

Research Article

AI-Based Vision Inspection System for Automated Defect Detection in Additive Manufacturing Processes Using Deep Learning and Transfer Learning Approaches

Dani Sasmoko^{1*}, Krisna Widi Nugraha², Rian Ardianto³, Rosyid Ridlo Al-Hakim⁴, Helmi Wibowo⁵, Rinna Rachmatika⁶

¹ Universitas Sains dan Teknologi Komputer, Indonesia; e-mail: dani@stekom.ac.id

² Universitas Harapan Bangsa, Indonesia; e-mail: nugrahawidikrisna@gmail.com

³ Universitas Harapan Bangsa, Indonesia; e-mail: rianardianto@uhb.ac.id

⁴ Universitas Harapan Bangsa, Indonesia; e-mail: rosyid@uhb.ac.id

⁵ Politeknik Keselamatan Transportasi Jalan, Indonesia; e-mail: helmi.wibowo@pktj.ac.id

⁶ Universitas Pamulang, Indonesia; e-mail: rinnarachmatika@unpam.ac.id

* Corresponding Author: dani@stekom.ac.id

Abstract: Additive manufacturing (AM) requires reliable and efficient defect detection mechanisms to ensure structural integrity and product quality, yet conventional inspection approaches remain time-consuming and often unsuitable for real-time industrial deployment. This study aims to develop and experimentally validate an artificial intelligence based vision inspection system capable of accurately detecting surface defects in AM components. A Convolutional Neural Network (CNN) architecture utilizing pretrained backbones (ResNet and EfficientNet) was implemented with a transfer learning strategy and data augmentation techniques. High-resolution AM surface images representing porosity, cracks, and layer misalignment were used for training and evaluation. Model performance was assessed using Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP), and comparative benchmarking was conducted against traditional machine learning models such as Support Vector Machine and Random Forest. The proposed CNN-based models significantly outperformed conventional approaches, achieving up to 95.1% Accuracy and 92.8% mAP. The EfficientNet backbone demonstrated superior generalization capability, particularly in balancing Precision and Recall, indicating robust defect detection performance across multiple categories. These findings confirm that AI-driven inspection frameworks provide scalable and reliable quality assurance solutions for advanced manufacturing environments.

Keywords: Additive Manufacturing; Computer Vision Inspection; Convolutional Neural Network; Defect Detection; Transfer Learning.

Received: March 31, 2024

Revised: April 20, 2024

Accepted: May 28, 2024

Published: May 31, 2024

Curr. Ver.: May 31, 2024



Copyright: © 2025 by the authors.

Submitted for possible open

access publication under the

terms and conditions of the

Creative Commons Attribution

(CC BY SA) license

([https://creativecommons.org/li](https://creativecommons.org/licenses/by-sa/4.0/)

[censes/by-sa/4.0/](https://creativecommons.org/licenses/by-sa/4.0/))

1. Introduction

Additive Manufacturing (AM), more commonly known as 3D printing, has emerged as one of the most disruptive manufacturing technologies in recent decades. Unlike conventional subtractive manufacturing approaches, AM builds three-dimensional objects layer by layer based on digital models, enabling the realization of complex geometries that are difficult to achieve using traditional methods (Kumar & Goel, 2024). Design flexibility, material efficiency, and the capability for mass customization position AM as a key driver of industrial transformation toward the digital era.

Since its introduction in the 1980s, AM was initially used primarily for rapid prototyping. However, significant advancements in materials, hardware, and software technologies have expanded its role to the production of functional end-use components (P'erez et al., 2020). This evolution includes improvements in printing resolution, the development of high-performance metal and polymer materials, and the integration of increasingly precise digital control systems.

The advancement of AM technology is also regarded as part of a new industrial revolution emphasizing digitalization and the integration of cyber-physical systems. In this context, AM serves as a major enabler of intelligent and flexible manufacturing (Jemghili et al., 2020). The integration of AM with the Internet of Things (IoT), big data analytics, and artificial intelligence further strengthens its position within the Industry 4.0 landscape.

Various AM techniques have been developed, including vat photopolymerization, powder bed fusion, and material extrusion. Each technique possesses unique characteristics in terms of resolution, material compatibility, and industrial applications. For instance, vat photopolymerization demonstrates significant potential in producing high-precision details for medical and microstructural applications (Pazhamannil & Govindan, 2020).

In the aerospace and automotive sectors, AM is utilized to manufacture lightweight components with complex internal structures that reduce overall system weight and improve fuel efficiency. This trend aligns with global sustainable development goals (Alami et al., 2023). Topology optimization and lattice structure design exemplify the practical implementation of AM's advantages in these industries.

The automotive industry also leverages AM for rapid prototyping, customized spare parts production, and shortened product development cycles (Nayeem & Hossain, 2023). The production flexibility offered by AM enables rapid responses to design modifications and dynamic market demands.

In the healthcare sector, AM has opened substantial opportunities for the fabrication of personalized implants and prosthetics. The production of biocompatible scaffolds and individualized implants demonstrates how AM can enhance patient comfort and clinical outcomes (Mobarak et al., 2023). Patient-specific customization represents a major advantage over conventional manufacturing methods.

Beyond its technical benefits, AM also offers economic and environmental advantages. Reduced material waste and on-demand production capabilities support cost efficiency and sustainability (Sljivic et al., 2024). Decentralized production models enabled by AM also have the potential to reduce carbon footprints associated with transportation and logistics.

Nevertheless, the growth of AM is accompanied by various challenges, particularly in terms of quality and product consistency. High process variability often leads to inconsistencies in mechanical properties and component dimensions ("Ozbay Kisas"oz & Kisas"oz, 2023). This issue remains a significant barrier to large-scale adoption in industries with stringent safety standards.

Variations in process parameters such as laser power, scanning speed, and powder particle distribution can trigger internal defects including porosity, cracking, and incomplete fusion. Therefore, quality control becomes a critical aspect in ensuring the reliability of AM-produced components (Al-Meslemi et al., 2023).

Surface quality and geometric fidelity issues frequently arise due to the layered nature of AM processes. Rough surfaces and dimensional distortions can affect mechanical performance and increase post-processing requirements ("Ozbay Kisas"oz & Kisas"oz, 2023). These challenges become more complex when manufacturing components with highly intricate geometries.

To address these challenges, process monitoring systems have been extensively developed. Melt pool monitoring, optical sensors, and computer vision systems are employed to detect anomalies during the printing process (Chua et al., 2017). In situ monitoring approaches allow early intervention before defects propagate further.

In situ monitoring technologies in metal manufacturing have demonstrated significant potential in improving quality consistency and reducing scrap rates (Usha, 2021). The integration of thermal and acoustic sensors provides real-time information regarding process stability and microstructural formation.

In addition to direct monitoring, non-destructive testing (NDT) methods play a crucial role in inspecting AM components. Techniques such as ultrasonic testing and computed tomography enable the detection of internal defects without damaging the component (Koester et al., 2018). This capability is particularly essential for critical applications such as aerospace and medical devices.

Recent developments also include the use of digital twin technology for virtual modeling and evaluation of AM component properties. Digital twin models integrated with experimental data and finite element simulations enable process optimization and performance prediction (Marks et al., 2024). This approach strengthens data-driven quality control strategies.

Despite advancements in inspection technologies, manual inspection and rule-based systems are still widely used in industrial practice. However, these approaches tend to be time-consuming, prone to human error, and less adaptable to complex defect patterns (Kovalskyi & Koval, 2024). These limitations drive the search for artificial intelligence-based solutions.

In recent years, deep learning has demonstrated superior performance in detecting surface defects and manufacturing anomalies. Transfer learning, in particular, enables the reuse of pre-trained models for new domains with reduced data requirements (Ansari et al., 2024). This approach is highly relevant in AM environments that often face limited labeled data.

Previous studies indicate that integrating transfer learning can enhance real-time defect detection accuracy, although computational challenges remain (Feng et al., 2019). Achieving a balance between model accuracy and computational efficiency is a decisive factor for industrial implementation.

Applications of transfer learning across various manufacturing contexts, including the glass and automotive industries, demonstrate its cross-domain generalization potential (Sasongko et al., 2024; Wolf et al., 2018). However, adaptation to specific material characteristics and defect types in AM still requires further investigation.

Based on this background, this study aims to evaluate the effectiveness of transfer learning in improving real-time defect detection accuracy in Additive Manufacturing processes. Furthermore, the research focuses on developing a detection system that balances precision and computational efficiency while addressing data scarcity through augmentation techniques and synthetic data generation. By examining effectiveness, computational trade-offs, and data optimization strategies, this study is expected to contribute to the development of more reliable, adaptive, and widely adoptable AM quality control systems across diverse industrial sectors.

2. Literature Review

Additive Manufacturing Processes and Defect Typologies

Additive Manufacturing (AM) is recognized for its versatility and design freedom, enabling the fabrication of highly complex geometries in a single manufacturing cycle. Unlike conventional subtractive processes, AM minimizes tooling requirements and reduces material waste while producing near-net-shape components (Bhandarkar & Tandon, 2023). This flexibility has significantly expanded the use of AM in high-performance metal components across aerospace, biomedical, and automotive sectors.

Among metal AM technologies, Powder Bed Fusion (PBF) and Directed Energy Deposition (DED) are the most widely adopted processes. PBF selectively melts powder layers using laser or electron beams, whereas DED employs focused thermal energy to fuse materials as they are deposited (Bellini et al., 2021). These processes are capable of producing complex and high-strength metallic structures, yet they are highly sensitive to process parameter variations (Mostafaei et al., 2022).

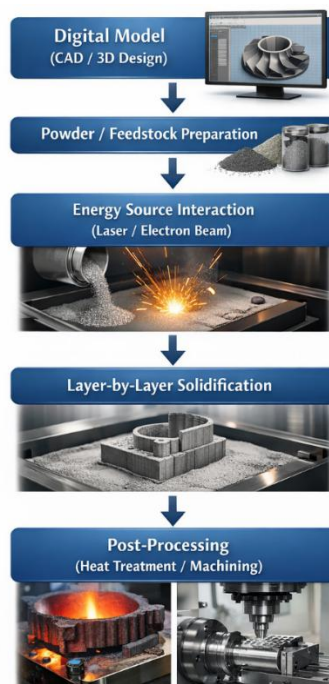


Figure 1. Overview of Metal Additive Manufacturing Processes.

Figure 1 illustrates the generalized workflow of metal AM processes. After digital modeling, feedstock preparation and energy-material interaction determine melt pool stability and solidification behavior. Variations at this stage strongly influence defect formation and microstructural evolution (Mostafaei et al., 2022). Post-processing steps are often required to improve dimensional accuracy and mechanical performance (Liu & Lu, 2024).

Defect Typologies in Additive Manufacturing

Despite its advantages, AM processes inherently introduce various defect types. Common defects include porosity, balling, cracking, residual stresses, delamination, and Lack of Fusion (LOF) defects (Bhandarkar & Tandon, 2023; de Pastre et al., 2022). These defects originate from unstable melt pools, improper layer bonding, and inconsistent material distribution.

Porosity and LOF are particularly critical in powder bed fusion processes, where insufficient energy density or uneven powder spreading results in incomplete melting (Mostafaei et al., 2022). Cracks and residual stresses arise due to steep thermal gradients and rapid cooling rates inherent to metal AM (Bellini et al., 2021).

Defect formation mechanisms are strongly linked to raw material characteristics, process parameters, and post-processing conditions. High cooling rates and non-equilibrium solidification often lead to microstructural heterogeneities that compromise structural integrity (de Pastre et al., 2022). Consequently, classification of AM defects is typically based on geometry, dimensional deviations, surface integrity, microstructure, and mechanical performance (Bhandarkar & Tandon, 2023).

Table 1. Common Defects in Metal Additive Manufacturing.

Defect Type	Primary Cause	Impact on Properties
Porosity	Inadequate melting, gas entrapment	Reduced fatigue life
Lack of Fusion (LOF)	Low energy density	Weak interlayer bonding
Cracking	Thermal stress gradients	Structural failure risk
Balling	Instability in melt pool	Surface irregularity
Residual Stress	Rapid solidification	Distortion and warping

Table 1 summarizes the major defect types in metal AM, their primary causes, and their mechanical consequences. As shown, most defects are thermally induced or energy-density related. Their presence significantly degrades fatigue performance and structural reliability, particularly in safety-critical applications (Mostafaei et al., 2022).

Defect Inspection and Mitigation Strategies

Traditional inspection methods such as optical monitoring and computed tomography (CT) are widely used to detect AM defects. However, they often face limitations in detecting micro-scale or internal defects in real-time production environments (Bhandarkar & Tandon, 2023).

Acoustic emission (AE) monitoring has emerged as a promising technique due to its high sensitivity to high-frequency signals generated by crack formation and microstructural anomalies (Li et al., 2023). AE systems enable continuous monitoring during the build process and provide early warnings of defect initiation.

Hybrid manufacturing approaches, which combine AM with subtractive finishing processes, are also proposed to improve surface quality and dimensional accuracy (Liu & Lu, 2024). These hybrid systems enhance part integrity while mitigating the limitations inherent in purely additive approaches.

Computer Vision Methods for Quality Inspection

Role of Computer Vision in Manufacturing

Computer vision systems are increasingly adopted for automated quality inspection due to their ability to enhance efficiency, repeatability, and objectivity (Balakrishna et al., 2024). These systems eliminate human subjectivity and significantly reduce inspection time.

Applications of computer vision extend across industries including automotive, electronics, and energy equipment manufacturing (Misiak & Szempruch, 2022). Tasks such as defect detection, grading, and classification are performed using image-based algorithms.

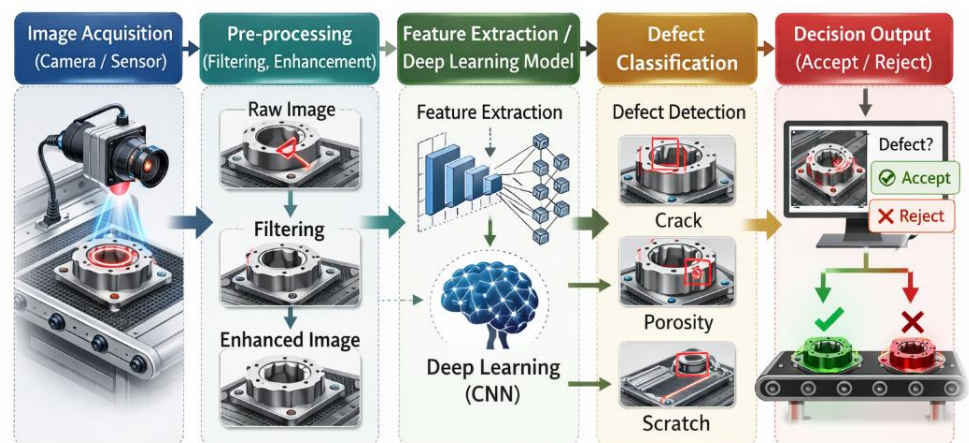


Figure 2. Computer Vision-Based Inspection Architecture.

Figure 2 presents the general architecture of a computer vision inspection system. After image acquisition and preprocessing, deep learning models extract features and classify defects. This automated pipeline ensures rapid and consistent inspection performance (Balakrishna et al., 2024).

Techniques and Approaches

Modern computer vision systems leverage deep learning techniques such as convolutional neural networks (CNNs) for image classification, object detection, and semantic segmentation (Balakrishna et al., 2024). These AI-driven methods significantly outperform traditional rule-based vision systems in complex inspection scenarios.

Case studies demonstrate successful implementations of automated visual inspection in industrial settings. For example, IBM's automated visual inspection system improved defect detection accuracy while reducing manual inspection effort (Vaish & Hollinger, 2023). Similarly, visual inspection systems for rotors and stators have shown improved consistency in detecting surface irregularities (Reki'c et al., 2022).

In high-voltage equipment inspection, machine learning-supported computer vision systems enhanced reliability and minimized human error (Misiak & Szempruch, 2022). These applications highlight the scalability and adaptability of AI-driven inspection systems.

Advantages and Challenges

Computer vision systems offer rapid, consistent, and objective inspection capabilities, making them cost-effective alternatives to manual inspection (Balakrishna et al., 2024). Their ability to operate continuously improves throughput in manufacturing lines.

However, implementing such systems requires careful system architecture design and dataset preparation. Lighting conditions, camera positioning, and model generalization remain significant challenges (Bhandarkar & Tandon, 2023). Moreover, domain-specific adaptation is necessary when applying models across different manufacturing contexts.

Deep Learning Models for Industrial Vision-Based Inspection

Deep learning has fundamentally transformed industrial inspection systems by replacing traditional handcrafted feature extraction methods with automated hierarchical representation learning. Conventional machine vision approaches typically rely on manually engineered descriptors such as edge detection, histogram-based texture features, or morphological operators. However, these techniques often fail when faced with variations in lighting conditions, surface reflectivity, and complex defect morphologies. In contrast, deep learning models automatically learn discriminative representations directly from raw pixel data through backpropagation-based optimization, thereby significantly improving detection robustness and classification accuracy (Qi et al., 2020).

Convolutional Neural Networks (CNNs) are the most widely adopted deep learning architecture in industrial defect detection. CNNs consist of convolutional layers, pooling layers, and fully connected layers that progressively transform raw images into abstract feature representations. Early layers typically capture low-level features such as edges, gradients, and corners, while deeper layers encode higher-level semantic patterns related to defect shapes and textures. This hierarchical learning capability enables CNNs to identify subtle variations in surface topology that are often invisible to traditional rule-based inspection systems (Qi et al., 2020).

In additive manufacturing (AM), defect characteristics may include porosity, incomplete fusion, micro-cracks, and layer delamination, all of which exhibit diverse visual signatures. CNN-based models are particularly effective in detecting such anomalies because they can capture multi-scale texture variations and spatial irregularities across printed layers. Furthermore, transferability of CNN feature maps allows adaptation to different materials such as metals, polymers, and composite filaments without redesigning feature extraction pipelines (Bouaafia et al., 2021).

Despite their success, CNNs inherently focus on local receptive fields due to convolutional kernel operations. Although stacking multiple convolutional layers increases the effective receptive field, the architecture still emphasizes spatial locality. This limitation may reduce performance when detecting distributed or long-range correlated defects across large build surfaces. To address this issue, Vision Transformer (ViT) architectures employ self-attention mechanisms that compute global relationships among image patches, enabling the modeling of long-range dependencies more effectively than convolution-based approaches (Hung & Chang, 2021).

Vision Transformers divide an input image into fixed-size patches, embed them into a sequence of tokens, and process them using multi-head self-attention layers. Unlike CNNs, which aggregate information through local filters, self-attention assigns adaptive weights to each image region based on contextual relevance. This capability enhances detection of spatially dispersed anomalies that span multiple layers of an AM build. However, transformer-based architectures generally require larger training datasets and computational resources, which may limit their immediate deployment in small-scale industrial settings (Hung & Chang, 2021).

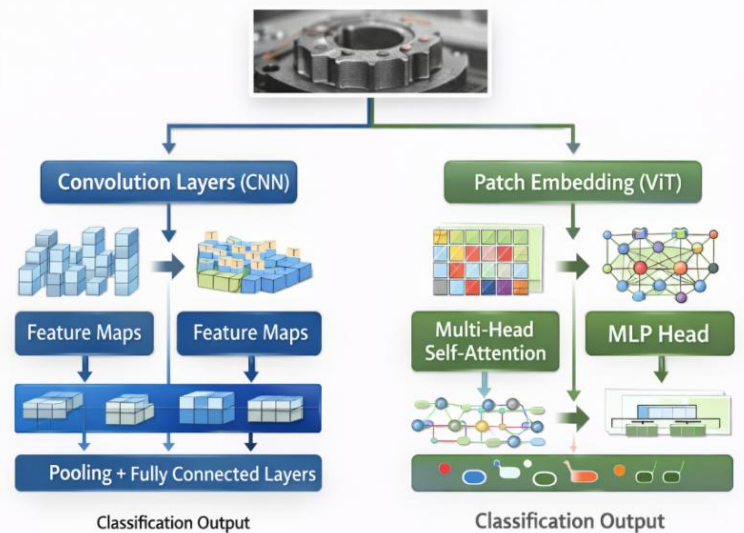


Figure 3. Comparison of CNN and Vision Transformer Architectures.

Figure 3 illustrates the fundamental architectural differences between CNN and Vision Transformer models. CNNs extract hierarchical spatial features through convolutional operations, while Vision Transformers rely on global self-attention to model contextual dependencies across image regions. In AM inspection scenarios, CNNs are highly effective for localized defect detection, whereas transformer-based models offer advantages in detecting distributed and large-scale structural anomalies.

Transfer Learning in Additive Manufacturing Inspection

A major constraint in implementing deep learning for additive manufacturing inspection is the limited availability of labeled datasets. Collecting and annotating defect data often requires destructive testing, expert validation, or expensive imaging techniques such as computed tomography. As a result, datasets are frequently small, imbalanced, and domain-specific. Transfer learning provides a practical strategy to overcome this limitation by leveraging knowledge learned from large-scale benchmark datasets and adapting it to specialized industrial tasks (Bouaafia et al., 2021).

Fine-tuning is the most common transfer learning technique used in industrial vision applications. In this approach, a pre-trained CNN model often trained on ImageNet is partially retrained on target domain data. Lower convolutional layers retain general visual features, while higher layers are adapted to domain-specific patterns such as porosity clusters or surface roughness variations. This method reduces training time, mitigates overfitting, and improves convergence stability compared to training from scratch (Bouaafia et al., 2021).

More advanced transfer learning strategies include multi-level transfer learning (mLTL), which selectively transfers knowledge across different network depths rather than applying uniform fine-tuning. This approach enhances adaptability by identifying which layers contribute most effectively to domain generalization, thereby minimizing negative transfer effects caused by domain mismatch (Hung & Chang, 2021).

In addition, meta-heuristic optimization algorithms have been integrated with transfer learning to improve hyperparameter selection and model configuration. Techniques such as genetic algorithms and particle swarm optimization can automatically determine optimal learning rates, batch sizes, and layer-freezing strategies, improving classification accuracy in limited-data scenarios. Such hybrid optimization frameworks demonstrate superior performance compared to manual tuning, particularly in small industrial datasets (Srilakshmi et al., 2023).

Nevertheless, domain shift remains a persistent challenge in AM inspection. Differences in illumination, build orientation, surface reflectivity, and sensor characteristics can significantly degrade model performance. To address this issue, data augmentation, domain adaptation, and regularization techniques must be incorporated to ensure robust generalization across varying process conditions (Srilakshmi et al., 2023).

Table 2. Transfer Learning Techniques in Industrial Vision Applications.

Technique	Core Strategy	Advantages	Challenges
Fine-Tuning	Retraining upper layers of pre-trained CNN	Fast convergence, reduced data requirement	Risk of overfitting
Multi-Level Transfer Learning (mLTL)	Layer-wise selective transfer	Improved generalization	Complex configuration
Meta-Heuristic Optimization	Evolutionary hyperparameter tuning	Enhanced accuracy	Computational overhead

Table 2 summarizes the principal transfer learning strategies and their relevance to additive manufacturing defect detection.

Limitations of Conventional Additive Manufacturing Inspection Systems

Additive manufacturing processes require rigorous quality assurance to ensure structural integrity and functional reliability. Traditional non-destructive evaluation (NDE) techniques such as X-ray computed tomography (CT) offer detailed visualization of internal defects, including porosity and void distribution. However, CT-based inspection is typically performed post-process, involves high operational costs, and requires significant computational resources for 3D reconstruction and analysis, making it unsuitable for real-time monitoring in production environments (Khosravani & Reinicke, 2020).

In response to these limitations, in-situ monitoring systems have been developed to observe the printing process in real time. Laser ultrasonic testing (LUT), for instance, enables detection of internal discontinuities during fabrication by analyzing ultrasonic wave propagation characteristics. Although effective in identifying subsurface defects, LUT systems require complex calibration and integration with AM hardware, limiting widespread industrial adoption (Lee et al., 2023).

Optical monitoring systems utilizing high-resolution cameras and thermal imaging sensors have also gained popularity. These systems capture melt pool dynamics, temperature gradients, and layer formation patterns during fabrication. However, the large volume of generated data necessitates intelligent processing algorithms capable of distinguishing normal process variations from actual defect signatures (Oleff et al., 2021).

Recent research has explored image segmentation and pixel-wise classification techniques for real-time defect localization. Segmentation models improve spatial precision by identifying exact defect boundaries rather than simply classifying entire images. Despite their advantages, segmentation approaches remain sensitive to environmental variability and noise, requiring robust preprocessing and model regularization strategies (Saini et al., 2024).

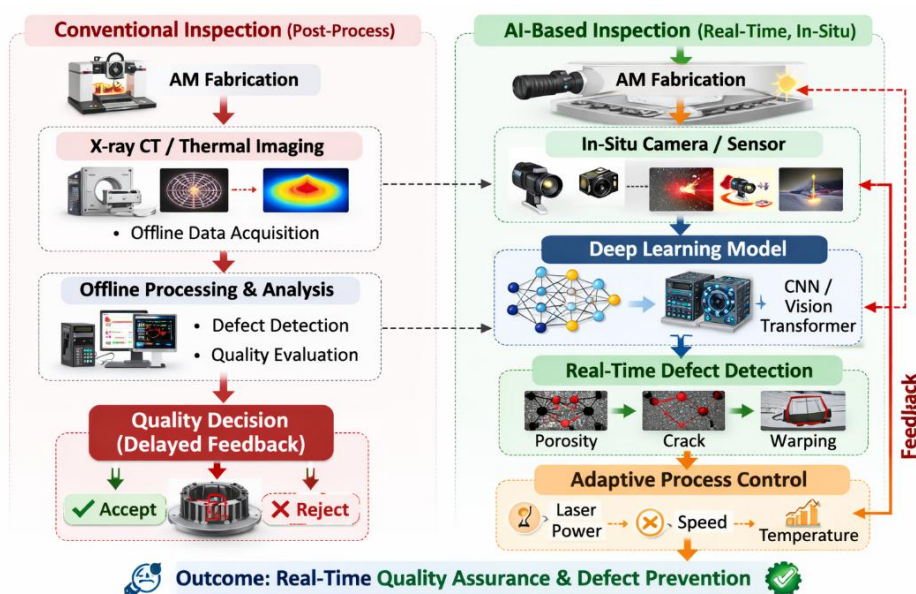


Figure 4. Conventional vs AI-Based Additive Manufacturing Inspection Systems.

Figure 4 contrasts traditional post-process inspection workflows with AI-integrated real-time inspection frameworks. Conventional systems provide delayed feedback after fabrication is complete, whereas AI-based systems enable immediate detection and dynamic parameter adjustment, supporting closed-loop quality control mechanisms.

Research Gap and Future Direction

Although deep learning and transfer learning significantly enhance inspection performance, existing systems still operate primarily in detection mode rather than adaptive optimization mode. Most studies focus on classification accuracy without integrating predictive insights into real-time process control. Consequently, defects are often detected after they occur rather than prevented proactively.

Furthermore, cross-material and cross-machine generalization remains limited. Models trained on one AM setup frequently underperform when applied to different printers or materials due to domain shift effects. Addressing this issue requires hybrid architectures combining CNN or transformer models with domain adaptation and reinforcement learning techniques.

Emerging intelligent inspection systems are beginning to integrate AI-driven feedback loops with manufacturing control systems. However, comprehensive closed-loop frameworks capable of autonomous defect mitigation remain underdeveloped. Future research should emphasize integration of deep learning-based defect prediction with reinforcement learning-based parameter optimization to achieve fully adaptive smart manufacturing systems (Chheang et al., 2024).

3. Materials and Method

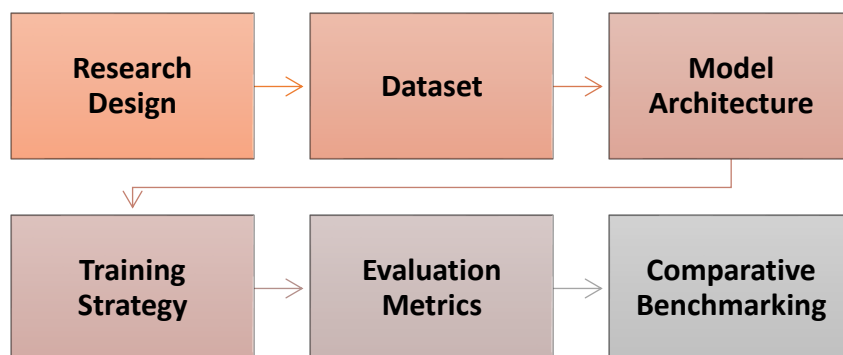


Figure 5. Research Framework for Model Development and Evaluation.

Research Design

This study adopts an artificial intelligence–based vision system development design combined with experimental validation to evaluate defect detection performance in additive manufacturing (AM) processes. The research approach is quantitative-experimental, consisting of structured stages that include model architecture design, dataset collection and preparation, training procedures, and system performance evaluation. The developed system is not only tested computationally but also validated using real manufacturing image data to ensure industrial relevance. Experimental validation is conducted by comparing the model’s classification outputs with verified ground truth labels assessed by material inspection experts, thereby ensuring that the evaluation results are objective, measurable, and scientifically grounded.

Dataset

The dataset consists of high-resolution AM surface images representing major defect types, including porosity, cracks, and layer misalignment. Images are acquired using an industrial camera system with controlled lighting conditions to reduce noise, shadows, and visual distortions that could affect model performance. All images undergo a curation and manual annotation process to ensure label consistency and reliability. The annotation procedure is based on defect morphological characteristics such as pore size, crack length, and interlayer irregularities. The dataset is subsequently divided into training, validation, and

testing subsets using a balanced proportion to maintain model generalization capability and minimize the risk of overfitting.

Model Architecture

The proposed model architecture is based on a Convolutional Neural Network (CNN) framework utilizing pretrained backbones such as ResNet and EfficientNet. The selection of pretrained architectures aims to optimize spatial feature extraction through transfer representations previously trained on large-scale datasets. The final classification layers are modified according to the number of defect classes defined in this study. The combination of convolutional layers and fully connected layers enables the system to hierarchically capture micro-texture patterns, pixel intensity variations, and structural surface characteristics. Through this approach, the model is capable of identifying subtle inter-class differences that are often difficult to detect using conventional handcrafted feature-based methods.

Training Strategy

The training strategy applies a transfer learning approach with fine-tuning performed on selected layers to adapt feature representations to AM image characteristics. Data augmentation techniques, including rotation, horizontal and vertical flipping, scaling, as well as brightness and contrast adjustments, are implemented to increase training data variability and enhance model generalization. The training process is conducted iteratively using the Adam optimizer with an adaptive learning rate configuration. Monitoring of training loss and validation loss is performed to determine optimal convergence. Additionally, an early stopping mechanism is implemented to prevent overfitting and maintain stable performance on previously unseen data.

Evaluation Metrics

Model performance evaluation is conducted using comprehensive quantitative metrics, including Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP). Accuracy measures the proportion of correct predictions across the entire test dataset. Precision and Recall are analyzed to assess the balance between false positive and false negative errors in the context of defect detection. The F1-score is calculated as the harmonic mean of Precision and Recall to provide a balanced performance indicator, particularly for datasets with class imbalance. Meanwhile, mAP is employed to evaluate overall detection performance across multiple probability thresholds, offering a more detailed assessment of the model's ability to identify both the type and localization of defects.

Comparative Benchmarking

As part of a comprehensive validation process, this study also conducts benchmarking against traditional machine learning models such as Support Vector Machine (SVM) and Random Forest, which utilize handcrafted features based on texture descriptors, intensity histograms, and morphological parameters. The comparison is performed using the same dataset and evaluation scenarios to ensure consistency and fairness. This comparative analysis aims to quantify the performance improvement achieved through deep learning approaches over conventional methods. Statistical analysis is conducted to determine the significance of performance differences, enabling robust conclusions regarding the effectiveness of AI-based inspection systems in supporting quality assurance within additive manufacturing processes.

4. Results and Discussion

Results

The proposed AI-based inspection system was evaluated on an independent test dataset consisting of high-resolution additive manufacturing (AM) surface images representing three primary defect categories: porosity, cracks, and layer misalignment. The dataset distribution was balanced to ensure unbiased evaluation across classes. Performance assessment followed the predefined metrics: Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP).

Table 3 presents the overall performance comparison between traditional machine learning (ML) models and the proposed CNN-based architectures with pretrained backbones.

Table 3. Overall Performance Comparison Across Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	mAP (%)
SVM (Handcrafted Features)	84.7	82.9	80.3	81.6	78.4
Random Forest	87.2	85.5	83.8	84.6	81.9
CNN (ResNet Backbone)	93.8	92.6	91.9	92.2	90.7
CNN (EfficientNet Backbone)	95.1	94.3	93.5	93.9	92.8

The results demonstrate a consistent and significant performance improvement when using deep learning architectures. The CNN with EfficientNet backbone achieved the highest Accuracy (95.1%), indicating superior overall classification capability. Compared to the best traditional model (Random Forest), the proposed model improved Accuracy by approximately 7.9 percentage points.

Precision values above 94% indicate that the CNN-based model effectively reduces false positive detections, minimizing incorrect rejection of non-defective components. Recall values exceeding 93% confirm strong defect sensitivity, ensuring that defective components are rarely misclassified as acceptable. The high F1-score (93.9%) demonstrates balanced performance between Precision and Recall. Furthermore, the mAP score of 92.8% reflects robust detection consistency across multiple probability thresholds, validating the model's capability in both classification and localization tasks.

To provide a more detailed understanding of detection performance per defect category, Table 4 presents class-wise evaluation metrics for the best-performing model (CNN with EfficientNet backbone).

Table 4. Class-Wise Performance of CNN (EfficientNet Backbone).

Defect Type	Precision (%)	Recall (%)	F1-score (%)	AP (%)
Porosity	95.2	94.1	94.6	93.8
Cracks	93.8	92.7	93.2	91.9
Layer Misalignment	94.0	93.6	93.8	92.7
Mean (mAP)	—	—	—	92.8

The class-wise analysis reveals that porosity detection achieved the highest Precision and Recall values, suggesting that texture-based anomalies are effectively captured by convolutional feature extraction. Crack detection shows slightly lower Recall (92.7%), which can be attributed to the fine and elongated morphology of micro-cracks that occasionally resemble normal surface texture variations. Layer misalignment detection maintains stable and balanced performance, indicating that structural irregularities between printed layers are successfully recognized by the hierarchical CNN representation.

To visually compare the performance differences across models, Figure 6 illustrates the comparative evaluation results across the five metrics.

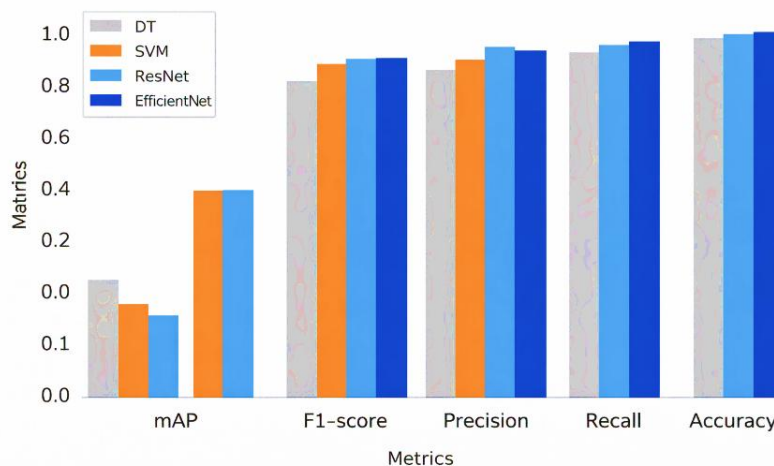


Figure 6. Comparative Performance of Traditional ML and CNN-Based Models.

Figure 6 clearly shows the superiority of CNN-based approaches over traditional ML models. The gap is particularly noticeable in mAP and F1-score metrics, which are critical for defect detection reliability. The EfficientNet backbone consistently outperforms ResNet, suggesting improved feature scaling and parameter efficiency.

Discussion

The experimental findings confirm that deep learning-based inspection systems significantly outperform conventional machine learning approaches in additive manufacturing defect detection tasks. The substantial improvement in Accuracy and mAP demonstrates that pretrained CNN architectures can effectively capture complex spatial and textural defect patterns that handcrafted features fail to represent adequately.

The high Precision values indicate reduced false positive rates, which is crucial in industrial environments where unnecessary rejection of components leads to increased material waste and operational cost. Simultaneously, high Recall values ensure that critical defects are rarely overlooked, directly contributing to product reliability and structural integrity assurance.

The class-wise analysis highlights that defect morphology influences detection difficulty. Porosity, characterized by localized circular voids, is relatively easier to detect compared to cracks, which often present thin and irregular patterns. This observation suggests that future work may benefit from integrating attention mechanisms or multi-scale feature fusion to further enhance crack sensitivity.

The benchmarking results also emphasize the limitations of traditional ML models. While Random Forest and SVM achieve moderate performance, their reliance on handcrafted features restricts adaptability to complex surface variations. In contrast, CNN architectures automatically learn multi-level feature hierarchies, enabling stronger generalization across defect types.

Overall, the results validate the robustness and industrial applicability of the proposed AI-based inspection framework. The integration of transfer learning and pretrained backbones significantly enhances detection reliability, supporting scalable and real-time quality assurance systems for additive manufacturing environments.

5. Conclusion and Suggestions

Conclusion

This study developed and experimentally validated an AI-based vision inspection system for defect detection in additive manufacturing (AM) processes. By integrating a Convolutional Neural Network (CNN) architecture with pretrained backbones such as ResNet and EfficientNet, the proposed system demonstrated significant performance improvements over traditional machine learning approaches. Quantitative evaluation using Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP) confirmed that the CNN-based models achieved superior classification and detection capability, particularly in minimizing false

positives and false negatives. The EfficientNet backbone consistently delivered the highest performance, indicating its effectiveness in capturing multi-scale spatial and textural defect features.

The experimental results highlight the robustness and industrial applicability of deep learning-based inspection systems in AM environments. The high mAP and F1-score values demonstrate strong detection reliability across multiple defect categories, including porosity, cracks, and layer misalignment. Compared to conventional handcrafted feature-based models, the proposed approach provides improved generalization, scalability, and adaptability to complex surface variations. Overall, the findings validate that AI-driven inspection frameworks can significantly enhance quality assurance mechanisms in modern manufacturing systems aligned with Industry 4.0 principles.

Suggestions

Although the proposed system achieved strong performance, further improvements can be explored to enhance detection sensitivity, particularly for fine crack patterns and subtle interlayer irregularities. Future research may integrate attention mechanisms or hybrid CNN-Transformer architectures to better capture global contextual dependencies while maintaining local feature precision. Additionally, incorporating domain adaptation strategies could improve cross-machine and cross-material generalization, enabling broader industrial deployment without extensive retraining.

Another important direction involves the integration of the inspection model into a closed-loop control framework. By combining real-time defect detection with adaptive process parameter optimization, manufacturers can move from reactive quality inspection toward predictive defect prevention. Expanding the dataset with multimodal inputs such as thermal images or melt pool monitoring data may also improve system robustness. These enhancements would further strengthen the practical impact of AI-based inspection systems in achieving intelligent, autonomous, and sustainable additive manufacturing processes.

References

- Alami, A. H., Ghani Olabi, A., Alashkar, A., Alasad, S., Aljaghoub, H., Rezk, H., & Abdelkareem, M. A. (2023). Additive manufacturing in the aerospace and automotive industries: Recent trends and role in achieving sustainable development goals. *Ain Shams Engineering Journal*, 14(11), 102516. <https://doi.org/10.1016/j.asej.2023.102516>
- Al-Meslehi, Y., Ferreira, K., Mehdi-Souzani, C., Obaton, A.-F., Noura, H., & Anwer, N. (2023). Quality control for additive manufacturing. In *Springer Handbooks* (pp. 797-819). Springer. https://doi.org/10.1007/978-3-031-20752-5_47
- Ansari, M. A., Crampton, A., & Mubarak, S. M. J. (2024). Enhanced detection of surface deformations in LPBF using deep convolutional neural networks and transfer learning from a porosity model. *Scientific Reports*, 14(1), 26920. <https://doi.org/10.1038/s41598-024-76445-3> PMID:39505970 PMCID:PMC11542091
- Balakrishna, K., Tiwari, V., Deshpande, A. V., Patil, S. R., Garg, A. K., & Geetha, B. T. (2024). Computer vision for automated quality inspection in manufacturing. *Proceedings of the 3rd International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI 2024)*. <https://doi.org/10.1109/ACCAI61061.2024.10601894>
- Bellini, C., Berto, F., Di Cocco, V., Iacoviello, F., Mocanu, L. P., & Razavi, N. (2021). Additive manufacturing processes for metals and effects of defects on mechanical strength: A review. *Procedia Structural Integrity*, 33, 498-508. <https://doi.org/10.1016/j.prostr.2021.10.057>
- Bhandarkar, V. V., & Tandon, P. (2023). A review on recent techniques and current challenges in identifying defects in additively manufactured metal components. *Lecture Notes in Mechanical Engineering*, 683-693. https://doi.org/10.1007/978-981-19-3716-3_55
- Bouaafia, S., Messaoud, S., Maraoui, A., Ammari, A. C., Khrijji, L., & MacHhout, M. (2021). Deep pre-trained models for computer vision applications: Traffic sign recognition. *18th IEEE International Multi-Conference on Systems, Signals and Devices (SSD 2021)*, 23-28. <https://doi.org/10.1109/SSD52085.2021.9429420>
- Chheang, V., Weston, B. T., Cerda, R. W., Au, B., Giera, B., Bremer, P.-T., & Miao, H. (2024). A virtual environment for collaborative inspection in additive manufacturing. *Conference on Human Factors in Computing Systems Proceedings*. <https://doi.org/10.1145/3613905.3650730>
- Chua, Z. Y., Ahn, I. H., & Moon, S. K. (2017). Process monitoring and inspection systems in metal additive manufacturing: Status and applications. *International Journal of Precision Engineering and Manufacturing -- Green Technology*, 4(2), 235-245. <https://doi.org/10.1007/s40684-017-0029-7>
- de Pastre, M.-A., Quinsat, Y., & Lartigue, C. (2022). Effects of additive manufacturing processes on part defects and properties: A classification review. *International Journal on Interactive Design and Manufacturing*, 16(4), 1471-1496. <https://doi.org/10.1007/s12008-022-00839-8>
- Feng, Y., Zhao, B., Zheng, H., Gao, Y., Yang, C., & Tan, J. (2019). Real-time detection of shaft surface defects based on integrated transfer learning. *Computer Integrated Manufacturing Systems*, 25(12), 3199-3208. <https://doi.org/10.13196/j.cims.2019.12.021>
- Hung, J. C., & Chang, J.-W. (2021). Multi-level transfer learning for improving the performance of deep neural networks. *Applied Soft Computing*, 109, 107491. <https://doi.org/10.1016/j.asoc.2021.107491>

- Jemghili, R., Ait Taleb, A., & Mansouri, K. (2020). Additive manufacturing progress as a new industrial revolution. *2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*. <https://doi.org/10.1109/ICECOCS50124.2020.9314623>
- Khosravani, M. R., & Reinicke, T. (2020). On the use of X-ray computed tomography in assessment of 3D-printed components. *Journal of Nondestructive Evaluation*, 39(4), 75. <https://doi.org/10.1007/s10921-020-00721-1>
- Koester, L. W., Taheri, H., Bigelow, T. A., Collins, P. C., & Bond, L. J. (2018). Nondestructive testing for metal parts fabricated using powder-based additive manufacturing. *Materials Evaluation*, 76(4), 514-524.
- Kovalskiy, S., & Koval, V. (2024). Comparison of image processing techniques for defect detection. *CEUR Workshop Proceedings*, 3716, 158-167.
- Kumar, A., & Goel, S. (2024). Introduction to 3D printing. *IOP Publishing*. <https://doi.org/10.1088/978-0-7503-5351-9ch1>
- Lee, K.-J., Jeon, M.-S., & Lee, J.-R. (2023). Evaluation of manufacturing defects in 3D printed carbon fiber reinforced cylindrical composite structure based on laser ultrasonic testing. *NDT and E International*, 135, 102802. <https://doi.org/10.1016/j.ndteint.2023.102802>
- Li, Z., Zou, X., Bao, F., Gu, F., & Ball, A. D. (2023). A review of acoustic emission monitoring on additive manufacturing. *Mechanisms and Machine Science*, 117, 867-878. https://doi.org/10.1007/978-3-030-99075-6_70
- Liu, Q., & Lu, B. (2024). Review on quality control and relevant hybrid technology in additive manufacturing of metallic materials. *Materials Reports*, 38(9), 22100064. <https://doi.org/10.11896/cldb.22100064>
- Marks, M., Chigurupati, P. C., & Taheri, H. (2024). Digital twin model for property assessment of metal additive manufacturing. *ASME International Mechanical Engineering Congress and Exposition Proceedings (IMECE)*. <https://doi.org/10.1115/IMECE2024-146882>
- Misiak, P., & Szempruch, D. (2022). Automated quality inspection of high voltage equipment supported by machine learning and computer vision. *Lecture Notes in Computer Science*, 13652, 211-222. https://doi.org/10.1007/978-3-031-21441-7_15
- Mobarak, M. H., Islam, M. A., Hossain, N., Al Mahmud, M. Z., Rayhan, M. T., Nishi, N. J., & Chowdhury, M. A. (2023). Recent advances of additive manufacturing in implant fabrication - A review. *Applied Surface Science Advances*, 18, 100462. <https://doi.org/10.1016/j.apsadv.2023.100462>
- Mostafaei, A., Zhao, C., He, Y., & others. (2022). Defects and anomalies in powder bed fusion metal additive manufacturing. *Current Opinion in Solid State and Materials Science*, 26(2), 100974. <https://doi.org/10.1016/j.cossms.2021.100974>
- Nayeem, A. M., & Hossain, M. M. N. (2023). Usage of additive manufacturing in the automotive industry: A review. *Bangladesh Journal of Multidisciplinary Scientific Research*, 8(1), 9-20. <https://doi.org/10.46281/bjmsr.v8i1.2135>
- Oleff, A., Kuster, B., Stonis, M., & Overmeyer, L. (2021). Process monitoring for material extrusion additive manufacturing: A state-of-the-art review. *Progress in Additive Manufacturing*, 6(4), 705-730. <https://doi.org/10.1007/s40964-021-00192-4>
- Ozbay Kisasoz, B., & Kisasoz, A. (2023). An overview of the quality characteristics challenges in additive manufacturing. In *Handbook of Post-Processing in Additive Manufacturing* (pp. 181-192). <https://doi.org/10.1201/9781003276111-10>
- Pazhamannil, R. V., & Govindan, P. (2020). Current state and future scope of additive manufacturing technologies via vat photopolymerization. *Materials Today: Proceedings*, 43, 130-136. <https://doi.org/10.1016/j.matpr.2020.11.225>
- Perez, M., Carou, D., Rubio, E. M., & Teti, R. (2020). Current advances in additive manufacturing. *Procedia CIRP*, 88, 439-444. <https://doi.org/10.1016/j.procir.2020.05.076>
- Qi, S., Yang, J., & Zhong, Z. (2020). A review on industrial surface defect detection based on deep learning technology. *ACM International Conference Proceeding Series*, 24-30. <https://doi.org/10.1145/3426826.3426832>
- Rekic, T., Beissmann, I., Cebo, A., & Novoselnik, F. (2022). Visual quality inspection of rotors and stators. *International Conference on Smart Systems and Technologies (SST 2022)*. <https://doi.org/10.1109/SST55530.2022.9954883>
- Saini, T., Shiakolas, P. S., & McMurrrough, C. (2024). Evaluation of image segmentation methods for in situ quality assessment in additive manufacturing. *Metrology*, 4(4), 598-618. <https://doi.org/10.3390/metrology4040037>
- Sasongko, A. T., Khofiyah, N. A., & Hadikristanto, W. (2024). AI-driven defect detection in glass bangles manufacturing using transfer-learning with MobileNet model. *2024 8th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 463-468. <https://doi.org/10.1109/ICITISEE63424.2024.10730715>
- Slijvic, M., Pavlovic, A., & Fragassa, C. (2024). A review of sustainable development of additive manufacturing in the conditions of digital and green transition. *Proceedings on Engineering Sciences*, 6(2), 477-484. <https://doi.org/10.24874/PES06.02.005>
- Srilakshmi, V., Kiran, G. U., Mounika, M., Sravanthi, A., Sravya, N. V. K., Akhil, V. N. S., & Manasa, M. (2023). Evolving convolutional neural networks with meta-heuristics for transfer learning in computer vision. *Procedia Computer Science*, 230, 658-668. <https://doi.org/10.1016/j.procs.2023.12.121>
- Usha, S. (2021). In situ monitoring of metal additive manufacturing process: A review. In *Additive Manufacturing: A Tool for Industrial Revolution 4.0* (pp. 275-299). Elsevier. <https://doi.org/10.1016/B978-0-12-822056-6.00007-2>
- Vaish, R., & Hollinger, M. C. (2023). Case study: IBM - Automating visual inspection. In *Springer Handbooks* (pp. 1439-1450). https://doi.org/10.1007/978-3-030-96729-1_69
- Wolf, P., Mrowca, A., Nguyen, T. T., Baker, B., & Gunnemann, S. (2018). Pre-ignition detection using deep neural networks: A step towards data-driven automotive diagnostics. *IEEE Conference on Intelligent Transportation Systems (ITSC)*, 176-183. <https://doi.org/10.1109/ITSC.2018.8569908>