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# AI-ASSISTED OPTIMIZATION OF ADDITIVE MANUFACTURING: PROCESS CONTROL, DEFECT PREDICTION, AND SUSTAINABLE PRODUCTION

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**Abstract:** Although complex and customised parts can be manufactured by AM, the process can be easily affected by various process parameters, thermal behaviours, material properties and machine conditions. Monitoring and prediction of defects as well as parameter optimization and adaptive control are now being increasingly improved by the use of artificial intelligence (AI) and machine learning (ML). The current review highlights the use of AI in process optimisation in AM, focusing on 'In-situ Monitoring', 'Intelligent Process Control', 'Defect Prediction', and 'Sustainable Production'. The literature shows that supervised learning is employed for quality prediction and defect classification tasks, and reinforcement learning and hybrid physics-data-driven approaches have been proven to have the potential for dynamic process optimization tasks. Other benefits of using AI-assisted systems include fewer failed builds, less material waste, no rework, and lower energy use. Data imbalance, sensor variations, domain change, cross-machine generalisation, model understanding, computational delay, and certification, however, are the factors that limit industrial application. In the future, the research emphasis will be on the standardisation of datasets and physics-informed models, digital twins, explainable AI, the quantification of uncertainty, and robust closed-loop control systems. Overall, AI shows great promise in the continuous improvement of the reliability, adaptability and sustainability of AM.
***Keywords:*** *Additive manufacturing, Artificial Intelligence, Machine Learning, Process Optimisation, Defect prediction, Adaptive control, In-situ monitoring, Sustainable manufacturing.*

## 1. INTRODUCTION

Additive manufacturing (AM) has grown to become one of the key enabling technologies for high value engineering industries in producing geometrically complex, lightweight and customized parts in the aerospace, biomedical, automotive, energy and other applications. In contrast to conventional subtractive manufacturing, AM is an additive technique that produces components layer by layer, improves material utilisation, and provides greater design freedom. However, the interaction of AM parameters, feedstock properties, thermal history and machine parameters is still suspected to play a strong role in the quality and


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repeatability of AM processes. The behaviour of the melt-pool, porosity, residual stresses, the microstructure, dimensional accuracy and ultimately the performance of manufactured components can vary depending on changes in laser power, feed speed, scanning speed, and thickness of layers as well as heat accumulation (Chen et al., 2024; Kumar et al., 2022; Karkaria et al., 2024).

In situ process data are becoming readily available, creating opportunities for artificial intelligence (AI) and machine learning (ML) in AM. Process conditions can be continuously fed back using thermal imaging, Optical monitoring, Acoustic sensing, High-speed imaging, Photodiode signals, and machine operating data. These high-dimensional and complex datasets can be utilised by AI-driven models to detect abnormal behaviour in the process, forecast defects, optimise parameter combinations, and achieve more efficient quality control (Lupi et al., 2023; Sousa et al., 2025; Gunasegaram et al., 2024).

One of the most significant advances is going from defect detection on the ground to predictive and adaptive process control. Supervised learning can be used to establish relationships between process conditions and quality metrics, and reinforcement learning and hybrid physics–data-driven models offer opportunities for learning about dynamics parameters for optimization and closed-loop control (CL) (Pandiyan et al., 2023; Saimon et al., 2024; Li & Pattinson, 2025). Coupling predictive modelling with real-time sensing could enable manufacturing systems to detect defect signals before they become manufacturing issues and thus control manufacturing conditions before the defects are introduced in later layers (Strutz et al., 2023; Zhang et al., 2025).

The optimization of waste is also relevant to the sustainability of manufacturing when using AI. Improved process stability and early defect detection can reduce failed builds, wasted materials, and rework, and avoid unnecessary experiments and energy use, thereby improving resource efficiency (Qin et al., 2022). However, this is still hindered in the industrial sector by the lack of large-scale, comprehensive data sets; variability and drift between machines; model interpretability; the complexity or cost of computing; and the transferability of models from one material to others or under different processing conditions.For this reason, this review focuses on the role of AI-supported process optimisation for AM, especially in the fields of in situ monitoring, machine learning (ML)- assisted defect prediction, adaptive process control, and sustainable production. It also assesses existing challenges and future prospects to create industrially viable, reliable, interpretable and transferable AI-assisted AM systems.

## 2. REVIEW SCOPE AND RATIONALE

This review considers the facets of AI-assisted optimization as a supplementary process to the AM workflow, which can either improve production stability, quality assurance, and/or ensure sustainability reductions (Chen et al., 2026; Fianko et al., 2026). These computational systems build a closed-loop relationship between real-time process monitoring and defect prediction models, which reduces waste and low carbon consumption in manufacturing processes to promote sustainable manufacturing. This research covers the entire additive manufacturing process, ranging from process setup to validation using data on stochastic


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effects in the process and their mitigation, and on the evaluation of the structural integrity through the print preparation and test stage (Alli et al., 2024; Ng et al., 2024).

## 3. REVIEW METHODOLOGY

Based on the PICOC framework (Population, Intervention, Comparison, Outcome and Context) that may be employed to formulate research questions and drive the systematic literature search across multiple databases such as Scopus and Google Scholar (Ciccone et al., 2023). To select the specific papers, preference is given to peer-reviewed studies conducted in the last 10 years that study machine learning, physics informed neural networks and the effect of process parameters on the microstructure (Patel et al., 2025).

## 4. ADDITIVE MANUFACTURING PROCESSES

Both laser powder bed fusion (LPBF) and directed energy deposition (DED) of metals employ complex process parameters that control the thermal history, resulting part properties, and in-service performance of 3D printed metal parts, including laser power, scan speed in LPBF, and layer thickness in DED (Chen et al., 2024; Kumar et al., 2022). These processes are however often challenging due to inherent property variation of the materials building-up sequentially, as given in the technology, and due to the stochastic nature of the heat accumulation process (Karkaria et al., 2024).

### 4.1 Effective control

The geometric accuracy and porosity values are essential and literally guided by the intricate interplay between localized thermal gradients, melt pool dynamics, and laser-material interactions (Herzog et al., 2023). In particular, the altars in scan strategies and energy densities can be unpredictable, which requires making intelligent, real-time adjustments to ensure the structure's performance (Kim et al., 2025; Yu et al., 2026).

### 4.2 Monitoring Data Sources

In-process monitoring uses a variety of sensors like a visual camera or acoustic emission sensors to capture transient signals from the material deposition process (Elahi et al., 2023). The high fidelity data streams are usually processed by neural networks and support vector machines for trend and irregularity detection in real-time, which can result in the early detection of faults (Inayathullah&Buddala, 2024).

### 4.3 AI-Based Process Control

Currently, machine learning structures are already being used to enable adaptive process regulation, offering a way to overcome the obstacle of static PID regulating practices (Lupi et al., 2023; Sousa et al., 2025). These models can provided assistance in the optimal selection of the input parameters by processing the sensory data taken in-situ, for detecting faults and proactively adjusting the energy inputs, moving from a reactive detection approach to a proactive mitigation (Gunasegaram et al., 2024).


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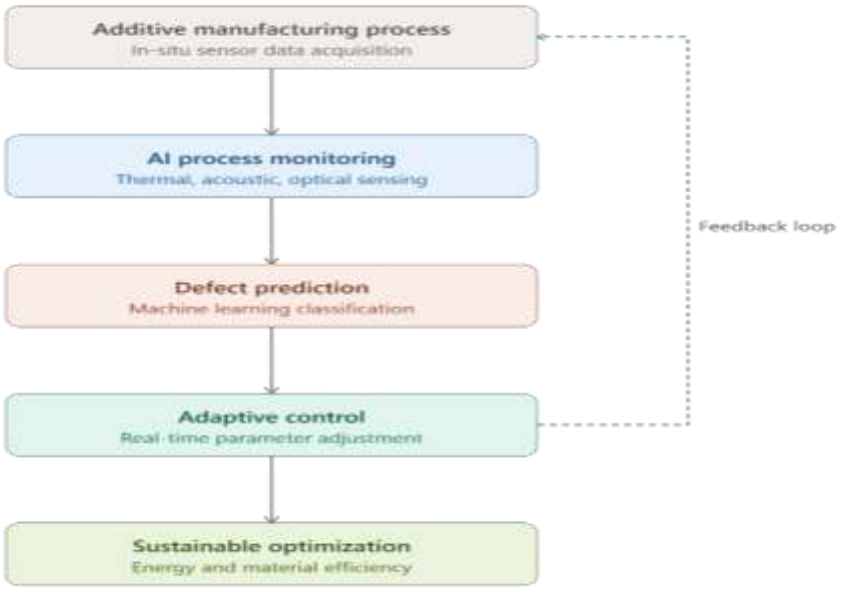



***Figure 1: Integrated AI-Assisted Process Optimization Framework for Additive Manufacturing***

Source: Authors' own illustration based on the conceptual synthesis of the reviewed literature (Lupi et al., 2023; Gunasegaram et al., 2024; Zhang et al., 2025; Qin et al., 2022).

## 5. MODELING PROCESS DYNAMICS

These computational frameworks use supervised reinforcement and hybrid control strategies for high nonlinear relationship modeling between stochastic process input and final output of a part (Wu et al., 2024). Supervised learning works well in detecting irregularities by learning the patterns (Pandiyan et al., 2023; Saimon et al., 2024), whereas the reinforcement learning agents learn to optimize the parameters based on dynamic interactions with the environment to classify irregularities to minimize system instability (Li & Pattinson, 2025).

### 5.1 Adaptive Control Systems

The latter is complemented with physics-based priors, which, combined with data-driven modeling, enable correcting process deviations with high-frequency feedback loops in hybrid control strategies (Strutz et al., 2023; Zhang et al., 2025). They actively control the modulation of laser power or scan velocity in response to the measured real-time thermal signal and have been proven to be effective in negating the pore generating oscillations and other transient fabrication defects, before they grow and spread (Mondal & Goswami, 2024; Zhao et al., 2026).

### 5.2 Defect Prediction Approaches

Based on the majority of their geometric, morphological, and microstructural characteristics, defects in additive manufacturing are systematically classified, including porosity, voids caused by lack of fusion, and cracking (Shaaban et al., 2026). Convolutional neural networks (CNNs) trained to recognize the dynamics in the generation of melt pools, plumes, and spatter can link in-situ thermal signatures to known structural failures, which can be precursors to early identification of anomalies (Luo et al., 2025; McKinney et al., 2024).


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Moreover, the deep learning architectures ensure self-correcting features, minimizing reliance on time-intensive manual inspection, through the learning process on calibrated datasets (Balhara et al., 2023; He et al., 2024).

### 5.3 Defect mechanisms and features

Defect formation is also associated with transient thermal signatures, which can be quantified by changes in width of the melt pool and the intensity of spatter as process features to be correlated to structural instability (Dong et al., 2025). In particular, pixel-wise segmentation and high speed thermal imaging enables localization of porosity and spattering events in a particular region of the sliceless such that geometric features can be mapped to the underlying melt pool physics (Deshpande et al., 2024).

## 6. PREDICTION AND CLASSIFICATION

Hybrid CNN-based model is the commonly used classification model of manufacturing defects that is composed of statistical wavelet feature vectors and raw image data, which can achieve F scores of above 97%, as compared to the classical CNN (Zhang & Zhao, 2021). In contrast, anomaly detection techniques take the advantage of unsupervised methods to capture anomaly behaviors or anomalies that do not have labeled defect signatures, which are to a large extent uncommon or lack of complete failure behavior data (Ehteshamfar et al., 2026). A major challenge, however, is the biasness in these manufacturing datasets since many more data are kept from conforming parts compared to parts that do not, which results in suboptimal models lacking the ability to generalize across different materials or infrequent failure modes (Atwya&Panoutsos, 2023; Raihan et al., 2024).

***Table 1. Comparison of AI Approaches for Additive Manufacturing Process Optimization***

| AI/ML Approach | Primary Application in AM | Input Data | Major Advantage | Key Limitation |
|---|---|---|---|---|
| Supervised Machine Learning | Defect classification and quality prediction | Process parameters, sensor signals | Effective when labelled data are available | Requires representative labelled datasets |
| Convolutional Neural Networks (CNNs) | Melt-pool, plume, spatter and surface-defect detection | Optical and thermal images | Automatic extraction of complex image features | High data and computational requirements |
| Unsupervised/Anomaly Detection | Detection of unknown or rare process abnormalities | Sensor signals and image data | Useful when defect labels are limited | Difficult interpretation and threshold selection |
| Reinforcement Learning | Adaptive parameter optimization and process control | Real-time process states and feedback | Supports dynamic decision-making | Requires careful training and validation |


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| AI/ML Approach | Primary Application in AM | Input Data | Major Advantage | Key Limitation |
|---|---|---|---|---|
| Physics-Informed/Hybrid AI | Process prediction and intelligent control | Process data combined with physical models | Improves physical consistency and may reduce data requirements | More complex model development |
| Digital Twin–AI Models | Process monitoring and virtual optimization | Multimodal real-time and historical data | Enables virtual testing and predictive optimization | Requires reliable model–machine synchronization |

Sources: Pandiyan et al. (2023); Saimon et al. (2024); Li and Pattinson (2025); Karkaria et al. (2024); Ehteshamfar et al. (2026); Zhang and Zhao (2021).

### 6.2 Sustainable Production Strategies

AI optimization plays a key role in improving sustainability by helping to reduce the waste of materials and energy, especially by controlling the amount of cement required for production and minimising build failures to reduce the need for rework that is energy intensive (Abdallah & Pervaiz, 2025; Gulia et al., 2026). These adaptive systems take into account the environmental impact throughout the production process of these items, from the use of raw materials to the final stage of product disposal (Su et al., 2024; Thomas et al., 2025).

### 6.3 Resource Efficiency Improvements

The systems allow for significant decreases in the amount of scrap produced and the amount of energy used for total energy expenditure, by tuning the generated tool path based on predictive algorithms to optimize material deposition. In addition, there is intelligent process planning that enables the use of recycled material and lightweight design of structure, thus, making life cycle CO2 footprint of manufactured components also less significant (Lodhi et al., 2024; Shehbaz & Peng, 2025). These improvements come at a cost, however, as they demand a tradeoff between the computational burden of high-fidelity optimization models, and the general goal of alleviating the overall environmental footprint of the full production process, which includes minimizing total energy use. (Bello &Maladzhi, 2025), (Miller et al., 2026).

## 7. LIFE CYCLE SUSTAINABILITY ASSESSMENT

is a key part to assess general AM environmental performance. This integration allows evaluating environmental trade-offs throughout the different lifecycle stages such as the treatment of raw materials, manufacturing, energy use, component incorporation, and end-of-life management (Alam, 2025). Beyond the environmental impact resulting from the material reduction and process efficiency gains, the computational power used in AI model training and operation must be taken into account. Thus, the key performance indicators (KPIs) to measure energy, resource and carbon usage, as well as the computational cost of AI-driven manufacturing systems, must be standardized and process-invariant. These indicators can facilitate more transparent comparisons of conventional and AI-supported manufacturing


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methods and can be used to assess the impact of the manufacturing process on the lifecycle sustainability benefits.

**Conclusions and Future**

Despite progress of these models from a lab environment and successful deployments on hardware platforms of various characteristics across diverse industrial sectors, the translation and application of these models under data fully heterogeneous across different devices still faces some challenges (Rathore, 2016). Additionally, limited data availability and even a lack of model transparency can further affect the trust of these systems in operational situations, and restrict industrial adoption (Lucas, 2025).

## 8. IMPLEMENTATION BARRIERS

The main barrier is the great realities of information high quality differences and infrastructure challenges, which regularly stop the easy switch of trained models between various hardware platforms (- & -, 2024). Furthermore, there is no standardized validation procedure and cybersecurity frameworks for industrial edge computing, making them highly vulnerable and unlikely to be safe enough for the necessary safety certifications in the case of opaque black-box models (Ghobakhloo et al., 2024; Xue et al., 2025). To overcome this situation, future research should focus on creating explainable Artificial Intelligence (AI) systems for diagnosis, which effectively transform latent representations models into easily understood metrics and indexes, to enhance the trust between the human and the machine (Jiang et al., 2026).

*Table 2. Major Challenges and Future Directions of AI-Assisted Additive Manufacturing*

| Current Challenge | Impact on AM | Recommended Future Direction |
|---|---|---|
| Limited and imbalanced datasets | Reduced prediction reliability for rare defects | Standardized and balanced AM datasets |
| Machine-to-machine variability | Poor transferability of trained models | Transfer learning and domain adaptation |
| Sensor variability and drift | Changes model input distributions | Sensor calibration and robust multimodal fusion |
| Black-box AI models | Reduces industrial trust and interpretability | Explainable AI and interpretable ML |
| Limited physical knowledge in data-driven models | May produce physically inconsistent predictions | Physics-informed and hybrid AI models |
| Real-time computational requirements | Delays adaptive process control | Edge AI and computationally efficient models |
| Cybersecurity risks | Vulnerability of connected control systems | Secure industrial AI architectures |
| Lack of standardized validation | Limits qualification and certification | Standardized benchmarking and validation protocols |
| Sustainability–computation trade-off | AI itself adds computational energy demand | AI-integrated lifecycle and energy assessment |


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Sources: Atwya and Panoutsos (2023); Raihan et al. (2024); Ghobakhloo et al. (2024); Mehdiyev et al. (2025); Karkaria et al. (2024); Xue et al. (2025).

**Future Research Priorities**

Continued research should focus on designing physics-aware machine learning models that incorporate fundamental physics principles to enhance the models' capabilities and minimize the need for extensive labeled datasets (Kim, 2025; Mehdiyev et al., 2025). Moreover, these architectures need to get rid of the data-driven architecture and enhance their performance by incorporating the domain knowledge such that the model provides results consistent with the physical laws (Liu & Sun, 2023).

**Conclusions and Implications**

However, while these AI-powered systems promise significant benefits, their adoption in industries is hindered by several factors, including the complexity of integrating these systems into existing manufacturing processes in real time and the initial high cost of installation (Alli et al., 2024). To achieve future success, adaptive paradigms and self-learning approaches must be developed which can process high-resolution, in-situ data streams in real-time (Grasso et al., 2021), and at the same time overcomes the concerns about latency and network security of existing industrial communication paradigms (Mattera et al., 2024). Overall, it is the ability to span the divide between AM practitioners and AI researchers that will help ensure the research is translated into practice in a reliable and scalable fashion in industry (King 2025). Additionally, challenging the traditional and ‘empirical' certification cycles, which hinder the agility of additive processes, calls for realization of AI-driven, ‘digital-first' validation routes that can ensure the reliability, required to achieve safety-critical parts (Harun et al., 2025).

**REFERENCES:**

[1] M. Chen, J. Wang, L. Wang, Y. Liu, R. Liu, Q. Jin, J. Yang, W. Tang, R. Wang, and Z. Shu, “AI-enabled end-to-end processing in additive manufacturing: From pre-processing to post-processing,” Additive Manufacturing Frontiers, Art. no. 200315, 2026, doi: 10.1016/j.amf.2026.200315.

[2] M. V. Ehteshamfar, X. Xu, and S. Yang, “Quality-centric digital twins in additive manufacturing: A review of the state-of-the-art, challenges, and future directions,” Digital Twin, vol. 3, no. 2, 2026, doi: 10.1080/27525783.2026.2613469.

[3] K. K. Gajula, “AI-Augmented Web Development: A Competency Framework for the Next Generation Workforce,” Journal of Science Engineering Technology and Management Science, 2025.

[4] M. U. Farooq and S. Deng, “Data-driven sustainability assessment of advanced manufacturing processes,” The International Journal of Advanced Manufacturing Technology, vol. 142, pp. 4245–4288, 2026, doi: 10.1007/s00170-025-17185-0.

[5] S. K. Fianko, I. K. Nooni, T. C. Dzogbewu, E. Agbemava, and D. J. de Beer, “AI as an enabler of sustainable additive manufacturing: Environmental impact and circular design,” The International Journal of Advanced Manufacturing Technology, 2026, doi: 10.1007/s00170-026-17389-y.

[6] K. Gulia, P. Kumar, S. Jain, A. Yadav, B. Johnston, and N. Nandal, “Methodological implementation of machine learning for optimized powder bed fusion in additive manufacturing,” Journal of Integrated Science and Technology, vol. 14, no. 3, Art. no. 1542, 2026, doi: 10.62110/sciencein.jist.2026.v14.1542.

[7] D. G. Kumar, N. V. Sireesha, D. S. N. M. Rao, R. Thumu, A. B. Krishna, and P. Narendra, “Optimized fault detection and classification in transmission lines with SVM,” in 2026 1st

International Conference on Innovation & Growth in Next-Gen Intelligent Technology & Engineering (IGNITE), Pune, India, 2026, pp. 1–7, doi: 10.1109/IGNITE69592.2026.11706644.
[8] K. K. Gajula, "Intelligent AI Systems and Advanced Machine Learning: Recent Advances and Real-World Applications," Journal of Intelligent Decision Making and Information Science, vol. 3, no. 7s, pp. 1831–1845, 2026.
[9] S. Abdallah and S. Pervaiz, "A review on AI-based real-time defect detection in 3D printing process: A path to sustainable and quality assurance," 2025, doi: 10.1115/IMECE2025-165848.
[10] M. S. Alam, "AI-driven sustainable manufacturing for resource optimization," TechRxiv, 2025, doi: 10.36227/techrxiv.176107759.92503137/v1.
[11] K. A. Bello and R. W. Maladzhi, "Innovative and best practices in sustainable strategies for waste reduction in additive manufacturing," Hybrid Advances, vol. 11, Art. no. 100527, 2025, doi: 10.1016/j.hybadv.2025.100527.
[12] K. K. Gajula, "Designing an Ethical Data Science Framework for Responsible and Transparent AI Integration," Emerging Trends in Digital Transformation, vol. 1, no. 1, pp. 74–87, 2025.
[13] Y. Dong, H. Li, L. Wang, J. Chen, V. I. Sucală, and J. Jiang, "Review on recycled materials for additive manufacturing," International Journal of Precision Engineering and Manufacturing-Green Technology, 2025, doi: 10.1007/s40684-025-00788-z.
[14] R. E. and K. B., "Industry 5.0 in manufacturing: Enhancing resilience and responsibility through AI-driven predictive maintenance, quality control, and supply chain optimization," International Journal for Multidisciplinary Research, vol. 6, no. 4, 2024, doi: 10.36948/ijfmr.2024.v06i04.25733.
[15] Y. A. Alli, H. Anuar, M. R. Manshor, C. E. Okafor, A. F. Kamarulzaman, N. Akçakale, F. N. M. Nazeri, M. Bodaghi, J. Suhr, and N. A. M. Nasir, "Optimization of 4D/3D printing via machine learning: A systematic review," Hybrid Advances, vol. 6, Art. no. 100242, 2024, doi: 10.1016/j.hybadv.2024.100242.
[16] L. Chen, G. Bi, X. Yao, J. Su, C. Tan, W. Feng, M. Benakis, Y. Chew, and S. K. Moon, "In-situ process monitoring and adaptive quality enhancement in laser additive manufacturing: A critical review," 2024, doi: 10.1016/j.jmsy.2024.04.013.
[17] S. Deshpande, V. Venugopal, M. Kumar, and S. Anand, "Deep learning-based image segmentation for defect detection in additive manufacturing: An overview," The International Journal of Advanced Manufacturing Technology, vol. 134, pp. 2081–2105, 2024, doi: 10.1007/s00170-024-14191-6.
[18] M. Ghobakhloo, M. Fathi, M. Iranmanesh, M. Vilkas, A. Grybauskas, and A. Amran, "Generative artificial intelligence in manufacturing: Opportunities for actualizing Industry 5.0 sustainability goals," Journal of Manufacturing Technology Management, vol. 35, no. 9, pp. 94–121, 2024, doi: 10.1108/JMTM-12-2023-0530.
[19] K. K. Gajula, "Reinforcement Learning with Transparent Policies: An Explainable AI Approach to Adaptive Cyber Security," American Journal of AI Cyber Computing Management, vol. 5, no. 4, pp. 322–328, 2025.
[20] D. Gunasegaram, A. S. Barnard, M. J. Matthews, B. H. Jared, A. Andreaco, K. Bartsch, and A. B. Murphy, "Machine learning-assisted in-situ adaptive strategies for the control of defects and anomalies in metal additive manufacturing," Additive Manufacturing, vol. 81, Art. no. 104013, 2024, doi: 10.1016/j.addma.2024.104013.
[21] M. Atwya and G. Panoutsos, "In-situ porosity prediction in metal powder bed fusion additive manufacturing using spectral emissions: A prior-guided machine learning approach," Journal of Intelligent Manufacturing, vol. 35, no. 6, pp. 2719–2742, 2024, doi: 10.1007/s10845-023-02170-9.

[22] H. Balhara, A. Karthikeyan, A. Hanchate, T. G. Nakkina, and S. Bukkapatnam, "Imaging systems and techniques for fusion-based metal additive manufacturing: A review," Frontiers in Manufacturing Technology, vol. 3, 2023, doi: 10.3389/fmtec.2023.1271190.
[23] A. S. Bale, Y. R. Vada, B. E. Oshiojum, et al., "ChatGPT in software development: Methods and cross-domain applications," International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 9s, pp. 636–643, 2023.
[24] F. Ciccone, A. Bacciaglia, and A. Ceruti, "Optimization with artificial intelligence in additive manufacturing: A systematic review," Journal of the Brazilian Society of Mechanical Sciences and Engineering, vol. 45, no. 6, 2023, doi: 10.1007/s40430-023-04200-2.
[25] K. K. Gajula, "A Hybrid Interpretable AI Framework for Detecting Financial Fraud in Dynamic Transaction Networks," International Journal of Communication Networks and Information Security, 2022.
[26] M. Elahi, S. O. Afolaranmi, J. L. M. Lastra, and J. A. P. García, "A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment," 2023, doi: 10.1007/s44163-023-00089-x.
[27] M. S. S. Sai, A. B. Krishna, P. Ganthi, S. K. Kankanala, S. Tinnaluri, and V. Simhadri, "Machine learning algorithms for predicting the loan status," Journal of Survey in Fisheries Sciences, vol. 10, no. 2S, pp. 3677–3685, 2023.
[28] M. Grasso, A. Remani, A. Dickins, B. M. Colosimo, and R. Leach, "In-situ measurement and monitoring methods for metal powder bed fusion: An updated review," Measurement Science and Technology, vol. 32, no. 11, Art. no. 112001, 2021, doi: 10.1088/1361-6501/ac0b6b.
[29] K. K. Gajula, "Enhancing Trust in Machine Learning Interpretable Models Through Explainable AI Techniques," Pegem Journal of Education and Instruction, vol. 13, no. 4, pp. 909–915, 2023.
[30] Y. R. Vada, "A survey on erasable closed patterns from compound-datasets," International Journal of Pure and Applied Mathematics, 2018.
[31] K. K. Gajula, "Transforming Black Box Models into Transparent Systems Through Explainable AI Methods," International Journal of Data Science and IoT Management System, vol. 4, no. 2, pp. 27–33, 2025.
[32] T. Rajani, K. K. Gajula, M. A. Shaik, Y. Sneha, A. K. Vootla, and K. S. Prasad, "ResUNet-X: Next-Generation Residual U-Net for Accurate Cardiac Imaging," in Proceedings of the International Conference on Signal Processing, Computation, Electronics and Communication Technologies, 2025.


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