8) Food Industry

The food industry has embraced 3D printing technology to create new and innovative food products. Overall, 3D printing allows for the creation of intricate shapes and designs that would otherwise be difficult to achieve through traditional methods. This has resulted in the development of novel and unique snacks, desserts, and even complete meals that are both aesthetically pleasing and delicious. The technology also has the potential to produce complex geometrical shapes in a shorter period, making it easier to produce healthier food products with precise control over the used ingredients [24].

9) Fashion Industry

Advances in 3D printing have been embraced by the fashion industry to create unique and innovative clothing and accessories. Printing 3D designs onto fabric eliminates the need for glue, and the bonding between the fabric and printing materials is primarily due to physical locking rather than chemical bonding [25]. From light and complex parts to unique and innovative clothing and accessories, 3D printing has created new opportunities to produce customized and personalized clothing.

10) Automotive Industry

The automotive industry is using 3D printing to create lighter and stronger parts for cars, leading to improved fuel efficiency and performance. The technology also allows for the rapid prototyping and testing of new designs, minimizing the time and expenses required to launch a new product [26]. Additionally, custom, and specialized parts are being manufactured using 3D printing to maintain unique and vintage cars, offering owners a more convenient option for vehicle preservation[27].

11) Architecture and Construction

Technology is also being used to create customized and unique building components, such as wall panels and tiles, which would be impossible to produce using conventional methods [28]. With the ability to create precise and intricate structures, 3D printing has the potential to change the way buildings are designed and built. New and novel construction methods are necessary to accomplish the worldwide aim of lowering carbon dioxide emissions. These technologies should not only promote green building practices but also reduce the costs of creating and managing facilities while maintaining a competitive advantage.

III. REAL-TIME MONITORING IN 3D PRINTING

Monitoring aids play a crucial role in enhancing the quality of printed parts in additive manufacturing processes. These aids encompass various techniques and technologies designed to detect and mitigate the defects, ensure process stability, and optimize the printing parameters. Real-time monitoring systems, such as optical and thermal imaging, acoustic sensors, and vibration analysis, provide valuable insights into the printing process, enabling the operators to identify anomalies and make timely adjustments to maintain the quality standards[29]. Real-time monitoring improves print quality, reduces material waste, enhances process reliability, and serves as a foundation for adaptive control systems in smart additive manufacturing environments. There are different Types of Real-Time Monitoring:

- **Vision-Based Monitoring:** Cameras are positioned around the printer to capture images or videos of the printing process. These images are analyzed using image processing and computer vision techniques to identify defects such as layer misalignment, missing material deposition, cracks, and geometric deviations.
- **Thermal Monitoring:** Thermal monitoring in additive manufacturing is a critical component in understanding and controlling the complex thermal

gradients and cooling rates that significantly affect the microstructure and mechanical properties of the final product.

- **Acoustic Monitoring:** Acoustic monitoring in additive manufacturing refers to a technique where sound or acoustic signals are utilized to assess and monitor the printing process. During additive manufacturing, such as 3D printing, the equipment produces specific acoustic signatures or sounds associated with the deposition and fusion of material layers. The acoustic monitoring method involves using sensors or microphones to capture and interpret the emitted sounds during different stages of the additive manufacturing process.
- **Vibration Monitoring:** Vibration monitoring involves the use of accelerometers and vibration sensors to measure mechanical oscillations during printing. Excessive vibration can lead to dimensional inaccuracies, surface roughness, and structural defects. Monitoring vibration patterns helps identify unstable operating conditions and machine wear.
- **Multi-Sensor Monitoring:** Sensor fusion techniques integrate information from multiple sources, resulting in improved defect detection accuracy and more robust process monitoring. Multi-sensor systems are becoming a major trend in intelligent additive manufacturing due to their ability to provide comprehensive situational awareness.

A. *Challenges of 3D printing monitoring*

Despite significant advancements in 3D printing monitoring and control technologies, persistent challenges hinder their widespread industrial implementation, primarily manifested in insufficient detection accuracy, control latency, limited system generalizability, and prohibitive operational costs.

1) Defect identification & in-process monitoring challenges

The inherent complexity of defect typologies and morphological variability during printing processes poses fundamental limitations. In fused deposition modeling (FDM) and comparable technologies, dynamic surface quality variations induce unstable diagnostic signatures. Furthermore, the scarcity of defect samples in production environments exacerbates data imbalance issues, compromising detection accuracy. While high-resolution imaging and multisensory data fusion enhance diagnostic capabilities, they concurrently escalate computational loads, degrading real-time performance [30]. Sensor deployment is further constrained by spatial limitations and process-induced interference, rendering optimal positioning and calibration critical yet unresolved challenges [31].

2) Material-process interaction complexities

Emerging challenges arise from advanced material systems, exemplified by continuous fiber-reinforced composites prone to voids, delamination, and interfacial debonding defects governed by intricate multiscale mechanisms with limited controllability [32]. The pronounced parameter disparities across materials and equipment platforms further obstruct the standardization and transferability of monitoring-control frameworks.

3) AI & Digital twin implementation barriers

While AI-enhanced systems and digital twins demonstrate theoretical promise, their industrial adoption faces multifaceted obstacles. Deep learning models require extensive domain-specific training data, exhibiting poor adaptability to equipment heterogeneity, material variations, and environmental fluctuations [33]. Multimodal data fusion (e.g., thermal, mechanical, and optical signals) necessitates precise temporal synchronization and feature alignment, demanding substantial computational resources and customized development for reliable digital twin construction.

4) Closed-loop control system limitations

Current implementations predominantly operate in "monitor-dominant, control-secondary" modes, lacking robust autonomous adjustment mechanisms[34]. Control strategies exhibit excessive dependence on material-specific properties, path-planning algorithms, or equipment configurations, severely limiting cross-platform adaptability. Sensor-to-actuator latency—encompassing data processing, decision-making, and mechanical response—further impedes real-time control precision, particularly in high-speed printing scenarios.

IV. CURRENT TRENDS IN ADAPTIVE CONTROL

Current adaptive control in 3D printing is moving toward intelligent, data-driven, and fully autonomous manufacturing systems[35]. Traditional control methods are increasingly being replaced by advanced techniques such as machine learning, reinforcement learning, digital twins, and multi-sensor fusion. These approaches enable real-time decision-making, improved process stability, and automatic correction of printing parameters during fabrication. In particular, closed-loop control systems and AI-integrated frameworks are widely used to enhance print quality and reduce defects. Table 1 summarizes the major current trends in adaptive control for 3D printing along with their key characteristics and applications.

TABLE I. CURRENT TRENDS IN ADAPTIVE CONTROL FOR 3D PRINTING

Trend	Key Technologies	Benefits	Applications
Closed-Loop Control Systems	Sensors, PID controllers, feedback loops	Improved accuracy, reduced defects, enhanced stability	Melt pool control, temperature regulation, layer height correction
Machine Learning-Based Adaptive Control[36]	Random Forest, SVM, Neural Networks, Gradient Boosting	Data-driven decisions, improved adaptability, defect prevention	Quality prediction, parameter optimization, anomaly detection
Deep Learning and Computer Vision-Based Control	CNN, Vision Transformers, YOLO, Image Processing	Automated defect detection, real-time quality assessment	Surface inspection, layer defect correction, print quality monitoring
Reinforcement Learning (RL)	Q-Learning, Deep Q Networks (DQN), PPO, RL Agents	Self-learning capability, continuous improvement, autonomous control	Dynamic speed adjustment, laser power control, process optimization
Bayesian Optimization-Based Control	Bayesian Optimization, Gaussian Processes	Reduced experimentation, faster optimization, improved control accuracy	PID tuning, process parameter adjustment, quality enhancement

Digital Twin-Driven Adaptive Control	Digital Twins, Simulation Models, IoT, AI	Predictive decision-making, reduced failures, process optimization	Smart manufacturing, predictive maintenance, process simulation
Multi-Sensor Fusion-Based Control	Sensor Fusion, Data Analytics, AI Models	Better fault detection, increased robustness, enhanced reliability[37]	Multi-material printing, industrial additive manufacturing
Edge AI and Real-Time Computing	Edge Computing, Embedded AI, IoT Devices	Low latency, real-time response, reduced cloud dependency	Industrial 3D printers, smart factories
Cyber-Physical Systems (CPS)	CPS, IoT, Cloud Computing, AI	Enhanced connectivity, intelligent automation	Industry 4.0 manufacturing environments
Autonomous and Self-Correcting Printing Systems	AI, Digital Twins, RL, Multi-Sensor Systems	Zero-defect manufacturing, reduced downtime, improved productivity	Fully autonomous additive manufacturing

A. *Future Opportunities in Autonomous 3D Printing*

Future opportunities in autonomous 3D printing are strongly driven by the convergence of digital twins, artificial intelligence, reinforcement learning, and real-time sensor-based control systems. Recent studies show that digital twin frameworks can continuously synchronize physical printers with virtual models, enabling real-time monitoring in additive manufacturing. Similarly, AI and machine learning–based approaches are increasingly being integrated with additive manufacturing systems to support defect prediction, process optimization, and intelligent decision support across different stages of production. Multiple AI modules collaborate to detect defects, diagnose process issues, and implement corrective actions without human intervention, significantly reducing failure rates and material waste . Overall, these advancements indicate a clear shift toward fully autonomous, self-optimizing 3D printing systems, where real-time intelligence, predictive modeling, and closed-loop control converge to enable zero-defect, adaptive, and highly efficient manufacturing ecosystems.

V. LITERATURE REVIEW

This section reviews recent studies related to real-time monitoring, defect detection, adaptive control, and artificial intelligence techniques in 3D printing. The review also identifies key research gaps that motivate the development of more robust, scalable, and autonomous monitoring and control systems for additive manufacturing.

Ju et al., (2026) three widely used segmentation models, U-Net, YOLOv8, and SegNet, were compared in terms of their performance and segmentation quality. A dataset was constructed using chocolate and three designs were printed three times in 27 cases. Using the dataset, the model learns sagging and thinning defects. The experimental results showed that U-Net demonstrated the best performance in defect detection. YOLOv8 displayed moderate performance with low sensitivity, highlighting its suitability for applications where speed is more important than accuracy. SegNet achieved the highest AUC value, suggesting that its performance can be enhanced via further optimization [38].

Skoury et al., (2026) presents a data-driven digital twin that couples real-time monitoring, predictive modelling and adaptive feedback. Machine parameters are continuously linked to material rheology and print outcomes, forming a virtual representation of the process. A clustering-based analysis classifies material mixtures and drives feedback control of printing parameters, improving stability, accuracy and efficiency. The digital twin is demonstrated on a large-scale setup with two machines operating in parallel and five services forming a closed feedback loop. Experiments show reduced material consumption by 7.5% and more consistent, higher-quality prints when using the predictive digital twin. These results indicate that integrating digital twins into large-scale 3D printing can support more robust, adaptive and scalable production [39].

Geng et al., (2025) addresses how to intelligently optimize printing parameters to adapt to varying concrete material attributes and improve printing quality. A dual-path framework co-driven by physical information equations (PIE) and machine learning (ML) is proposed. PIE is embedded into convolutional neural networks (CNN) to enhance rheological properties prediction, while also coupled with the random forest (RF) model to predict printing parameters. Results show this approach efficiently matches yield stress (YS), plastic viscosity (PV), extrusion speed (ES), and printing speed (PS), significantly enhancing printing performance. This research provides construction engineers and 3D printing operators with a physics-guided, interpretable intelligent tool that reduces trial-and-error and improves construction reliability. The integration strategy also opens promising directions for future studies on large-scale printing involving multi-scale material-process-structure optimization and time-dependent rheological modeling [40].

Nogueira et al., (2025) proposes the design, development and deployment of a low-cost, small and compact buoy platform for coastal monitoring, which was built almost entirely on 3D printing technology in a modular way. The buoy called EMAC buoy -V3.0- (EMAC: Estación de Monitoreo Ambiental Costero) was significantly improved in the last few years based on cost-effective optimization and physical constraints inherent to coastal waters, providing the advantages of simplicity and flexibility. This study considered oceanographic and meteorological measurements of a buoy moored in the San Matías Gulf on the northern Patagonian Continental Shelf [41].

Wang et al., (2024) introduces a novel approach for deep neural network (DNN) adaptation to the dynamic environments through self-supervised learning and applies it to during in-situ monitoring. Specifically, we introduce a self-supervised learning strategy that leverages the auxiliary reconstruction task during in-situ monitoring, subsequently applying self-supervised fine-tuning to classification tasks with a new imbalanced-aware classification loss. Our methodology was rigorously evaluated using a real-world dataset for 3D printing defect detection. The experimental outcomes affirm the robustness of our approach, showcasing a higher defect detection accuracy rate than baselines. This substantially mitigates the adverse effects associated with printing defects, thereby increasing the reliability and quality of 3D printing processes [42].

Chen et al., (2024) discusses in-situ adaptive defect remediation strategies that advance LAM towards zero-defect autonomous operations, focusing on real-time closed-loop feedback control and defect correction methods. Research gaps such as the need for standardization, improved reliability and sensitivity, and decision-making strategies beyond early stopping are highlighted. Future directions are proposed, with an emphasis on multimodal sensor fusion for multiscale defect prediction and fault diagnosis, ultimately enabling self-adaptation in LAM processes [43].

TABLE II. COMPARATIVE ANALYSIS OF RECENT STUDIES ON 3D PRINTING SYSTEMS

Authors	***Approach***	***Advantages***	***Challenges***	***Recommendations***
Ju et al. (2026)	U-Net, YOLOv8, SegNet for segmentation-based defect detection	High segmentation accuracy (U-Net best); YOLOv8 provides fast inference; SegNet shows strong AUC potential	YOLOv8 has low sensitivity; SegNet requires further optimization; dataset limited to controlled cases	Improve dataset diversity and real-world conditions; optimize SegNet hyperparameters; balance speed–accuracy trade-off
Skoury et al. (2026)	Digital twin with real-time monitoring, clustering-based feedback control	Improved stability and print quality; 7.5% material reduction; adaptive closed-loop optimization	High system complexity; requires continuous sensor integration; scalability issues in large deployments	Enhance scalability of digital twin systems; integrate robust IoT sensor frameworks; reduce computational overhead
Geng et al. (2025)	Physics-informed CNN + Random Forest hybrid model	Better interpretability; improved prediction of rheology and printing parameters; reduces trial-and-error	Dependence on accurate physical modeling; computational complexity; limited generalization across materials	Extend to multi-material systems; improve generalization using larger datasets; optimize computational efficiency
Nogueira et al. (2025)	Low-cost modular 3D-printed buoy system (EMAC V3.0)	Cost-effective; flexible modular design; successful real-world coastal monitoring	Limited to specific environmental conditions; durability concerns in harsh marine environments	Improve material durability; expand deployment across diverse marine conditions; integrate real-time analytics
Wang et al. (2024)	Self-supervised learning with reconstruction task for defect detection	High robustness; improved accuracy under imbalanced datasets; adaptive learning in real-time	Requires large unlabeled data; training complexity; sensitivity to parameter tuning	Develop lightweight self-supervised models; improve real-time efficiency; enhance imbalance handling strategies
Chen et al. (2024)	Survey on in-situ adaptive defect remediation and closed-loop control in LAM	Comprehensive overview of autonomous defect correction; highlights future research directions	Lack of standardization; limited reliability of sensors; weak multimodal integration	Develop standardized frameworks; improve multimodal sensor fusion; enable fully autonomous zero-defect manufacturing

A. Research Gaps

The reviewed studies highlight several important research gaps in AI-driven 3D printing monitoring and control systems (Table 1). Most existing works, such as segmentation-based defect detection models and self-supervised learning approaches, are limited by restricted dataset diversity and lack of real-world industrial-scale validation. Digital twin and physics-informed models improve adaptability and accuracy, but they suffer from high computational complexity and poor scalability in practical deployments. In addition, current systems show weak generalization across different materials, limited real-time processing capability, and insufficient integration of multimodal sensor data. Furthermore, there is still a lack of standardized frameworks for autonomous defect detection and remediation in large-scale additive manufacturing. Addressing these gaps is essential to develop more robust, scalable, and fully autonomous 3D printing systems, as summarized in Table 1.

VI. CONCLUSION AND FUTURE WORK

This paper reviews the key aspects of 3D printing, including its fundamental processes, monitoring techniques, adaptive control methods, and recent advancements in intelligent manufacturing. The discussion shows that real-time monitoring using vision systems, sensors, and multimodal approaches plays an important role in identifying defects and improving process stability. Adaptive control strategies supported by machine learning, digital twins, and physics-informed models further enhance printing accuracy and efficiency. However, several limitations still exist, such as scalability issues, high computational cost, limited real-time performance, and weak generalization across different materials and systems. In summary, although significant progress has been made toward intelligent and automated 3D printing, further improvements are required to achieve reliable, real-time, and fully autonomous manufacturing systems in industrial environments.

REFERENCES

[1] S. Kim *et al.*, “Real-time in-process control methods of process parameters for additive manufacturing,” 2024. doi: 10.1016/j.jmsy.2024.05.008.

[2] A. A. Kadam;, R. R. Thallada;, R. Davis;, and S. A. Kadam, “Precision Control System and Method for Real-Time Precision Control of 3D Printer Nozzle,” 202521063720, 2025

[3] R. S. Snehamruth, “Data-Driven Optimization of Pharmaceutical Manufacturing Processes using Quality by Design (QbD) Frameworks,” *Int. J. Curr. Eng. Technol.*, vol. 14, no. 6, pp. 557–566, 2024, doi: 10.14741/ijcet/v.14.6.19.

[4] E. B. Mejia *et al.*, “Real-time process monitoring and automated control for direct ink write 3D printing of frontally polymerizing thermosets,” *npj Adv. Manuf.*, vol. 2, no. 1, p. 18, May 2025, doi: 10.1038/s44334-025-00032-1.

[5] P. R. Marapatla, “Journey to Excellence: Strategic Framework for Enterprise BI Migration,” *Int. J. Comput. Exp. Sci. Eng.*, vol. 11, no. 4, Oct. 2025, doi: 10.22399/ijcesen.4121.

[6] M. Kondrat, A. Nazim, K. Zidek, J. Pitel, P. Lazorík, and M. Duhancik, “Real-Time Monitoring of 3D Printing Process by Endoscopic Vision System Integrated in Printer Head,” *Appl. Sci.*, 2025, doi: 10.3390/app15179286.

[7] M. Mehrpouya, A. Dehghanghadikolaei, B. Fotovvati, A. Vosooghnia, S. S. Emamian, and A. Gisario, “The potential of additive manufacturing in the smart factory industrial 4.0: A review,” 2019. doi: 10.3390/app9183865.

[8] F. W. Baumann and D. Roller, “Survey on Additive Manufacturing, Cloud 3D Printing and Services,” *J. Manuf. Mater. Process.*, vol. 1, no. 2, p. 15, Aug. 2017, doi: 10.3390/jmmp1020015.

[9] L. Ladani, “Additive Manufacturing of Metals, Materials, Processes, Tests andd Standards,” *Destech Publ.*, 2020.

[10] V. Petrovic, J. Vicente Haro Gonzalez, O. Jordá Ferrando, J. Delgado Gordillo, J. Ramón Blasco Puchades, and L. Portolés Griñan, “Additive layered manufacturing: sectors of industrial application shown through case studies,” *Int. J. Prod. Res.*, vol. 49, no. 4, pp. 1061–1079, Feb. 2011, doi: 10.1080/00207540903479786.

[11] N. Guo and M. C. Leu, “Additive manufacturing: Technology, applications and research needs,” 2013. doi: 10.1007/s11465-013-0248-8.

[12] J.-P. Kruth, M. C. Leu, and T. Nakagawa, “Progress in Additive Manufacturing and Rapid Prototyping,” *CIRP Ann.*, vol. 47, no. 2, pp. 525–540, 1998, doi: 10.1016/S0007-8506(07)63240-5.

[13] P. J. Bártolo, *Stereolithography*. Boston, MA: Springer US, 2011. doi: 10.1007/978-0-387-92904-0.

[14] B. Derby, “Inkjet printing of functional and structural materials: Fluid property requirements, feature stability, and resolution,” *Annu. Rev. Mater. Res.*, 2010, doi: 10.1146/annurev-matsci-070909-104502.

[15] T. DebRoy *et al.*, “Additive manufacturing of metallic components – Process, structure and properties,” 2018. doi: 10.1016/j.pmatsci.2017.10.001.

[16] V. V. Bhandarkar, B. Das, and P. Tandon, “Real-time remote monitoring and defect detection in smart additive manufacturing for reduced material wastage,” *Meas. J. Int. Meas. Confed.*, 2025, doi: 10.1016/j.measurement.2025.117362.

[17] G. A. R. Sampedro, M. A. P. Putra, and M. Abisado, “3D-AmplifAI: An Ensemble Machine Learning Approach to Digital Twin Fault Monitoring for Additive Manufacturing in Smart Factories,” *IEEE Access*, vol. 11, pp. 64128–64140, 2023, doi: 10.1109/ACCESS.2023.3289536.

[18] A. S. M, R. Velu, and A. K. S, “Mechanical and self-monitoring properties of coextrusion 3D printed continuous carbon fibre reinforced polymer composites,” *Procedia CIRP*, vol. 131, pp. 74–79, 2025, doi: 10.1016/j.procir.2024.09.015.

[19] N. B. A. Karna, M. A. P. Putra, S. M. Rachmawati, M. Abisado, and G. A. Sampedro, “Toward Accurate Fused Deposition Modeling 3D Printer Fault Detection Using Improved YOLOv8 With Hyperparameter Optimization,” *IEEE Access*, 2023, doi: 10.1109/ACCESS.2023.3293056.

[20] N. Lishchenko, J. Piteľ, and V. Larshin, “Online Monitoring of Surface Quality for Diagnostic Features in 3D Printing,” *Machines*, vol. 10, no. 7, p. 541, Jul. 2022, doi: 10.3390/machines10070541.

[21] A. Joon, R. Tarafdar, S. Mathur, and H. Sinha, “Leveraging Artificial Intelligence for Enhanced Efficiency in the Semiconductor Manufacturing Process Optimization,” in *2025 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC)*, IEEE, May 2025, pp. 1–6. doi: 10.1109/ASSIC64892.2025.11158617.

[22] J. C. Ruiz-Morales *et al.*, “Three dimensional printing of components and functional devices for energy and environmental applications,” 2017. doi: 10.1039/c6ee03526d.

[23] Q. Yan *et al.*, “A Review of 3D Printing Technology for Medical Applications,” 2018. doi: 10.1016/j.eng.2018.07.021.

[24] N. Nachal, J. A. Moses, P. Karthik, and C. Anandharamakrishnan, “Applications of 3D Printing in Food Processing,” 2019. doi: 10.1007/s12393-019-09199-8.

[25] Y.-Q. Xiao and C.-W. Kan, “Review on Development and Application of 3D-Printing Technology in Textile and Fashion Design,” *Coatings*, vol. 12, no. 2, p. 267, Feb. 2022, doi: 10.3390/coatings12020267.

[26] B. J. Tuazon, N. A. V. Custodio, R. B. Basuel, L. A. D. Reyes, and J. R. C. Dizon, “3D Printing Technology and Materials for Automotive Application: A Mini-Review,” in *Key Engineering Materials*, 2022. doi: 10.4028/p-26o076.

[27] B. Jeganathan, “Exploring the Power of Generative Adversarial Networks (GANs) for Image Generation: A Case Study on the MNIST Dataset,” *Int. J. Adv. Eng. Manag.*, vol. 7, no. 1, pp. 21–46, Jan. 2025, doi: 10.35629/5252-07012146.

[28] S. El-Sayegh, L. Romdhane, and S. Manjikian, “A critical review of 3D printing in construction: benefits, challenges, and risks,” *Arch. Civ. Mech. Eng.*, vol. 20, no. 2, p. 34, Mar. 2020, doi: 10.1007/s43452-020-00038-w.

[29] K. Khanafer, J. Cao, and H. Kokash, “Condition Monitoring in Additive Manufacturing: A Critical Review of Different Approaches,” 2024. doi: 10.3390/jmmp8030095.

[30] V. Pandiyan *et al.*, “Deep learning-based monitoring of laser powder bed fusion process on variable time-scales using heterogeneous sensing and operando X-ray radiography guidance,” *Addit. Manuf.*, 2022, doi: 10.1016/j.addma.2022.103007.

[31] A. Isiani, L. Weiss, H. Bardaweel, H. Nguyen, and K. Crittenden, “Fault Detection in 3D Printing: A Study on Sensor Positioning and Vibrational Patterns,” *Sensors*, 2023, doi: 10.3390/s23177524.

[32] A. R. Sani, A. Zolfagharian, and A. Z. Kouzani, “Artificial Intelligence-Augmented Additive Manufacturing: Insights on Closed-Loop 3D Printing,” 2024. doi: 10.1002/aisy.202400102.

[33] L. Chen *et al.*, “Multisensor fusion-based digital twin for localized quality prediction in robotic laser-directed energy deposition,” *Robot. Comput. Integr. Manuf.*, 2023, doi: 10.1016/j.rcim.2023.102581.

[34] X. Chi *et al.*, “Machine Learning-Based Online Monitoring and Closed-Loop Controlling for 3D Printing of Continuous Fiber-Reinforced Composites,” *Addit. Manuf. Front.*, 2025, doi: 10.1016/j.amf.2025.200196.

[35] J. Kachhia, R. Natharani, and K. George, “Deep Learning Enhanced BCI Technology for 3D Printing,” in *2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, IEEE, Oct. 2020, pp. 0125–0130. doi: 10.1109/UEMCON51285.2020.9298124.

[36] N. K. Narendra Kumar Reddy Choppa, “Contextual Frameworks for Agentic AI: Engineering Adaptive Memory and Retrieval Mechanisms,” *Comput. Fraud Secur.*, vol. 2024, no. 11, pp. 395–406, Nov. 2024, doi: 10.52710/cfs.747.

[37] R. G. Kim, M. Abisado, J. Villaverde, and G. A. Sampedro, “A Survey of Image-Based Fault Monitoring in Additive Manufacturing: Recent Developments and Future Directions,” *Sensors*, vol. 23, no. 15, p. 6821, Jul. 2023, doi: 10.3390/s23156821.

[38] E. Ju, J. Seol, S. Kim, S. Kim, S. J. Kim, and H. Il Son, “Comparison of deep learning models for 3D food printing monitoring system,” *J. Food Eng.*, 2026, doi: 10.1016/j.jfoodeng.2025.112903.

[39] L. Skoury, O. Asaf, A. Sprecher, A. Menges, and T. Wortmann, “Data-informed Digital Twin for large-scale 3D printing in construction,” *Autom. Constr.*, 2026, doi: 10.1016/j.autcon.2025.106706.

[40] S. Y. Geng, B. Y. Cheng, W. J. Long, Q. L. Luo, B. Q. Dong, and F. Xing, “Co-driven physics and machine learning for intelligent control in high-precision 3D concrete printing,” *Autom. Constr.*, 2025, doi: 10.1016/j.autcon.2025.106294.

[41] S. F. Nogueira *et al.*, “Design and development of a cost-effective buoy using 3D printing for coastal monitoring,” *HardwareX*, 2025, doi: 10.1016/j.ohx.2025.e00657.

[42] F. Wang *et al.*, “In-Situ 3D Printing Monitoring in Dynamic Environments via Self-Supervised Deep Neural Network Adaptation,” in *2024 IEEE 20th International Conference on Automation Science and Engineering (CASE)*, IEEE, Aug. 2024, pp. 1897–1902. doi: 10.1109/CASE59546.2024.10711824.

[43] L. Chen *et al.*, “In-situ process monitoring and adaptive quality enhancement in laser additive manufacturing: A critical review,” *J. Manuf. Syst.*, vol. 74, pp. 527–574, Jun. 2024, doi: 10.1016/j.jmsy.2024.04.013.