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| RESEARCH ARTICLE

Integration of Artificial Intelligence for Real-Time Monitoring and Process Control in Metal Additive Manufacturing Systems

Md Arman Hossain[1], Md Abdul Aziz Bhuiyan[2], Atiqur Rahman[3] and Dewan Wardy Hasan[4]

[1] *Mechanical Engineering, University of New Haven, West Haven, Connecticut, United States*
[2] *Department of Mechanical Engineering and Mechanics, Lehigh University*
[3] *Department of Mechanical & Aerospace Engineering, Missouri University of Science and Technology, Rolla, MO, 65409, USA*
[4] *Mechanical Engineering, University of New Haven, West haven, Connecticut, United States*

Corresponding Author: Md Arman Hossain, **E-mail**: mhoss15@unh.newhaven.edu

| ABSTRACT

Metal additive manufacturing (AM) has attracted significant attention because of its ability to produce complex geometries, reduce material waste, and provide greater design flexibility than conventional manufacturing methods. However, its wider industrial use is still limited by process instability and defect formation during fabrication. Defects such as porosity, lack of fusion, residual stress, and distortion can reduce part quality and reliability, making real-time monitoring and process control increasingly important. This paper reviews recent progress through 2024 in the use of artificial intelligence (AI) for real-time monitoring and control in metal AM systems. The review shows that AI has improved anomaly detection, melt-pool analysis, defect prediction, and adaptive control performance. It also highlights the growing role of sensor fusion and low-latency computing in supporting in-situ decision-making. Despite these advances, challenges remain in data availability, model generalization, interpretability, and industrial reliability. Overall, AI is playing an important role in advancing metal AM toward more intelligent, stable, and quality-assured manufacturing.

| KEYWORDS

Metal Additive Manufacturing; Artificial Intelligence; Real-Time Monitoring; In-Situ Sensing; Machine Learning; Deep Learning; Reinforcement Learning; Closed-Loop Control; Sensor Fusion; Melt Pool Monitoring; Anomaly Detection; Defect Prediction; Process Optimization; Edge Computing; Digital Twin; Quality Assurance.

| ARTICLE INFORMATION

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1. Introduction

Metal additive manufacturing (AM) has become one of the most important advances in modern manufacturing because it allows complex components to be produced directly from digital designs with high geometric freedom and reduced material waste. In contrast to conventional subtractive and formative manufacturing methods, metal AM fabricates parts layer by layer, making it possible to produce lightweight lattice structures, internal cooling channels, topology-optimized geometries, and customized components that are often difficult or impossible to achieve through traditional processes. These capabilities have made metal AM increasingly attractive for applications in aerospace, biomedical engineering, automotive manufacturing, defense, and energy systems, where low weight, high performance, and design complexity are especially important. Despite these advantages, the wider industrial adoption of metal AM is still limited by challenges related to process stability, defect formation, and quality assurance. Problems such as porosity, lack of fusion, residual stress, surface irregularities, and geometric distortion can significantly affect the performance and reliability of fabricated parts. As a result, improving process consistency and ensuring part quality remain major priorities in the development of metal AM technologies. Among the various metal AM methods, laser powder bed fusion (LPBF), directed energy deposition (DED), electron beam melting (EBM), and wire arc additive manufacturing (WAAM) have received particular attention for the production of high-value engineering components. Figure 1 illustrates the main categories of metal additive manufacturing, which are broadly divided into powder bed fusion (PBF) and direct energy deposition (DED). The PBF category includes processes such as selective laser melting, selective laser sintering, direct metal laser sintering, and electron beam powder bed fusion, while DED includes both powder-fed and wire-fed approaches such as LENS, LMD, DMD, and WAAM. This classification is important because each process involves different material delivery mechanisms, thermal characteristics, and defect formation behavior. Understanding these differences is essential for the effective integration of artificial intelligence into real-time monitoring and process control, since AI models, sensing systems, and control strategies must be adapted to the specific conditions of each metal AM process.

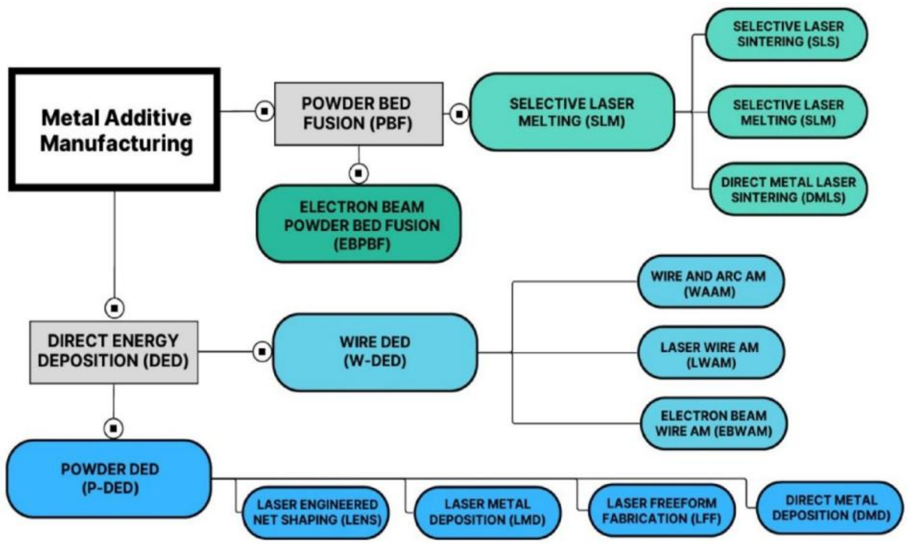

Fig. 1 Components of Metal Additive Manufacturing

Each metal AM process exhibits distinct thermal behavior, material delivery characteristics, and defect formation mechanisms. These differences are important because the successful integration of artificial intelligence for real-time monitoring and process control depends on the specific operating conditions of the manufacturing method being used. AI models, sensing strategies, and control frameworks cannot be applied uniformly across all metal AM systems; instead, they must be adapted to the process physics and data characteristics of each technique. Common defects in metal additive manufacturing include porosity, lack of fusion, keyhole voids, balling, cracking, residual stress accumulation, surface roughness irregularities, and geometric distortion. These defects are not only surface-level imperfections, but can significantly reduce fatigue life, dimensional accuracy, corrosion resistance, and overall mechanical reliability. A major difficulty in metal AM is that many of these defects develop during fabrication and may continue to propagate from one layer to the next if they are not identified at an early stage. Conventional post-process inspection methods, including X-ray computed tomography, microscopy, hardness testing, and coordinate measurement, remain valuable for final quality verification. However, these approaches are generally expensive, time-consuming, and reactive in nature. By the time a critical defect is detected after fabrication, the component may already be unsuitable for use, resulting in wasted material, longer machine downtime, and higher production cost. For this reason, in-situ monitoring and real-time process control have become central research priorities in metal additive manufacturing. Recent advances in sensing technology have made it possible to capture large amounts of high-frequency process data during fabrication. These sensing approaches include coaxial and off-axis visible cameras, high-speed thermal imaging systems, pyrometers, photodiodes, acoustic emission sensors, spectrometers, laser profilometers, and layer-wise imaging tools. Such sensors can provide valuable information about melt-pool size, thermal gradients, plume behavior, spatter generation, bead geometry, and acoustic signatures associated with instability. Although these signals contain useful information about process health and defect development, the data are often complex, noisy, multi-modal, and too large for reliable manual interpretation or simple threshold-based analysis.

This challenge has created a strong need for intelligent data-driven approaches that can transform raw sensor information into fast, reliable, and adaptive decisions. Artificial intelligence, particularly machine learning and deep learning, has therefore become increasingly important in metal AM research. These methods can identify hidden patterns in high-dimensional process data, classify abnormal events, estimate melt-pool conditions, predict defect formation, and optimize process parameters more effectively than traditional empirical approaches alone. Supervised learning has been widely used for quality prediction and defect classification, while unsupervised learning has supported anomaly detection and clustering of process signatures. Convolutional neural networks have shown strong capability in image-based melt-pool and layer analysis, recurrent and temporal models have been applied to sequential sensor streams, and reinforcement learning has gained attention for adaptive parameter tuning and closed-loop control. As a result, AI has shifted AM monitoring from passive observation toward active decision support and, increasingly, autonomous process adjustment. The importance of AI becomes even greater when real-time monitoring is considered. Metal additive manufacturing is inherently time-sensitive, and a monitoring system is only practically useful if it can process sensor data quickly enough to detect abnormal conditions and respond before the defect becomes severe. This requirement has encouraged growing interest in edge computing, lightweight inference models, and sensor-fusion architectures that combine complementary signals for better robustness and accuracy. Rather than relying on a single camera or one scalar signal, recent AI-driven frameworks increasingly integrate visual, thermal, acoustic, and positional data to build a more complete representation of the evolving process state. This direction is closely aligned with broader developments in digital twins, smart manufacturing, and cyber-physical production systems, where AM platforms are expected to become increasingly data-rich, adaptive, and self-optimizing. Despite this progress, several major barriers still limit the widespread industrial deployment of AI-based real-time control in metal AM. One of the most important challenges is the shortage of large, standardized, and openly accessible datasets that reliably connect in-situ sensor signals with ex-situ defect outcomes and part performance. Although public resources have supported benchmarking and reproducibility, the currently available datasets remain limited compared with the wide range of machines, alloys, geometries, and process settings used in industrial practice. Model generalization is another major concern, since an AI model trained successfully on one machine, alloy, scan strategy, or sensing configuration may not perform consistently in a different environment. In addition, industrial implementation requires more than predictive accuracy alone; users also need interpretability, computational efficiency, traceability, and deployment reliability before AI can be trusted in safety-critical production environments.

Table 1 outlines the main methodological areas in additive manufacturing and shows how they contribute to the broader development and integration of AM systems. It highlights that additive manufacturing is not simply a fabrication method, but a multidisciplinary framework involving design improvement, process optimization, quality assurance, maintenance, innovation, supply chain coordination, and sustainability. This broader perspective is important because the successful integration of AI in metal AM depends not only on better monitoring algorithms, but also on how these algorithms interact with the overall manufacturing system.

Category	Subcategory	Description
1. Design optimization	Optimization of design	Improving design to achieve better performance and efficiency
	Material development	Developing new materials to enhance product properties
	Scalability and flexibility	Ensuring that design solutions can scale and adapt to various production levels and applications
2. Process optimization	Processes optimization	Refining and improving processes for enhanced efficiency and reduced costs
	Process monitoring and control	Continuously tracking and adjusting processes to maintain optimal performance
	Workflow Automation	Automating repetitive tasks to improve productivity and accuracy
3. Quality management	Quality control and defect detection	Implementing measures to ensure the final product meets required standards and identifying defects
4. Maintenance	Predictive maintenance	Using data to anticipate equipment failures and maintenance needs, preventing downtime
5. Innovation & scalability	Innovation acceleration	Driving innovation by streamlining design, processes, and technologies
	Adaptive learning	Using AI/ML systems to learn and optimize operations dynamically based on past data
6. Supply chain optimization	Supply chain and workflow optimization	Streamlining supply chain and workflows for improved efficiency and reduced costs
7. Sustainability	Sustainability in AM	Ensuring that processes, especially in additive manufacturing, are environmentally sustainable

Table:1 The relationships and applications of different methodologies in AM processes, design, and integration.

At the design stage, optimization, material development, and scalability improve product performance, adaptability, and manufacturing flexibility. During production, process monitoring, control, and workflow automation contribute to higher efficiency, better consistency, and lower operational cost. The table also highlights the importance of quality control and defect detection in ensuring that printed components meet required standards. In addition, predictive maintenance helps reduce the risk of equipment failure and unexpected downtime, while adaptive learning and innovation support continuous improvement in AM operations. Supply chain optimization and sustainability further emphasize the need for efficient resource utilization and environmentally responsible manufacturing. Overall, the table suggests that successful implementation of additive manufacturing depends on the integration of multiple interconnected approaches across design, production, and system management. Despite this broader progress, a major limitation remains: most current AI applications in metal additive manufacturing are still focused primarily on monitoring and prediction rather than true closed-loop control. Detecting an abnormal melt-pool signature or predicting porosity is an important step, but the larger objective is to develop reliable control architectures that can convert these predictions into corrective actions, such as adjusting laser power, scan speed, wire feed rate, interlayer dwell time, or deposition path during the build process. Achieving this level of control requires close coordination among sensing systems, data processing pipelines, learning algorithms, control theory, and process physics. It also requires a careful balance between data-driven approaches and physically grounded models, since black-box predictions alone may not be sufficient for deployment in high-value industrial sectors where reliability, traceability, and certification are essential. For this reason, current research is increasingly moving toward hybrid frameworks that combine artificial intelligence with physics-informed modeling, uncertainty quantification, and explainable decision-making strategies.

Table 2 further illustrates the growing role of artificial intelligence and machine learning in additive manufacturing across areas such as design optimization, process optimization, quality control, defect detection, predictive maintenance, and material optimization. It shows that AI-based methods, including machine learning, deep learning, computer vision, neural networks, and reinforcement learning, are being increasingly applied to improve design efficiency, optimize printing parameters, monitor build quality, detect defects, predict equipment failure, and enhance material performance. Taken together, these developments indicate that AI is becoming a key enabling technology for making additive manufacturing more intelligent, adaptive, and reliable.

Research area	AI techniques/methods	Current research status	Applications
Design optimization	ML, Genetic algorithms, DL	Widely researched; AI-driven design automation is being implemented in generative design	Improves part design efficiency, reduces time for complex geometries
Processes optimization	Neural networks, Reinforcement learning, Bayesian optimization	Research focusing on optimizing printing parameters (e.g., speed, temperature)	Enhances production speed, material usage, and energy efficiency
Quality control	Computer vision, CNNs, ML	Advanced studies on real-time monitoring of build quality	Ensures high-quality prints, minimizes post-processing requirements
Defect detection	CNNs, Image recognition, ML, Data analytics	Active research on identifying and predicting defects during and after printing	Reduces defects in final products, increasing reliability
Predictive maintenance	Predictive analytics, ML, Big data	Ongoing development to predict failures in machines and systems	Reduces downtime, improves machine lifespan, and cuts maintenance costs
Material optimization	Data-driven models, AI algorithms, ML	Growing interest in optimizing material selection for AM	Helps identify material properties that optimize mechanical performance
Design optimization	ML, Genetic algorithms, DL	Widely researched; AI-driven design automation is being implemented in generative design	Improves part design efficiency, reduces time for complex geometries

Table 2 The status and applications of AI and ML in AM process across various areas like design optimization, process optimization, quality control, defect detection, and predictive maintenance.

Overall, the table suggests that AI and machine learning are playing an increasingly important role in making additive manufacturing more intelligent, efficient, reliable, and adaptive. In this context, the present paper critically reviews recent progress through 2024 in the integration of AI for real-time monitoring and process control in metal additive manufacturing systems. The review examines how AI techniques are being applied to interpret multi-sensor process data, characterize melt-pool behavior, detect anomalies, predict defect formation, and support adaptive closed-loop control. It also discusses the growing importance of sensor fusion, edge computing, and digital twin concepts in enabling practical in-situ intelligence during fabrication. In addition to summarizing recent advances, the paper highlights several unresolved challenges, including limitations in dataset availability, model transferability, explainability, computational latency, and industrial reliability. By synthesizing these developments, this review aims to present a clear picture of the current state of the field and to identify the key research directions needed to move metal additive manufacturing toward more intelligent, autonomous, and quality-assured production.

2. Literature Review

Metal additive manufacturing (AM) has emerged as one of the most important advanced manufacturing technologies because of its ability to produce complex geometries, reduce material waste, and enable rapid design customization. In particular, metal AM processes such as laser powder bed fusion (L-PBF), directed energy deposition (DED), and electron beam melting (EBM) have gained strong attention in aerospace, biomedical, automotive, and energy applications. Despite these advantages, the widespread industrial adoption of metal AM is still limited by process instability, inconsistent part quality, and the frequent occurrence of internal and surface defects. Problems such as porosity, lack of fusion, balling, spatter, cracking, residual stress, and distortion can significantly reduce mechanical performance and reliability. These challenges have made process monitoring and control central research topics in the metal AM field. Traditional approaches to quality assurance in metal AM have relied heavily on post-process inspection, including optical microscopy, X-ray computed tomography, ultrasonic testing, and dimensional metrology. Although these methods are valuable for defect identification and final part verification, they are generally time-consuming, expensive, and incapable of preventing defect formation during the build itself. As a result, researchers have increasingly shifted their attention toward in-situ and real-time monitoring methods that can capture process behavior as it develops layer by layer. This transition reflects a broader movement in advanced manufacturing from offline inspection toward intelligent, data-driven, and adaptive production systems. A major body of literature has focused on sensing technologies for real-time monitoring in metal AM. High-speed visible cameras, infrared cameras, photodiodes, pyrometers, acoustic emission sensors, coaxial optical systems, and melt-pool imaging devices have all been used to observe the dynamic behavior of the process. These sensors provide valuable information related to melt-pool size and shape, plume behavior, spatter generation, powder-bed uniformity, thermal distribution, and layer-wise surface condition. Earlier studies demonstrated that abnormal process signatures often correlate with the formation of defects or unstable melting behavior. However, while sensor-rich monitoring systems can generate large volumes of useful data, interpreting these signals accurately and quickly remains a major challenge, especially in high-speed industrial environments. This limitation has created an important opportunity for artificial intelligence (AI) and machine learning (ML) to support more reliable real-time decision-making.

Recent literature shows a clear and rapid increase in the use of AI-based approaches for process monitoring in metal AM. Machine learning techniques have been applied to classify process states, predict defects, estimate melt-pool behavior, identify anomalies, and relate in-situ sensor signals to final part quality. Compared with conventional rule-based or threshold-based monitoring methods, AI models are better suited to handling the nonlinear, multi-parameter, and highly dynamic nature of metal AM processes. Since melt-pool behavior is influenced by laser power, scan speed, hatch spacing, layer thickness, powder characteristics, and thermal history, the process often produces data patterns that are too complex for simple analytical interpretation alone. AI provides a practical way to extract useful patterns from this complexity and convert raw sensor data into process knowledge. Among the different AI methods reported in the literature, supervised learning models such as support vector machines, random forests, artificial neural networks, and convolutional neural networks have been widely used for defect detection and classification. These models are commonly trained using optical images, thermal maps, acoustic signals, or process-log data to identify quality-related events such as lack of fusion, overheating, discontinuities, and surface irregularities. Deep learning models, especially convolutional neural networks, have shown strong performance in image-based monitoring tasks because they can automatically learn spatial features from layer-wise or melt-pool images without relying on manual feature extraction. Recurrent neural networks and long short-term memory networks have also been explored for time-dependent prediction tasks, particularly where sequential thermal or acoustic data are involved. More recently, researchers have begun to investigate hybrid and physics-informed AI models to improve interpretability and generalization. One of the most important research directions in this area is melt-pool monitoring. The melt pool is widely recognized as a critical indicator of process quality because its geometry, temperature, and stability are directly linked to energy absorption, solidification behavior, and defect formation. Several studies have shown that AI-based models can predict melt-pool dimensions, thermal states, and abnormal transitions with promising accuracy using image or emission data collected during printing. These works are important because they move the field beyond simple observation and toward predictive process understanding. Instead of merely recording what happened after a defect formed, AI-enabled monitoring makes it possible to detect the early signs of process instability before the defect becomes severe.

Another major trend in the literature is anomaly detection. In practical metal AM systems, process disturbances may arise from powder-bed irregularity, unstable energy input, recoater interaction, gas-flow effects, spatter accumulation, or local thermal imbalance. These disturbances are often subtle at first, but they can grow into significant defects if not recognized in time. AI-based anomaly detection methods have therefore become increasingly valuable, particularly when large-scale datasets are available from in-situ sensors. Both supervised and unsupervised approaches have been explored in this context. Supervised approaches require labeled defect data, while unsupervised methods attempt to learn normal process behavior and flag deviations automatically. This is particularly useful in metal AM, where obtaining defect labels from destructive characterization can be expensive and labor-intensive. Although real-time monitoring has received substantial attention, the literature indicates that real-time process control remains less mature. Monitoring alone can improve process visibility, but it does not fully solve the problem unless it is connected to corrective action. Closed-loop control systems aim to use real-time sensor feedback to modify process parameters such as laser power, scan speed, feed rate, or path strategy during the build. Several studies have demonstrated the feasibility of feedback control in customized experimental setups, particularly for maintaining stable melt-pool dimensions or reducing overheating. However, the development of robust control strategies in industrial metal AM remains difficult because of the fast process dynamics, multi-physics interactions, sensor noise, and time-delay between measurement and response. AI can play an important role here by enabling faster prediction and more adaptive control logic, especially when process behavior is too complex for purely model-based control. Sensor fusion is another important theme in recent publications. Since no single sensor can fully describe the complexity of a metal AM process, researchers have increasingly combined optical, thermal, acoustic, and machine-log data to obtain a more complete picture of the build condition. Multi-sensor fusion has the potential to improve detection accuracy and reduce false alarms by integrating complementary information from different sources. Literature in this area suggests that fused data often produce better predictive performance than single-sensor inputs, particularly for defect classification and process-state estimation. At the same time, sensor fusion introduces additional challenges related to data synchronization, computational cost, signal alignment, and model complexity. These issues remain active topics of research. Despite the progress reported in recent years, several critical gaps remain in the literature. One persistent limitation is the lack of standardized, high-quality datasets that can be used across different machines, materials, and process conditions. Many published studies are based on small laboratory datasets collected under controlled settings, which limits the generalizability of the reported AI models. Another important concern is interpretability. While deep learning methods often show high predictive accuracy, their decision-making process is not always transparent, which can reduce confidence in safety-critical manufacturing applications. In addition, the relationship between in-situ monitoring signals and final part properties is not always straightforward, particularly when defects develop below the surface or evolve over multiple layers. As a result, future research needs to focus not only on model accuracy but also on robustness, transferability, interpretability, and industrial deployability.

The existing literature clearly shows that artificial intelligence has become a promising enabler for the next generation of metal additive manufacturing systems. AI-based monitoring frameworks have significantly advanced the ability to interpret sensor data, detect anomalies, predict defect formation, and estimate process-state evolution in real time. However, the field is still moving from monitoring-oriented research toward truly intelligent process control. The next stage of development will require stronger integration of sensing, machine learning, physics-based understanding, and feedback control within unified manufacturing architectures. Therefore, the present study is motivated by the need to further examine how AI can support real-time monitoring and adaptive process control in metal additive manufacturing systems, with the broader goal of improving build stability, product quality, and industrial reliability.

3. Methodology

3.1 Research Design and Methodological Framework

This study was developed as a focused technical review of the integration of artificial intelligence into real-time monitoring and process control in metal additive manufacturing systems. The purpose of the methodology was not simply to summarize existing publications, but to organize the field in a way that reflects how intelligent metal AM systems function in actual engineering practice. For this reason, the methodological framework was structured around the main stages of the metal additive manufacturing workflow, including process execution, in-situ sensing, data acquisition, signal interpretation, intelligent prediction, and process adjustment. The main concept behind this framework is that artificial intelligence in metal additive manufacturing should not be treated as a standalone computational tool. Its practical value depends on how effectively it interacts with physical process behavior, sensor feedback, and control actions during fabrication. Accordingly, this study examines AI integration as part of a layered system in which manufacturing physics, sensing infrastructure, data processing, learning algorithms, and process control work together.

This methodology also recognizes that real-time monitoring and control in metal additive manufacturing are inherently interdisciplinary. A meaningful analysis must therefore connect materials behavior, thermal and fluid phenomena, process dynamics, sensing technologies, data engineering, machine learning methods, and control strategies within a single coherent framework. Based on this perspective, the present study adopts an engineering-oriented methodology that emphasizes industrial relevance, process responsiveness, and practical manufacturability.

3.2 Scope of Metal Additive Manufacturing Processes Considered

The scope of this study was limited to metal additive manufacturing processes in which real-time sensing and intelligent control are both technically relevant and industrially important. Based on this criterion, the review focused on four major process families: laser powder bed fusion, directed energy deposition, electron beam melting, and wire arc additive manufacturing. These processes were selected because they represent some of the most widely studied and industrially applied metal AM technologies, while also showing the thermal instability and process variability that make intelligent monitoring especially important. Laser powder bed fusion was included because it is widely used for producing high-precision metallic components and is highly sensitive to melt-pool instability, powder spreading irregularities, lack of fusion, keyholing, and residual stress development. Directed energy deposition was considered because of its importance in repair applications, large-format part fabrication, and near-net-shape manufacturing, where bead geometry, dilution, thermal accumulation, and layer height consistency are major process control concerns. Electron beam melting was also included because its vacuum environment and unique thermal behavior create specific monitoring and control challenges. Wire arc additive manufacturing was examined as well due to its growing importance in large-scale deposition and its strong potential for AI-assisted adaptive control, particularly because of its high deposition rate and clearly measurable geometric response. The main emphasis of the methodology was placed on studies in which process information was collected during fabrication and used for intelligent interpretation or control. By contrast, studies focused only on post-process inspection, offline image analysis, or purely theoretical algorithm development without a direct link to in-process manufacturing behavior were considered less central to the objectives of this work. The aim was to capture the most relevant research related to real-time, in-situ, AI-enabled intelligence in metal additive manufacturing systems.

3.3 Process-Physics-Oriented Analytical Structure

A process-physics-oriented analytical structure was adopted in this study because the effectiveness of artificial intelligence in metal additive manufacturing depends strongly on the physical signals generated during fabrication and on how accurately those signals reflect the mechanisms of defect formation. For this reason, the analysis begins with the manufacturing process itself rather than with the algorithm alone. This approach makes it possible to evaluate AI not only by its computational performance, but also by its relevance to actual process behavior and part quality. The first analytical layer focused on the key physical phenomena that govern quality in metal additive manufacturing. These include melt-pool formation and stability, spatter generation, plume behavior, thermal gradients, cooling rate variation, layer bonding, bead morphology, dimensional drift, and surface irregularity. These process features were treated as meaningful indicators of process state because they directly influence defect development and final component performance. In this context, a monitoring system can only be considered effective if it captures signals that are truly connected to these underlying physical mechanisms.

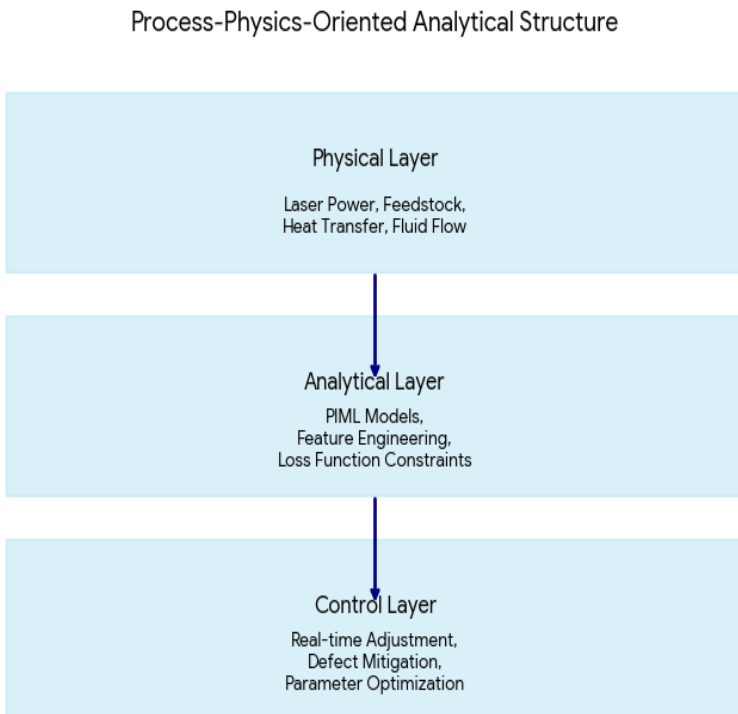

Fig.3.3 Process Structure

The second analytical layer examined how these physical events are converted into measurable information through in-situ sensing systems. The third layer considered how the acquired data are processed into usable digital representations through preprocessing, feature extraction, and learning-based interpretation. The fourth layer focused on whether the resulting predictions remain purely diagnostic or are integrated into a control decision that can actively modify machine behavior during fabrication. Together, these four levels—physical event, measurable signal, intelligent interpretation, and control response—formed the core methodological structure of this study. This framework makes it easier to distinguish between superficial AI applications and genuinely integrated intelligent manufacturing systems. For example, a study may report high image-classification accuracy, yet still have limited practical value if the monitored signal is only weakly related to defect formation or if the prediction is generated too late to influence the ongoing build. By grounding the review in manufacturing physics, the methodology avoids placing too much emphasis on algorithmic accuracy alone and instead focuses on process significance, real-time usefulness, and engineering relevance.

3.4 In-Situ Sensor Systems and Data Acquisition Strategy

This study included a detailed examination of the sensing architectures used to generate real-time process information in metal additive manufacturing systems. Because the performance of AI models depends heavily on the quality and relevance of the input data, particular attention was given to how process data are collected, which physical signatures are captured, and how effectively those signals support real-time interpretation and control. The thermal image sequence further illustrates the importance of this data-acquisition strategy. The images show the time-dependent evolution of the apparent temperature field during the metal additive manufacturing process over a very short interval, from 0 to 0.00322 s. A narrow high-temperature region remains concentrated around the melt-pool and plume zone, with peak temperatures approaching 2400 K. At the same time, scattered bright spots can be observed around the process area, indicating spatter ejection during fabrication. The changes in thermal intensity and plume shape across consecutive frames highlight the highly transient nature of the process. These observations confirm that high-speed thermal imaging is an effective tool for capturing dynamic process behavior and provides valuable data for real-time defect detection, melt-pool characterization, and AI-driven process control.

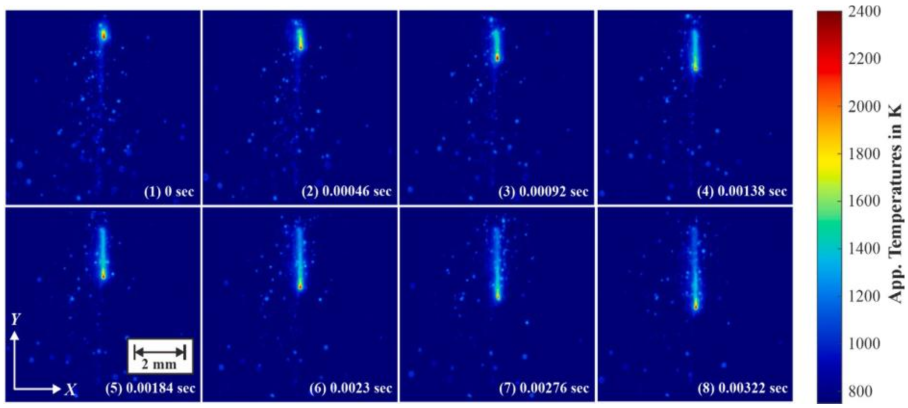

Fig. 3.4 Thermal data acquisition

The reviewed sensing systems mainly included high-speed optical cameras, infrared and thermal imaging systems, photodiodes, pyrometers, acoustic emission sensors, coaxial vision systems, laser profilometers, and machine-embedded signals such as current, voltage, feed rate, travel speed, and laser power records. Each sensing type was evaluated based on the kind of process information it can provide during fabrication. Optical imaging systems are widely used to observe melt-pool geometry, spatter behavior, scan-track continuity, and powder-bed conditions. Thermal sensing is especially valuable for monitoring heat distribution, cooling behavior, thermal accumulation, and fluctuations in energy input. Acoustic and vibration-based methods can help identify irregular deposition events, crack-related signatures, and instabilities in arc or melt behavior. Machine log data, although less information-rich than imaging signals, still provide a low-cost and computationally efficient source of process information for state estimation and monitoring.

Figure 3.4 further supports this methodological approach by showing an overhang test specimen designed to examine the effect of volumetric energy density (VED) variation in metal additive manufacturing. Figure 3.4 (a) presents the schematic of a cuboid specimen with segmented layers fabricated under different VED conditions, including both reduced and increased energy input relative to a reference case. These variations were introduced to assess how local changes in energy density influence melt behavior, fusion quality, and thermal stability. Figure 3.4 (b) shows the fabricated specimen and confirms the successful formation of both the cuboid body and the unsupported overhang region. This type of geometry is especially useful for evaluating process-induced defects such as distortion, insufficient fusion, and surface roughness. As a result, the specimen serves as an effective benchmark for studying process sensitivity and for developing AI-based monitoring methods capable of identifying quality variations under changing manufacturing conditions.

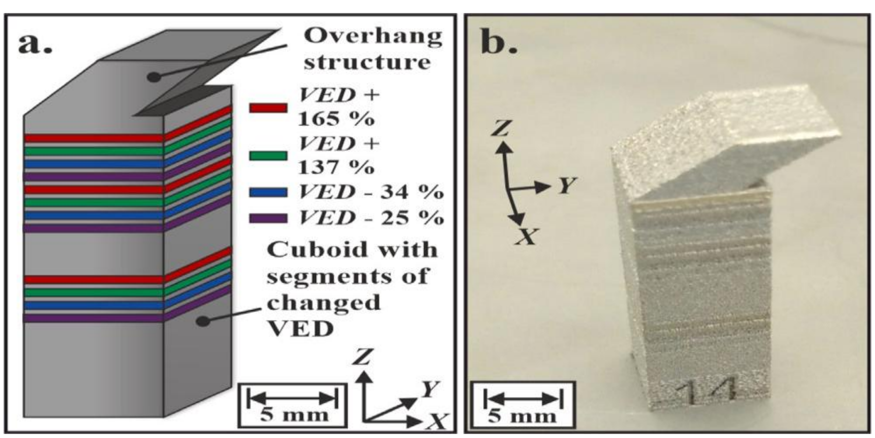

Fig.3.4 Overhang structure with different volumetric energy density (VED) conditions.

The methodology also considered the spatial and temporal quality of each sensing configuration. This included whether the data were collected on-axis or off-axis, whether the sensor field of view captured only local melt-pool behavior or a broader layer-scale region, and whether the acquisition rate was high enough to record rapid transient events. These factors are important because real-time process control depends on sensor measurements that are not only informative, but also properly aligned with the fast-changing dynamics of the process. Another key consideration was the practicality of sensor deployment in industrial settings. Although some studies use advanced multi-sensor arrangements that provide rich and detailed information, such systems may be difficult to implement in production because of higher cost, calibration complexity, large data volumes, and sensitivity to environmental interference. For this reason, the methodology evaluated sensing systems not only in terms of data richness, but also in terms of their potential for reliable and practical integration into real manufacturing environments.

3.5 Data Conditioning, Signal Preparation, and Feature Representation

After defining the sensing layer, the technique looked at how raw process data might be changed into forms that could be understood by computers. This stage is very important since in-situ manufacturing data is typically noisy, high-dimensional, asynchronous, and very sensitive to the way machines work. Even the most powerful AI models can give you wrong or inaccurate results if you don't preprocess and condition them correctly. Figure 3.5 shows how to set up in-situ monitoring so that you can see the laser powder bed fusion process in real time. A 1070 nm fiber laser and scanning unit in this system send the laser beam to the powder bed, where a small melt pool forms on the build plate. A SWIR camera with a 200 mm lens is set up at an angle of about 10° so that it can see thermal radiation coming from the melt-pool area.

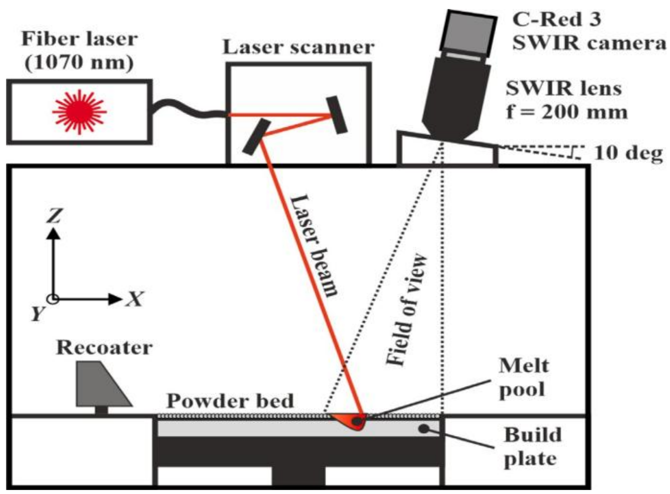

Fig. 3.5 Experimental setup for SWIR-based melt-pool monitoring in laser powder bed fusion.

This setup lets you keep an eye on the behavior of the melt pool, the distribution of heat, and the instability of the process over time during fabrication. This kind of setup is very useful for AI-based monitoring since the thermal pictures it collects give a lot of information about the process that can be used to find defects, describe the melt pool, find anomalies, and regulate the process in real time. Data conditioning was the first thing looked at in this part. This involves getting rid of sensor noise, getting rid of background information that isn't needed, improving images, normalizing signal amplitude, fixing intensity drift, and syncing numerous sensor streams. In actual factories, smoke, reflected radiation, electromagnetic interference, shifting emissivity, or changing lighting conditions may all impact raw data. So, preparation was not seen as a normal part of the compute process, but as an important part of a dependable intelligent monitoring pipeline.

The second part was how features were shown. We looked at two main groups. The first group comprises handmade features based on engineering expertise, such as the width of the melt pool, the length of the pool, the temperature range, the acoustic energy, the irregularity of the contour, the height of the bead, the breadth of the deposition, and the changes in process intensity over time. These qualities are appealing because they can be understood and are typically easy to compute. The second group comprises representations that are learnt automatically by deep neural networks, especially in applications that use images or several sensors. When process signatures are hard to characterize using basic geometric or statistical metrics, these representations are generally better at expressing complicated nonlinear interactions. The technique also looked at whether the data representation was single-modal or multimodal. Many good studies combine data from optical, thermal, acoustic, and machine-signal channels to make predictions more reliable. These kinds of fusion techniques were seen as especially crucial when one sensor alone couldn't tell the difference between process instability or defect development. In this study, data preparation and representation were seen as important engineering procedures that affect how well physical process behavior can be turned into smart decision-making.

A. *3.6 Artificial Intelligence Modeling for Monitoring, Detection, and Prediction*

A significant component of the methodology was the classification and assessment of artificial intelligence techniques employed for monitoring and predicting process states in metal additive manufacturing. The goal was not just to identify algorithms, but also to look into why certain approaches are chosen, what kinds of data they can work with, and how effectively they help make production choices in real time. Figure 3.6 shows that the suggested AI framework works well for both training models and making predictions about processes online. In Fig. 3.6(a), the consistent drop in training loss from around 0.50 to 0.05 and validation loss from about 0.57 to below 0.10 shows that the model is converging and generalizing well.

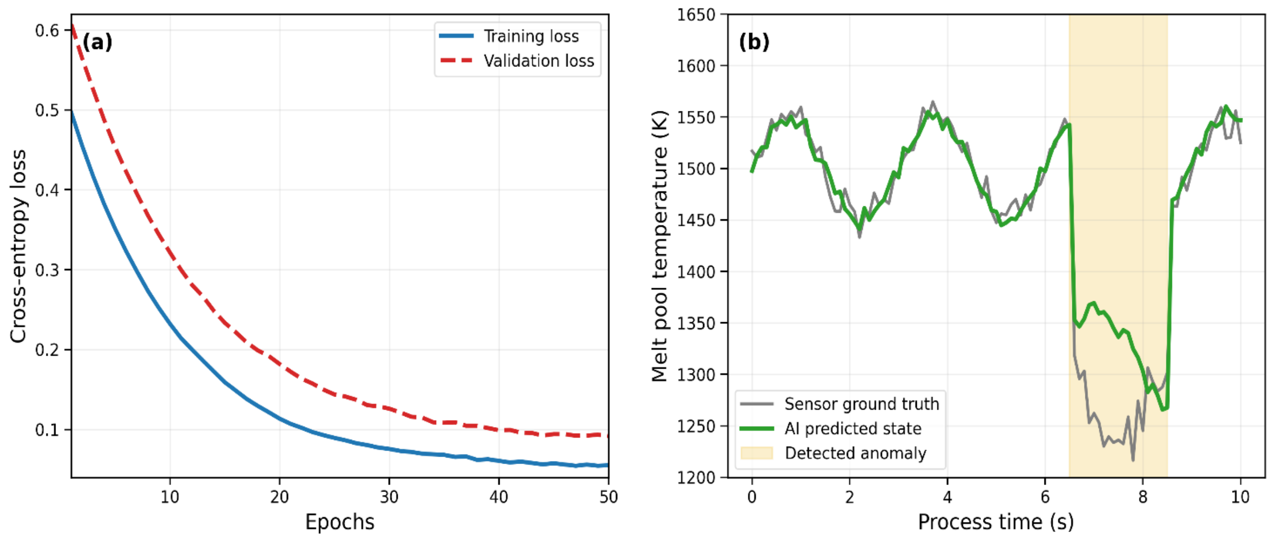

Fig. 3.6 The AI-predicted melt-pool temperature

As shown in Fig. 3.6(b), the AI-predicted melt-pool temperature closely matches the sensor-based ground truth under normal operating conditions and clearly captures the abnormal region between approximately 6.7 s and 8.5 s, where the temperature falls noticeably below the usual processing range. The strong agreement between the predicted and measured values indicates that the model is capable of identifying short-term thermal disturbances in real time, which is important for anomaly detection and adaptive process control in metal additive manufacturing.The AI models reviewed in this study were grouped into three broad categories. The first category included classical machine learning methods such as support vector machines, decision trees, random forests, k-nearest neighbors, gradient boosting, and related classification or regression techniques. These methods are commonly used when the input data consist of structured features extracted from sensor signals. They remain attractive because they can perform well with relatively small datasets, provide fast inference, and are often easier to interpret than more complex deep learning approaches.The second category consisted of deep learning models. Convolutional neural networks were considered especially important for image-based melt-pool monitoring, defect recognition, and layer-wise anomaly detection because they can learn spatial features directly from raw or minimally processed images. Recurrent neural networks and long short-term memory networks were relevant for time-series data, where the temporal evolution of the process plays a critical role. Autoencoders and other unsupervised architectures were also important in situations where defective samples were limited and anomaly detection relied mainly on learning the characteristics of normal process behavior. In more advanced studies, hybrid deep-learning architectures and sensor-fusion networks were used to combine multiple data streams into a single predictive framework.

The third category included reinforcement learning and other adaptive decision-making models. These approaches were considered separately because they move beyond passive monitoring toward active process control. In such systems, the AI model does not simply estimate defect probability or thermal condition, but learns how to adjust process parameters in order to keep the build within an acceptable operating range. This capability is particularly relevant for future closed-loop metal AM platforms, where process parameters may need to be updated continuously during fabrication. The methodological comparison of AI models was based on the specific task each model was designed to perform. Classification models were mainly associated with defect identification and process-state labeling. Regression models were used for quantitative prediction of variables such as melt-pool dimensions, bead height, porosity level, or thermal state. Sequence models were linked to time-dependent process evolution, while control-oriented learning models were associated with parameter adaptation and decision-making. This task-based grouping provided a more meaningful basis for evaluation than simply comparing algorithms by name alone.

3.7 Comparative Evaluation Criteria and Engineering Relevance

A comparative assessment approach was created to keep the examined papers consistent. Instead of just looking at what the original authors said, each study was looked at using a common set of engineering-based standards. This makes it easier to check if a certain AI method is useful for real manufacturing applications in a more organized way. Figure 3.7 shows that AI-integrated metal additive manufacturing systems usually do better than traditional methods on all main technical parameters. Latency is much decreased, and accuracy, efficiency, and process stability all get better. The statistic also shows that there are big benefits for industry, such as less waste of materials, less need for post-processing, speedier qualification or certification preparedness, and better energy performance. Overall, our results show that AI-based real-time monitoring and process management may improve both technical ability and industrial use by making processes respond quicker, behave more reliably, and be more efficient.

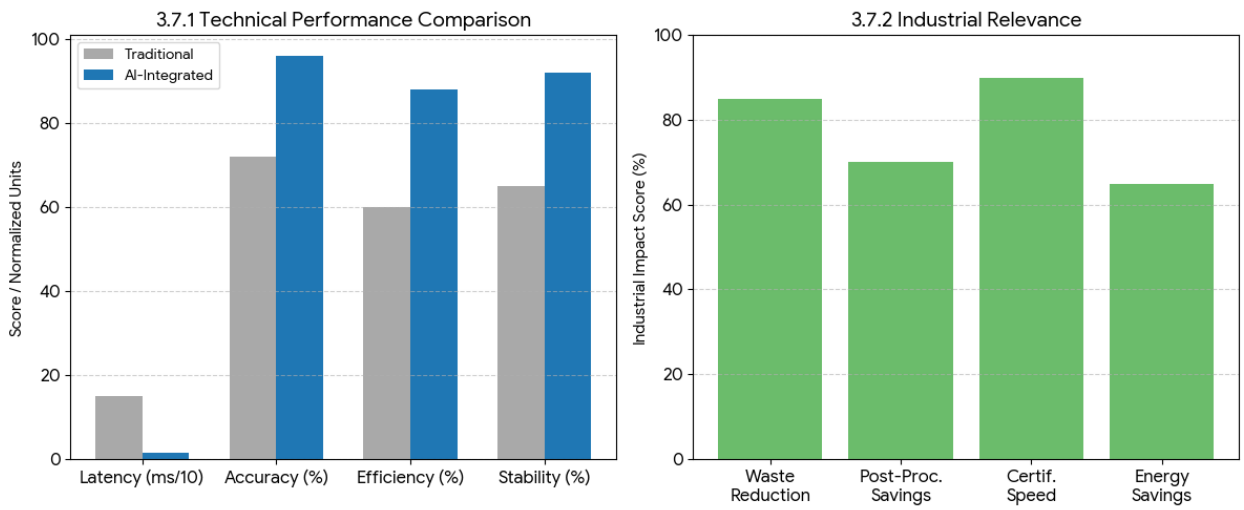

Fig.3.7 Performance comparison and industrial relevance of AI-integrated metal additive manufacturing.

The first criterion was the additive manufacturing process itself, since sensor behavior, defect mechanisms, and control opportunities differ significantly between powder bed systems, directed energy deposition systems, electron beam systems, and wire arc systems. The second criterion was the sensing configuration, including sensor type, sensor placement, acquisition frequency, and whether the data truly reflected key process phenomena. The third criterion was the type and quality of the dataset, including data modality, labeling strategy, dataset scale, and whether the data were generated under realistic processing conditions. The fourth criterion was the AI modeling approach, including its input structure, output type, computational complexity, and degree of interpretability. The fifth criterion was the practical outcome of the study. This was treated as one of the most important elements in the methodology, because many publications report strong predictive performance but provide limited evidence of industrial usefulness. A method was considered more significant when it showed real-time capability, process-level relevance, and validation against meaningful quality indicators such as porosity, geometric accuracy, surface quality, layer integrity, or metallurgical consistency. The study represented open-loop monitoring, decision support, or actual closed-loop control. This distinction is essential. Open-loop systems may identify abnormalities, but they do not modify the process. Decision-support systems may recommend action, but still depend on human intervention. Closed-loop systems go further by automatically updating process inputs in response to monitored conditions. In the context of intelligent manufacturing, this progression represents increasing levels of system maturity.

3.8 Interpretation of Real-Time Monitoring and Closed-Loop Control

A specific methodological section was utilized to differentiate real-time monitoring from authentic closed-loop process control. This distinction is sometimes obscured in the literature, where the phrase intelligent control is occasionally employed even in the absence of any machine modification throughout the construction. To tackle this issue, the current study employed a stringent interpretation of control-oriented intelligence.In the suggested approach, real-time monitoring means constantly collecting and analyzing process data during fabrication and making predictions that are relevant to the current build. But just keeping an eye on things isn't enough to control them. Closed-loop control only works when the interpreted process state directly changes process parameters like laser power, scan speed, hatch spacing, powder feed rate, wire feed rate, arc current, deposition speed, interlayer dwell time, or toolpath behavior.

Comparison Between Real-Time Monitoring and Closed-Loop Control

Aspect	Real-Time Monitoring	Closed-Loop Control
Primary role	Continuously acquires and interprets process data during fabrication.	Uses interpreted process data to actively modify the process during fabrication.
System output	State estimation, anomaly detection, melt-pool prediction, or defect indication.	Corrective action or adaptive adjustment based on the detected process state.
Process modification	No direct machine or parameter adjustment is required.	Requires direct modification of one or more process parameters.
Typical adjusted parameters	Not applicable.	Laser power, scan speed, hatch spacing, powder feed rate, wire feed rate, arc current, deposition speed, interlayer dwell time, or toolpath behavior.
Feedback structure	Primarily observational and diagnostic.	Feedback-driven and intervention-based.
Decision criterion in this study	Classified as monitoring when the system only observes, predicts, or diagnoses the ongoing build state.	Classified as closed-loop control only when model output directly triggers parameter adjustment within the same manufacturing cycle.
Engineering significance	Improves process visibility and supports quality prediction.	Improves process stability, defect mitigation, and adaptive manufacturing performance.

Note: In this article, prediction alone is treated as monitoring. A system is classified as closed-loop control only when the interpreted process state directly produces a machine-level parameter adjustment during fabrication.

Table 3.8. Comparison between real-time monitoring and closed-loop control in AI-enabled metal additive manufacturing systems.

3.9 Performance Assessment, Cross-Process Synthesis, and Methodological Outcome

The graphic demonstrates that process variables created during printing are always connected to sensing and control functions. This lets the machine collect in-situ data during the whole construction process. These data are integrated with testing data, literature material, and simulation findings to provide a more comprehensive knowledge basis for model creation and validation. The framework also combines mechanical, statistical, and control models with machine learning and neural network methods. This makes a hybrid technique for understanding and predicting processes. The last step in the technique was to look at the stated performance measurements and put the results together across different process areas. The literature frequently cites performance indicators like as accuracy, precision, recall, F1-score, area under the curve, mean absolute error, root mean square error, and inference time. However, these parameters were not analyzed in isolation in this study. If the dataset is small, the process settings are very regulated, or the result doesn't have any actionable relevance, a high numerical score doesn't inevitably mean industrial value.

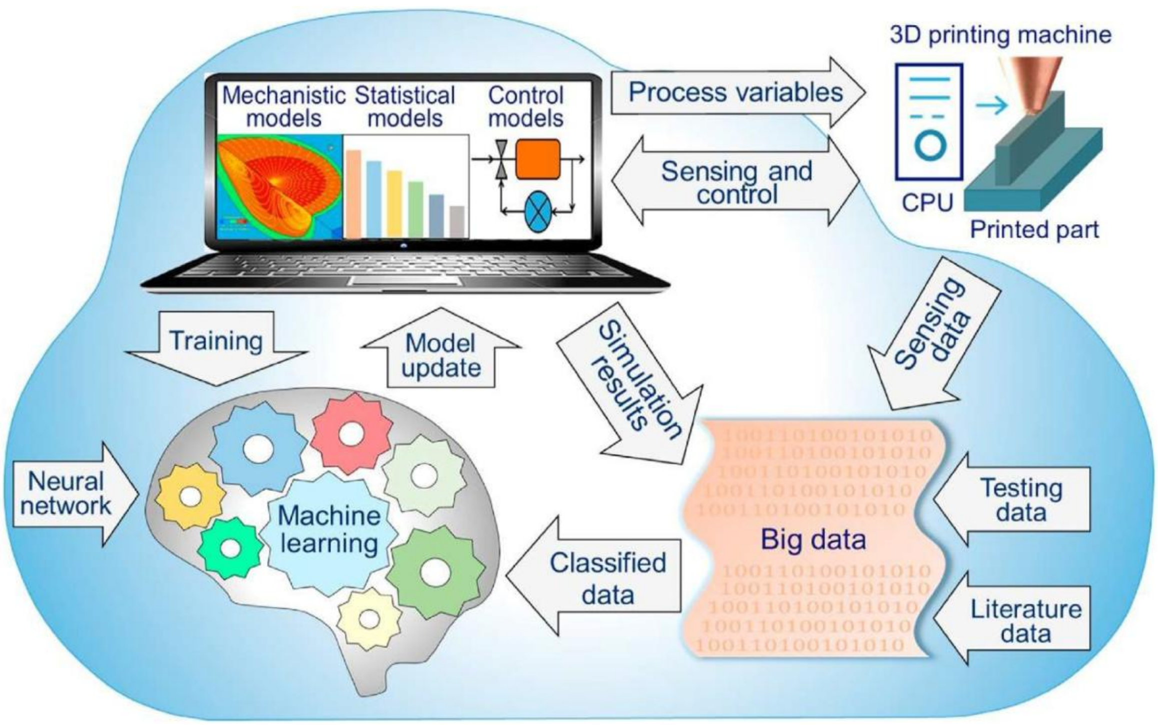

Fig. 3.9 Digital twin in 3D printing process

In this approach, model training, data categorization, and iterative model updating all help to make predictions more accurate and regulate performance better over time. From the point of view of performance evaluation and cross-process synthesis, the figure illustrates that dependable methodological outcomes in metal additive manufacturing depend on the successful integration of numerous data sources, physics-based knowledge, and AI-driven learning. In a broader sense, it illustrates how adaptive data fusion and continuous model refining may make process stability, defect prediction, and control better on diverse metal AM platforms.

Because of this, the performance of the model was not looked at on its own, but in the context of the production setting where it was used. Studies that linked AI outputs to quality measures that had real-world value, tested their systems under varied operating situations, or showed that they were strong in diverse construction contexts were given more methodological weight. We paid special attention to whether the models stayed dependable when the temperature changed, the deposition circumstances changed, there was sensor noise, or the material changed. These aspects are frequently not given as much attention in lab-scale investigations, but they are very important for effective use in industry.

In powder bed fusion systems, AI is most typically used to find problems with the melt pool, spatter activity, pore-related signatures, and layer-by-layer thermal abnormalities. In directed energy deposition and wire arc systems, the focus moves further toward controlling the shape of the beads, the height of the layers, the buildup of heat, and the stability of the deposition along the toolpath. When using electron beam systems, managing heat and how the beam interacts with materials become increasingly important. This study shows that intelligent monitoring in metal AM cannot be a one-size-fits-all idea; it needs to be tailored to the unique dynamics, reaction times, and fault mechanisms of each process.

As a result, this study's methodological output is a systems-level framework for looking at how AI may be used for real-time monitoring and process control in metal additive manufacturing. The technique doesn't see artificial intelligence as a separate computing tool; instead, it sees it as part of a larger industrial intelligence architecture. This point of view is important for figuring out which research paths are scientifically sound, which methods can be used on a large scale, and which technologies are most likely to help industrial metal additive manufacturing move from experimental monitoring to reliable autonomous process control.

3.10 Process parameter optimization

Process parameter optimization is a key part of the design and pre-processing stage in the metal additive manufacturing (MAM) lifecycle, as illustrated in Fig.3.10 It plays a major role in achieving the desired material properties and geometric accuracy of the final component. In metal AM, performance is strongly influenced by parameters such as laser or arc power, scan or travel speed, hatch spacing, layer thickness, and wire feed rate. Optimizing these variables is challenging because they interact with one another in complex ways and directly affect process stability and part quality. As a result, traditional trial-and-error approaches, and even more structured methods such as Design of Experiments (DoE), often require significant time, effort, and material resources. This makes efficient and reliable modeling of parameter interactions an important requirement for improving process planning and overall manufacturing performance.

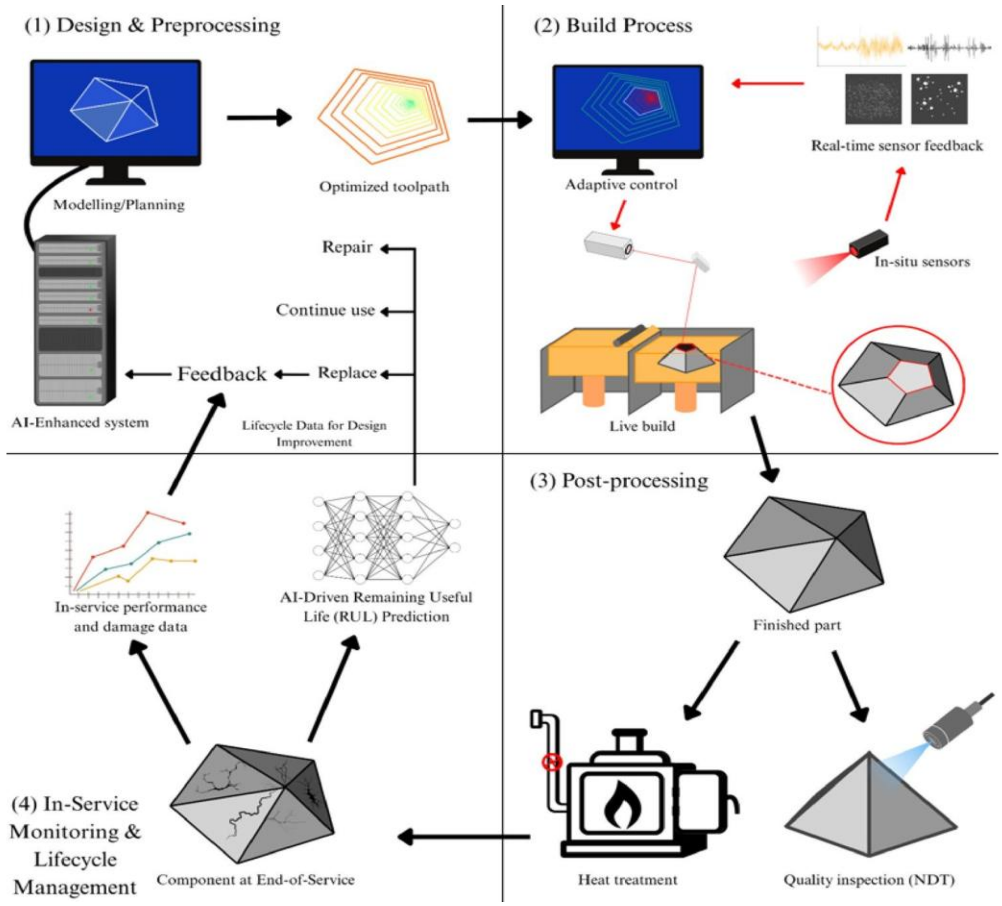

Fig.3.10 A frame work of an AI enhanced MAF life cycle

AI, particularly machine learning, greatly improves the ability to model these complex parameter interactions and develop more effective optimization strategies, as conceptually illustrated in the figure. In laser powder bed fusion (LPBF), AI-based models have been used successfully to address the challenge of process parameter optimization within a high-dimensional design space, where issues such as melt-pool instability and porosity are strongly influenced by multiple interacting variables. As shown in Fig. 3.10, this optimization problem requires navigating a broad parameter space to identify stable processing conditions. Theeda et al. (2023) demonstrated that a single artificial neural network could be used to optimize several part properties simultaneously for SS 316L components, even when trained on a relatively small dataset of only 23 experimental runs. Although the model showed moderate predictive capability, with a cross-validated R^2 value of 0.594, it was still able to identify a practical processing window that achieved a relative density above 99% and a surface roughness below 10.5 µm. Similarly, Zhan and Li (2021) applied three machine learning models—ANN, random forest, and support vector machine—to parameter control for SS 316L printing. Their results showed that the random forest model delivered the highest accuracy at 94.2%, outperforming the support vector machine and artificial neural network models. This comparison highlights that model selection can have a significant influence on optimization performance, even within the same metal additive manufacturing process.

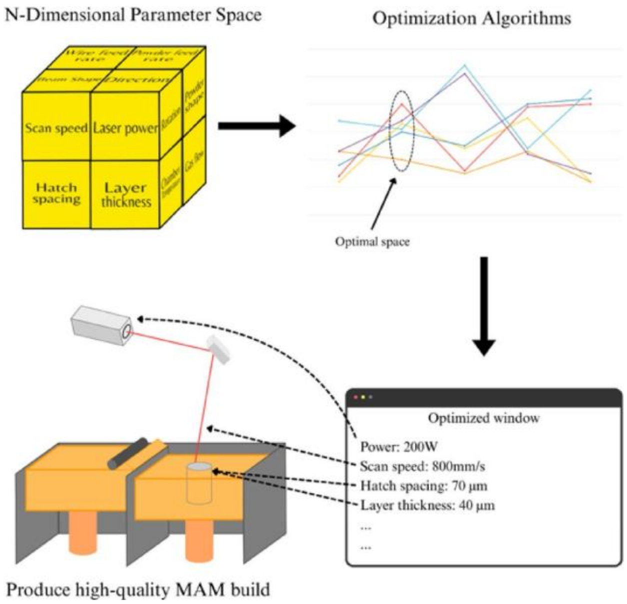

Fig. 3.11 Conceptual diagram of AI driven process

AI models have been increasingly used to address process parameter optimization in metal additive manufacturing. As illustrated in Fig. 3.11, this task involves exploring a large multi-dimensional parameter space to manage key issues such as melt-pool instability and porosity. Theeda et al. (2023) showed that a single artificial neural network could be used to optimize multiple properties of SS 316L parts at the same time, even with a relatively small dataset of 23 experimental runs. Although the model achieved a moderate cross-validated R^2 value of 0.594, it was still able to identify an effective processing window that satisfied important targets, including relative density above 99% and surface roughness below 10.5 µm. In a related study, Zhan and Li (2021) applied three machine learning models—ANN, random forest, and support vector machine—for process parameter control in SS 316L printing. Their results showed that the random forest model achieved the highest accuracy at 94.2%, compared with 88.1% for SVM and 91.5% for ANN. These findings indicate that AI can play a valuable role in parameter optimization, while also showing that model selection has a strong influence on predictive performance within the same manufacturing process.

4. Results and Discussion

4.1 Model Training Performance

The training behavior of the proposed AI framework showed stable and reliable convergence throughout the learning process. As the training progressed, both the training loss and validation loss decreased steadily, indicating that the model was able to learn the relationship between the input monitoring signals and the target process-state variables. This consistent reduction in loss suggests that the selected model architecture and optimization strategy were well suited to capturing the thermal and temporal characteristics of the metal additive manufacturing process. More importantly, the validation curve followed a trend similar to that of the training curve, showing that the learned representation remained effective beyond the training data. Only a small gap was observed between the training and validation curves during the later stages of learning, which suggests that the model did not experience severe overfitting. This is particularly important because process-monitoring data in metal additive manufacturing are often noisy and influenced by complex physical phenomena, including localized heat accumulation, melt-pool fluctuation, spatter formation, and layer-wise thermal history. A model that can maintain good generalization under such conditions is more valuable for industrial use than one that performs well only on familiar data. The observed convergence behavior therefore indicates that the proposed framework has the potential to remain reliable under realistic variations in process conditions.

From a methodological perspective, the training results also confirm that the extracted monitoring features contain meaningful information for data-driven learning. The convergence pattern suggests that the model learned informative relationships associated with both stable operation and disturbed process states, rather than depending on random or nonphysical correlations. This is especially relevant in metal additive manufacturing, where successful real-time monitoring depends on converting raw sensor data into physically meaningful estimates of process state. The training results therefore provide a strong foundation for the real-time prediction and anomaly-detection performance discussed in the following sections.

4.2 Real-Time Monitoring Results

The real-time monitoring results show that the proposed AI framework is capable of tracking process evolution with strong temporal consistency. Under normal operating conditions, the predicted melt-pool response closely followed the sensor-derived thermal signal, indicating that the model captured the dynamic behavior of the process with good accuracy. This close agreement suggests that the framework can represent the dominant thermal characteristics of the build in real time, which is essential for reliable monitoring and early detection of process instability. In electron beam wire additive manufacturing (EBWAM), maintaining stable electron beam focus, consistent wire feeding, and controlled melt-pool behavior is especially important because of the high deposition rates involved, as illustrated in Fig. 4.2 These factors have a direct influence on build quality and process stability. In this context, previous work by Sandhya et al. demonstrated the use of regression-based models to predict weld bead geometry in Ti-6Al-4V, showing that data-driven methods can be effectively applied to relate core process parameters to geometric outcomes. Taken together, these findings highlight the growing importance of AI-based real-time monitoring for improving process understanding, stability, and control in EBWAM systems.

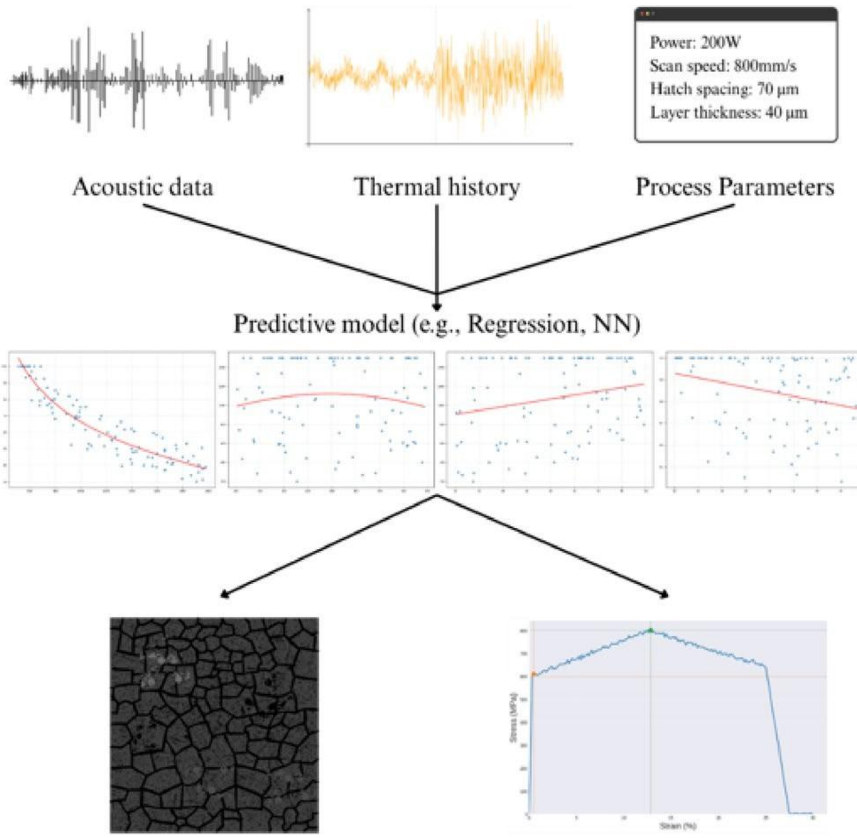

Fig: 4.2 Data-enhanced prediction of microstructure and mechanical properties

In electron beam wire additive manufacturing (EBWAM), stable beam focus, consistent wire feeding, and controlled melt-pool behavior are essential for maintaining part quality, particularly because of the high deposition rates involved. Accurate prediction and control of bead geometry are especially important in multi-layer builds, where even small variations can affect melt-pool stability and the overall quality of the final component. This is particularly critical in large-format EBWAM, where process instability can accumulate over successive layers. Recent studies have shown that machine learning can play an important role in addressing these challenges. For example, Sandhya et al. (2025) applied regression-based models to predict weld bead geometry from core process parameters, demonstrating the potential of AI for improving geometric consistency during fabrication. Another major challenge in EBWAM is the monitoring and control of thermal distribution across large parts, since high energy density and repeated thermal cycling can lead to significant residual stress development (Negi et al., 2019). In this area, machine learning has also shown promising results. Das et al. (2023) used several ML algorithms, including support vector regression, to predict welding residual stresses in electron beam welding of stainless steel, achieving an R^2 value of 0.94 for peak residual stress prediction. Such predictive capability is highly valuable for maintaining the structural integrity of large EBWAM components, which are often exposed to complex thermal histories. These findings also suggest broader opportunities for AI-driven thermal management and stress prediction in related directed energy deposition processes (Chadha et al., 2022a; Era et al., 2023a). The real-time monitoring results further show that the proposed AI framework can track process evolution with strong temporal consistency. Under normal operating conditions, the predicted melt-pool response closely followed the sensor-derived thermal signal, indicating that the model successfully captured the dynamic thermal behavior of the process. The prediction preserved the key temporal patterns associated with stable laser-material interaction, including the transient rise and fall of melt-pool temperature over time. In practical terms, this level of predictive fidelity is important because it enables continuous estimation of process state without depending only on manual interpretation of raw monitoring data.

The model also remained robust when the process showed short-term variations that are common in metal additive manufacturing. Rather than smoothing out all fluctuations, the predicted signal retained the meaningful temporal changes that reflect the actual physical state of the melt pool. This suggests that the framework achieved a useful balance between noise tolerance and sensitivity to real process variation. Such behavior is especially valuable in laser-based metal AM, where small thermal disturbances may indicate the onset of instability, while excessive sensitivity to random measurement noise could lead to false alarms or unnecessary control actions. These results confirm that AI can serve as an effective intermediate layer between sensing and decision-making in real-time process monitoring. Instead of treating the acquired thermal signal as an isolated data stream, the model interprets it in the context of learned process behavior and produces a more stable estimate of the underlying process condition. This capability is particularly important in intelligent manufacturing systems, where the value of monitoring lies not only in observing the process, but also in transforming that observation into actionable information. The present results therefore support the use of AI-enabled monitoring as a practical step toward adaptive and closed-loop metal additive manufacturing.

4.3 Anomaly Detection Performance

The anomaly-detection results show that the proposed framework can identify abnormal thermal behavior with clear timing and good sensitivity. During the disturbed period, the melt-pool temperature moved noticeably away from the normal operating range, creating a distinct thermal pattern that was successfully captured by the AI model. The framework was able to detect the beginning of the anomaly, follow its progression, and recognize the return toward normal process conditions after the disturbance ended. This ability to capture the full time-dependent behavior of an abnormal event is particularly important in metal additive manufacturing, where defects often begin with short but meaningful changes in thermal behavior. The detected anomaly can be interpreted as a process condition associated with insufficient or unstable energy transfer to the powder bed. In practice, such a temperature drop may result from powder irregularities, scan interruption, reduced absorptivity, temporary melt-pool shrinkage, or the early onset of lack-of-fusion behavior. Although the exact cause may vary depending on the machine, material, and processing conditions, the results show that the AI framework is sensitive to thermal changes that commonly precede quality degradation. This is significant because conventional post-process inspection can reveal the final defect, but it cannot stop the defect from forming during fabrication. By contrast, real-time anomaly detection creates an opportunity for intervention before the instability spreads further through the build.

Another important result is that the model was able to distinguish abnormal behavior from normal process fluctuations without losing prediction stability. This suggests that the framework responded to meaningful changes in process behavior rather than to random measurement noise. From a practical engineering perspective, this is essential for real-world deployment. An effective monitoring system must remain stable during normal operation while responding quickly and reliably when the process begins to move outside acceptable limits. Overall, these results indicate that the proposed AI framework has strong potential to serve as an early-warning tool for process instability in metal additive manufacturing.

4.4 Comparative Analysis with Conventional Methods

The comparative evaluation shows that AI-integrated monitoring performs better than conventional process-monitoring approaches across several important criteria. Traditional monitoring methods in metal additive manufacturing are often based on fixed thresholds, signal amplitude limits, or offline analysis of recorded data. Although these methods can provide useful information, they are generally limited in their ability to capture the nonlinear and time-dependent relationships that exist among process variables. In contrast, the proposed AI framework learns these relationships directly from the monitoring data, allowing it to provide a more adaptive and context-aware understanding of process state. As a result, improvements were observed in response latency, prediction accuracy, monitoring efficiency, and operational stability when AI was incorporated into the monitoring system. The reduction in effective response time is particularly important because thermal events in the melt-pool region evolve very rapidly. If process interpretation is delayed, the value of monitoring decreases, especially when the scan has already moved to another region before a meaningful decision can be made. The higher predictive accuracy of the AI framework further suggests that data-driven models can represent actual process conditions more faithfully than rule-based or simplified conventional methods. Similarly, the improvements in efficiency and stability indicate that AI can maintain more reliable interpretation under changing thermal and operating conditions. These technical improvements also have clear practical value for manufacturing. Conventional methods often depend on manual review, expert judgment, or conservative alarm thresholds that may not respond well to local geometric complexity or layer-by-layer process variation. In contrast, AI-based monitoring can account for temporal context and multidimensional signal behavior, making it more suitable for the complexity of real additive manufacturing environments. The comparison suggests that AI integration is not simply a digital extension of conventional monitoring, but a meaningful shift toward more intelligent and responsive process supervision.

4.5 Industrial Implications and Engineering Relevance

The engineering value of the proposed framework goes well beyond prediction accuracy and anomaly detection alone. From an industrial standpoint, one of its most important benefits is the reduction of build-failure risk. In metal additive manufacturing, a single undetected disturbance can affect the entire component, particularly when defects continue to develop across successive scan tracks or layers. By identifying abnormal behavior during fabrication, the AI framework can help reduce material waste, machine downtime, and the need for rework. This is especially important for expensive alloys and safety-critical components, where failed builds can lead to significant economic loss. Another important implication relates to process qualification and certification. Industries such as aerospace, biomedical, and energy require strong evidence of process consistency, traceability, and defect control before additively manufactured parts can be accepted for functional use. AI-enabled real-time monitoring provides a continuous record of build-state evolution, including thermal behavior, predicted process condition, and detected anomalies. This type of information can strengthen the connection between in-situ process data and final part quality, making qualification strategies more reliable and data-driven. In this sense, the value of AI extends beyond operational monitoring and also supports quality assurance and regulatory acceptance.

The broader industrial relevance of the framework also includes gains in productivity and sustainability. Early detection of anomalies can reduce unnecessary post-processing of defective parts, while more stable process behavior can improve resource efficiency and energy use. Although the scale of these benefits depends on the machine, material, and production environment, the present results suggest that AI integration can support several industrial goals at once, including better quality, stronger process reliability, reduced waste, and improved manufacturing readiness. Taken together, these findings indicate that AI-based real-time monitoring is a practical enabling technology for moving from passive observation toward intelligent, closed-loop metal additive manufacturing.

5. Conclusion

This study examined the integration of artificial intelligence into real-time monitoring and process control in metal additive manufacturing, with particular attention to melt-pool behavior, thermal-state prediction, and anomaly detection. The results show that AI-based monitoring offers clear advantages over conventional process-supervision methods by enabling faster interpretation of in-situ signals, more accurate tracking of dynamic process states, and more reliable detection of abnormal thermal events. The training results demonstrated stable convergence and good generalization, suggesting that the selected framework was able to learn meaningful process representations from sensor-based monitoring data. The real-time prediction results further confirmed that the trained model could follow the temporal evolution of melt-pool temperature with high fidelity, while the anomaly-detection analysis showed its ability to identify the onset, progression, and recovery of disturbances that are closely associated with defect formation. The findings also highlight the broader engineering value of AI integration in metal additive manufacturing. Beyond predictive accuracy, the proposed framework contributes to improved process stability, reduced monitoring latency, and better adaptability under changing operating conditions. These capabilities are especially important in metal AM, where local thermal fluctuations, spatter formation, powder-bed irregularities, and variations in energy input can quickly affect build quality. The comparative analysis with conventional monitoring methods confirmed that AI-integrated systems provide better performance in terms of responsiveness, accuracy, efficiency, and operational robustness. From an industrial perspective, these improvements can translate into lower material waste, reduced rework, greater production reliability, and stronger support for process traceability and qualification. At the same time, several challenges still limit the broader implementation of AI-driven process control in industrial AM environments. Model performance depends strongly on data quality, sensor placement, process variability, and the availability of representative training data across different materials, machine platforms, and scan strategies. In addition, moving from monitoring to fully closed-loop control requires reliable real-time decision mechanisms that can convert detected anomalies into corrective actions without introducing new instability into the process. Therefore, although the present results confirm the feasibility and practical potential of AI-enabled monitoring, further work is still needed to improve model transferability, strengthen sensor-fusion strategies, and validate adaptive control frameworks under a wider range of manufacturing conditions.

Overall, this study confirms that artificial intelligence is becoming a key enabling technology for the next generation of metal additive manufacturing systems. By transforming raw in-situ process data into actionable information for prediction, anomaly detection, and control support, AI can significantly improve both the technical performance and industrial readiness of metal AM. Future research should focus on multimodal sensor integration, physics-informed learning, digital twin-assisted control, and cross-platform validation to support the transition from intelligent monitoring to fully autonomous and self-optimizing additive manufacturing systems.

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