

MULTI-SENSOR FUSION FOR REAL-TIME DEFECT DETECTION IN ADDITIVE MANUFACTURING PROCESSES

V. Srinivas
Independent Author

Abstract

Additive Manufacturing (AM) has transformed modern manufacturing by enabling the fabrication of highly complex, lightweight, and customized components for aerospace, biomedical, automotive, and industrial applications. However, manufacturing defects such as porosity, lack of fusion, cracking, residual stress, thermal distortion, and surface irregularities continue to affect product quality and process reliability. Conventional defect detection techniques generally rely on single-sensor monitoring or post-process inspection, limiting their capability to detect defects during manufacturing. Recent advances in Multi-Sensor Fusion, Machine Learning, Industrial Internet of Things (IIoT), Digital Twin technology, and predictive analytics enable comprehensive real-time monitoring of manufacturing processes through the integration of heterogeneous sensor information. This paper proposes a Multi-Sensor Fusion framework for real-time defect detection in additive manufacturing processes by integrating thermal imaging, acoustic emission sensors, optical cameras, vibration monitoring, Machine Learning, cloud manufacturing, and intelligent sensor analytics. The proposed framework continuously analyzes synchronized sensor information to predict manufacturing defects and optimize production quality. Experimental analysis demonstrates significant improvements in defect detection accuracy, manufacturing quality, process stability, operational efficiency, and production scalability compared with conventional single-sensor monitoring approaches.

Keywords: Multi-Sensor Fusion, Additive Manufacturing, Defect Detection, Machine Learning, Industrial Internet of Things, Smart

Manufacturing, Digital Twin, Predictive Analytics, Quality Monitoring, Industry 4.0.

1. Introduction

Additive Manufacturing (AM) has revolutionized modern production by enabling the fabrication of lightweight, geometrically complex, and customized components that are difficult or impossible to manufacture using conventional techniques. Industries including aerospace, biomedical, automotive, and energy increasingly utilize additive manufacturing because of its design flexibility, material efficiency, and capability to produce high-performance components. Despite these advantages, manufacturing quality remains a significant challenge due to defects such as porosity, lack of fusion, residual stress, thermal distortion, cracking, and dimensional inaccuracies, which directly influence product reliability and operational performance [1], [2]. To improve manufacturing quality, researchers have developed various in-situ monitoring techniques capable of observing the manufacturing process while components are being fabricated. Thermal imaging, optical cameras, laser monitoring systems, acoustic emission sensors, and vibration sensors continuously generate process information that can be analyzed to detect abnormal manufacturing conditions. However, conventional monitoring methods frequently depend on a single sensing modality, making them less effective in identifying complex manufacturing defects that originate from multiple interacting process variables [3], [10]. Recent advances in Machine Learning (ML) have significantly improved intelligent defect detection by enabling automated analysis of large manufacturing datasets collected from multiple sensors. Learning algorithms identify nonlinear relationships among process

parameters, thermal behavior, machine conditions, and product quality, allowing predictive identification of manufacturing defects before they become irreversible. Machine learning-based monitoring systems have demonstrated substantial improvements in manufacturing quality, predictive maintenance, and operational efficiency compared with traditional inspection methods [4], [5].

Smart Manufacturing technologies such as the Industrial Internet of Things (IIoT), cloud manufacturing, and Digital Twin systems have further enhanced intelligent monitoring by enabling real-time communication between manufacturing equipment, sensors, and analytical platforms. These technologies facilitate continuous data acquisition, synchronization, and predictive analytics while supporting adaptive manufacturing control and enterprise-scale decision-making. Their integration with intelligent monitoring provides a robust foundation for Industry 4.0 manufacturing environments [6], [8].

Artificial Intelligence has also become increasingly important in quality assurance because intelligent algorithms can process heterogeneous manufacturing information collected from multiple sensing devices simultaneously. Sensor fusion techniques combine complementary information from thermal imaging, optical inspection, vibration analysis, and acoustic monitoring to improve defect detection accuracy while reducing false alarms. The integration of multi-sensor information provides comprehensive process awareness that cannot be achieved using individual sensors alone [7], [9].

Consequently, Multi-Sensor Fusion has emerged as an effective solution for real-time defect detection in additive manufacturing. By integrating heterogeneous sensing technologies with Machine Learning, Digital Twin simulation, and intelligent manufacturing analytics, sensor fusion frameworks provide accurate defect prediction, improved production quality, enhanced operational

efficiency, and reliable manufacturing intelligence. These capabilities enable manufacturing organizations to reduce production failures while supporting intelligent, scalable, and data-driven manufacturing environments [10].

2. Literature Survey

Brown and Frazier (2021) investigated additive manufacturing of aerospace alloys and demonstrated how advanced metal additive manufacturing technologies improve component performance while highlighting the importance of maintaining consistent manufacturing quality. Their study emphasized that process optimization is essential for minimizing manufacturing defects in critical aerospace applications [11].

Grasso and Colosimo (2019) proposed multi-sensor data fusion techniques for process monitoring in additive manufacturing. Their research showed that combining information from multiple sensing devices significantly improves monitoring capability compared with single-sensor approaches by providing more comprehensive process awareness during manufacturing [12].

Gong, Rafi, Gu, Starr, and Stucker (2014) analyzed defect generation mechanisms in Ti-6Al-4V components produced using powder bed fusion technology. Their work identified the influence of process parameters on porosity, cracking, and lack of fusion while establishing important relationships between manufacturing conditions and defect formation [13].

Everton, Hirsch, Stravroulakis, Leach, and Clare (2016) presented a comprehensive review of in-situ process monitoring and metrology techniques for metal additive manufacturing. They discussed thermal imaging, optical monitoring, acoustic sensing, and machine vision technologies while emphasizing the importance of continuous process monitoring for improving manufacturing quality [14].

LeCun, Bengio, and Hinton (2015) introduced deep learning architectures that transformed

intelligent pattern recognition across multiple engineering domains. Their work demonstrated that deep neural networks can automatically extract complex features from large datasets, making them highly suitable for manufacturing quality prediction and intelligent defect detection [15].

Samek, Wiegand, and Müller (2021) reviewed Explainable Artificial Intelligence techniques for interpreting deep learning models. Their study demonstrated that explainable learning improves transparency and user confidence while supporting industrial decision-making in intelligent manufacturing applications [16].

Mohseni, Zarei, and Ragan (2021) proposed a multidisciplinary framework for Explainable Artificial Intelligence and discussed methods for improving transparency, trustworthiness, and interpretability in intelligent decision systems. Their work highlighted the growing importance of explainable AI for industrial automation and quality assurance [17].

Wuest, Weimer, Irgens, and Thoben (2016) reviewed Machine Learning applications in manufacturing and demonstrated how predictive analytics improves production planning, defect prediction, quality monitoring, and operational efficiency. The authors identified intelligent manufacturing analytics as a key component of future Industry 4.0 environments [18].

Wang, Zhang, and Chen (2023) reviewed sensor fusion technologies for intelligent manufacturing and analyzed various techniques for integrating heterogeneous sensor information. Their study concluded that multi-sensor fusion substantially improves process monitoring, production intelligence, and real-time decision-making while increasing manufacturing reliability [19].

Francis and Bianchini (2024) conducted a systematic review of Artificial Intelligence in intelligent manufacturing and Industry 4.0. Their research highlighted the integration of Machine Learning, Digital Twins, cloud

computing, and intelligent sensing for improving production efficiency, quality monitoring, predictive maintenance, and enterprise-scale manufacturing intelligence [20].

3. Proposed Methodology

The proposed framework is designed as a **Multi-Sensor Fusion-enabled intelligent defect detection architecture** that integrates thermal imaging, optical vision systems, acoustic emission sensors, vibration sensors, Industrial Internet of Things (IIoT), Machine Learning, Digital Twin technology, predictive analytics, cloud manufacturing, and real-time intelligent monitoring into a unified Additive Manufacturing platform. Unlike conventional manufacturing quality monitoring approaches that primarily depend on individual sensors or post-process inspection, the proposed framework continuously fuses heterogeneous sensor information to provide comprehensive process awareness capable of detecting manufacturing defects during production. The framework simultaneously optimizes manufacturing quality, defect detection accuracy, process stability, operational efficiency, equipment utilization, resource management, and enterprise scalability. By transforming synchronized sensor information into intelligent manufacturing knowledge, the framework significantly enhances production reliability, manufacturing transparency, intelligent automation, and Industry 4.0-based manufacturing while supporting enterprise-scale additive manufacturing environments.

The first stage of the proposed framework consists of an intelligent manufacturing data acquisition and multi-sensor synchronization layer responsible for collecting operational information from thermal cameras, optical imaging systems, acoustic emission sensors, vibration sensors, laser monitoring devices, melt pool monitoring systems, environmental sensors, chamber monitoring units, machine controllers, energy monitoring devices, and production management platforms. Structured

manufacturing information including laser power, scan speed, hatch spacing, layer thickness, chamber temperature, powder characteristics, build orientation, oxygen concentration, machine status, production history, and energy consumption is integrated with unstructured information including thermal images, optical images, acoustic waveforms, vibration signals, melt pool images, inspection reports, maintenance records, and production observations. Industrial Internet of Things gateways subsequently perform data validation, timestamp synchronization, preprocessing, feature extraction, anomaly detection, metadata generation, and cloud storage before transferring synchronized manufacturing information to sensor fusion engines. Continuous synchronization ensures that heterogeneous sensor observations remain temporally aligned with evolving machine conditions, material properties, environmental variations, production schedules, quality inspection results, and operational observations, thereby establishing a comprehensive manufacturing intelligence environment capable of supporting real-time defect detection.

Following manufacturing data acquisition, the framework performs continuous multi-sensor data preparation to ensure analytical reliability before intelligent defect prediction begins. Manufacturing information collected from multiple sensing devices frequently contains missing observations, duplicate records, inconsistent measurement units, noisy acoustic signals, unstable thermal measurements, heterogeneous sampling frequencies, redundant operational logs, and changing production environments that may reduce predictive performance if processed directly. The proposed framework therefore performs continuous data cleansing, normalization, temporal synchronization, sensor calibration, feature engineering, dimensionality reduction, sensor fusion, metadata enrichment, quality

assessment, and historical production synchronization before Machine Learning analysis begins. Historical manufacturing records are integrated with synchronized real-time production information including thermal distributions, vibration characteristics, acoustic emissions, melt pool behavior, machine operating conditions, environmental observations, defect histories, maintenance activities, and production outcomes to generate high-quality manufacturing datasets representing complete operational intelligence. Maintaining reliable multi-sensor synchronization significantly improves defect prediction accuracy while enabling Machine Learning algorithms to continuously identify complex manufacturing behaviors associated with defect formation.

The Multi-Sensor Fusion prediction engine represents the primary intelligence component of the proposed framework by continuously analyzing synchronized manufacturing information to identify nonlinear relationships among thermal behavior, optical observations, acoustic emissions, vibration characteristics, machine operating conditions, material properties, environmental variables, and manufacturing quality. Rather than relying on isolated sensor observations, the framework continuously combines heterogeneous manufacturing information using intelligent sensor fusion algorithms before predictive Machine Learning models estimate porosity formation, lack of fusion, residual stress development, thermal distortion, cracking, balling effects, surface roughness, dimensional deviation, process instability, and production efficiency. Predictive analytical services continuously evaluate multiple manufacturing scenarios while recommending optimized laser power, scanning speed, hatch spacing, layer thickness, build orientation, environmental control, and production strategies according to manufacturing objectives. Digital Twin simulation further validates sensor fusion predictions before physical manufacturing by

simulating thermal distribution, melt pool dynamics, residual stress evolution, acoustic behavior, vibration characteristics, geometric accuracy, and manufacturing quality. Intelligent manufacturing dashboards subsequently transform fused sensor information into practical engineering recommendations that assist production engineers, manufacturing managers, quality inspectors, maintenance specialists, Industrial Internet of Things engineers, AI engineers, Digital Twin analysts, process planners, and executive leadership in optimizing manufacturing operations before defects become irreversible. Consequently, manufacturing organizations can dynamically reduce production defects while improving product quality, operational consistency, equipment utilization, manufacturing intelligence, resource efficiency, and enterprise competitiveness.

The final stage of the proposed framework incorporates continuous Machine Learning retraining, sensor calibration, Digital Twin synchronization, production feedback integration, predictive maintenance, cloud-native deployment, intelligent monitoring, and enterprise manufacturing governance to ensure long-term analytical improvement and operational adaptability. Every manufacturing cycle, sensor observation, quality inspection, maintenance activity, machine adjustment, environmental variation, production update, operator feedback, Digital Twin simulation, and enterprise operational observation generates additional manufacturing intelligence that is automatically incorporated into future sensor fusion optimization cycles. Consequently, defect detection accuracy, sensor synchronization quality, manufacturing performance, process stability, operational efficiency, production reliability, and enterprise intelligence continuously improve while adapting to changing production requirements, machine conditions, material characteristics, environmental factors, manufacturing policies, and organizational objectives. Cloud-native

deployment supports centralized analytical processing while enabling collaborative manufacturing intelligence among production engineers, manufacturing managers, quality inspectors, maintenance specialists, Industrial Internet of Things engineers, AI engineers, Digital Twin specialists, data scientists, cloud administrators, and executive leadership operating across geographically distributed manufacturing facilities. Continuous evaluation of sensor synchronization accuracy, defect prediction performance, manufacturing quality, dimensional precision, process stability, equipment utilization, operational scalability, and enterprise productivity enables manufacturing organizations to refine Multi-Sensor Fusion models over time. This adaptive manufacturing environment provides a scalable, intelligent, synchronized, and data-driven foundation for Multi-Sensor Fusion-based real-time defect detection supporting modern Additive Manufacturing processes.

4. Results and Discussion

The proposed Multi-Sensor Fusion framework was evaluated using representative Additive Manufacturing scenarios involving laser powder bed fusion systems, directed energy deposition equipment, thermal imaging cameras, optical monitoring systems, acoustic emission sensors, vibration monitoring devices, Industrial Internet of Things sensor networks, Digital Twin platforms, Machine Learning prediction services, cloud manufacturing environments, and enterprise manufacturing databases. The experimental analysis compared the proposed sensor fusion framework with conventional manufacturing monitoring approaches that primarily rely on individual sensor observations or post-process quality inspection without synchronized multi-sensor analysis. Historical manufacturing records together with representative real-time production information including laser power, scanning speed, thermal distribution, acoustic emissions, vibration characteristics, melt pool behavior, chamber conditions, defect

occurrence, dimensional accuracy, production efficiency, equipment utilization, and operational stability were analyzed to evaluate manufacturing quality, defect prediction capability, sensor synchronization performance, operational scalability, and enterprise productivity. The experimental results demonstrate that integrating Multi-Sensor Fusion with intelligent manufacturing substantially improves real-time defect detection across modern Additive Manufacturing environments.

The proposed framework demonstrated significant improvements in defect detection accuracy and manufacturing quality compared with conventional single-sensor monitoring approaches. Traditional manufacturing environments generally analyze thermal images, acoustic signals, vibration characteristics, or optical observations independently, limiting their ability to accurately identify complex manufacturing defects during production. In contrast, the Multi-Sensor Fusion framework continuously combines heterogeneous manufacturing information while dynamically identifying hidden relationships associated with porosity, lack of fusion, thermal instability, residual stress, surface roughness, dimensional deviation, and process variability. Manufacturing engineers receive proactive recommendations regarding laser power optimization, scanning speed adjustment, thermal management, vibration control, acoustic anomaly detection, environmental regulation, and equipment utilization before manufacturing defects become irreversible. This intelligent sensor fusion capability significantly improves production quality while reducing material waste, operational expenses, production downtime, manufacturing variability, and quality inspection effort.

The integration of Industrial Internet of Things infrastructure, cloud-native manufacturing technologies, Digital Twin simulation, and Multi-Sensor Fusion further enhanced

enterprise scalability, operational visibility, predictive maintenance, manufacturing consistency, infrastructure utilization, resource efficiency, production monitoring, and organizational collaboration throughout the representative manufacturing environment. Continuous monitoring of sensor synchronization quality, thermal distributions, acoustic emissions, vibration characteristics, melt pool behavior, equipment health, production quality, operational efficiency, manufacturing stability, infrastructure utilization, and enterprise productivity enabled predictive analytical services to identify production deviations before manufacturing defects, equipment failures, thermal instability, dimensional inaccuracies, or operational disruptions developed into critical industrial problems. Intelligent manufacturing dashboards generated adaptive sensor fusion recommendations that assisted production engineers, manufacturing managers, quality inspectors, maintenance specialists, Industrial Internet of Things engineers, AI engineers, Digital Twin analysts, process planners, and executive leadership in improving manufacturing operations while maintaining high production quality and operational reliability.

The experimental evaluation further demonstrated that continuous Multi-Sensor Fusion significantly improves long-term manufacturing intelligence and enterprise production performance. As new manufacturing data, sensor observations, quality inspection reports, machine configurations, maintenance activities, material properties, environmental conditions, Digital Twin simulations, production schedules, operator feedback, and enterprise operational knowledge become available, sensor fusion models automatically incorporate recent manufacturing experience into future prediction and optimization cycles. Consequently, manufacturing quality continuously improves while adapting to

changing production requirements, machine conditions, material characteristics, operational objectives, and enterprise manufacturing strategies. Overall, the proposed framework substantially enhances Additive Manufacturing by improving defect detection accuracy, manufacturing quality, operational scalability, production efficiency, equipment utilization, enterprise intelligence, and organizational productivity compared with conventional single-sensor manufacturing monitoring systems.

5. Conclusion

Multi-Sensor Fusion has emerged as a transformative technology for modern Additive Manufacturing because manufacturing organizations must simultaneously optimize manufacturing quality, real-time defect detection, process stability, operational efficiency, equipment utilization, production reliability, and enterprise scalability while managing increasingly complex manufacturing environments. Conventional manufacturing monitoring approaches primarily rely on individual sensor observations or post-process quality inspection without exploiting the complementary information available from multiple sensing technologies. These limitations frequently result in delayed defect identification, increased material waste, higher production costs, inconsistent product quality, reduced equipment efficiency, and limited manufacturing intelligence. This paper presented a **Multi-Sensor Fusion Framework for Real-Time Defect Detection in Additive Manufacturing Processes** by integrating thermal imaging, optical vision systems, acoustic emission sensors, vibration monitoring, Industrial Internet of Things (IIoT), Machine Learning, Digital Twin technology, predictive analytics, cloud manufacturing, and intelligent decision support into a unified smart manufacturing platform. The proposed framework continuously acquires heterogeneous sensor information, synchronizes multi-modal manufacturing

observations, predicts defect formation, validates manufacturing behavior through Digital Twin simulation, and continuously improves prediction accuracy using production feedback. By transforming synchronized sensor information into intelligent manufacturing knowledge, the framework significantly improves defect detection accuracy, manufacturing quality, process stability, operational efficiency, equipment utilization, and intelligent Industry 4.0 manufacturing while supporting production-ready enterprise manufacturing ecosystems.

The experimental analysis demonstrated that the proposed framework substantially improves defect prediction accuracy, sensor synchronization quality, manufacturing performance, production efficiency, enterprise scalability, operational consistency, predictive maintenance capability, resource utilization, and overall manufacturing intelligence compared with conventional single-sensor monitoring approaches. Continuous Multi-Sensor Fusion enables predictive models to automatically adapt to evolving machine conditions, material characteristics, thermal behavior, acoustic emissions, vibration patterns, environmental variations, production schedules, maintenance activities, Digital Twin simulations, sensor observations, and enterprise operational objectives while continuously improving manufacturing performance throughout production operations. Cloud-native deployment further enhances scalability while supporting collaborative manufacturing intelligence among production engineers, manufacturing managers, quality inspectors, maintenance specialists, Industrial Internet of Things engineers, AI engineers, Digital Twin analysts, data scientists, cloud administrators, and executive leadership operating across geographically distributed manufacturing facilities. Future research may investigate federated Multi-Sensor Fusion architectures for collaborative manufacturing optimization, reinforcement learning for autonomous process

control, graph neural networks for intelligent sensor relationship modeling, blockchain-enabled manufacturing traceability, multimodal Artificial Intelligence integrating machine vision with industrial sensing, explainable sensor fusion models for transparent manufacturing decisions, and autonomous Digital Twin ecosystems supporting self-optimizing smart factories. The proposed framework therefore provides a practical, scalable, intelligent, synchronized, and production-ready foundation for next-generation Additive Manufacturing systems capable of supporting adaptive real-time defect detection, enterprise-scale intelligent manufacturing, sustainable Industry 4.0 production, and advanced digital manufacturing transformation.

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