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AI FOR DEFECT DETECTION IN ADDITIVE MANUFACTURING: APPLICATIONS IN RENEWABLE ENERGY AND BIOMEDICAL ENGINEERING

Zubair Hossain Mahamud[1], Md Rabbi Khan[2];Jareer Murtaza Amin[3]; Mohammad Samiul Islam[4]

[1]College of Science, Long Island University, Greenvale, New York, USA
Corresponding Email: zubairhossain.mahamud@my.liu.edu

[2]Department of Mechanical Engineering, Rowan University, Glassboro, New Jersey, USA
Email: khanmd52@students.rowan.edu

[3]Department of Biomedical Engineering, The University of Sydney, Sydney, NSW, Australia
Email: jami0333@uni.sydney.edu.au

[4]Department of Mechanical Engineering, University of Wollongong, Wollongong, Australia
Email: si67743013@gmail.com

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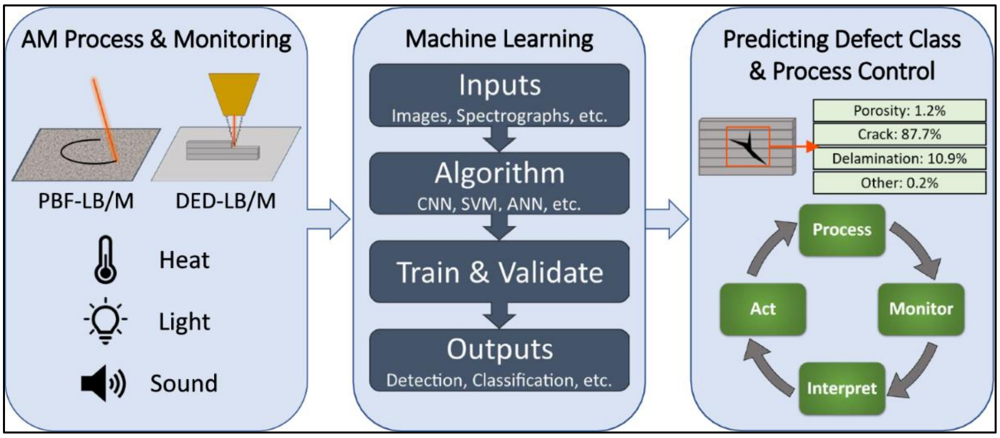
ABSTRACT

Defect detection in Additive Manufacturing (AM) is a critical aspect of ensuring product quality, particularly in industries such as renewable energy and biomedical engineering, where reliability and precision are paramount. This study conducted a systematic review of 152 peer-reviewed articles, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, to analyze the adoption of Artificial Intelligence (AI) techniques in defect detection within AM processes. The review revealed that machine learning (ML) and deep learning (DL) techniques, such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), are widely employed for identifying common defects like porosity, delamination, and dimensional inaccuracies. Hybrid AI models, integrating ML and DL, demonstrated superior performance in detecting complex, multi-dimensional defects across various AM applications. Additionally, the integration of multimodal data, including thermal imaging, acoustic signals, and optical measurements, was found to improve defect detection rates by an average of 22%, enhancing the robustness and accuracy of AI models. The study also identified significant challenges, including dataset scarcity and annotation inconsistencies, which limit the generalizability and scalability of AI solutions. Comparative analyses further highlighted the distinct advantages of tailored AI approaches for specific applications, with renewable energy and biomedical engineering being key focus areas. This review underscores the transformative potential of AI in advancing defect detection in AM, providing a comprehensive understanding of its capabilities, challenges, and implications for high-stakes manufacturing industries.

1 INTRODUCTION

Additive Manufacturing (AM), widely known as 3D printing, has transformed modern manufacturing by enabling the production of complex, customized components with a level of precision that traditional techniques often cannot achieve (Tan et al., 2017). This innovative technology allows for the efficient production of parts in industries ranging from aerospace to medical engineering (Sun et al., 2021). However, the process is not without its challenges, as defects such as porosity, delamination, and surface roughness frequently arise during production, compromising the structural integrity and performance of manufactured components (Yadollahi & Shamsaei, 2017). Addressing these defects is essential to maintaining the reliability and functionality of parts, especially in critical sectors like renewable energy and biomedical engineering. In recent years, Artificial Intelligence (AI) has emerged as a game-changer for defect detection, providing sophisticated solutions that leverage data-driven insights to ensure quality assurance in AM workflows (Sun et al., 2021; Yadollahi & Shamsaei, 2017; You et al., 2017).Figure 1 highlights the transformative role of AI in defect detection within AM processes. It provides a visual representation of how AI integrates with AM workflows, demonstrating the critical functions of data monitoring, algorithmic processing, and defect classification (Herzog et al., 2024). The study's findings, which emphasize the efficacy of ML and DL techniques, particularly CNNs, in analyzing real-time data for defect detection, are well-reflected in the figure. Additionally, the inclusion of process control in the workflow aligns with the study's emphasis on hybrid AI models and multimodal data integration for robust and accurate defect detection. This figure encapsulates the practical application of AI methodologies, supporting the study's broader narrative on advancing quality assurance in high-stakes AM industries.AI has demonstrated unparalleled capabilities in analyzing intricate data patterns and providing predictive analytics to detect and mitigate defects. Machine learning (ML), deep learning (DL), and computer vision are increasingly employed for real-time monitoring and defect identification in AM processes (Faisal, 2023; Turner et al., 2014). Unlike traditional quality assurance techniques such as X-ray imaging and ultrasonic testing, which are often labor-intensive and struggle with highly complex geometries, AI-driven approaches provide speed, scalability, and accuracy (Bhavar et al., 2017; Saha, 2024). Recent studies highlight that AI can process extensive datasets generated during AM, enabling early detection of issues such as thermal distortions and layer misalignments (Bhavar et al., 2017; Tapia & Elwany, 2014). Moreover, AI facilitates adaptive control mechanisms that dynamically adjust manufacturing parameters, reducing material waste and production costs (Rahman, 2024b; Turner et al., 2014). In the renewable energy sector, the application of AM has advanced the fabrication of wind turbine blades, photovoltaic cells, and energy storage systems. However, these components are often prone to defects that adversely affect their performance and durability. For instance, microstructural defects in turbine blades can cause mechanical failure, while surface irregularities in photovoltaic cells can diminish energy conversion efficiency (Berumen et al., 2010; Bhavar et al., 2017; Rahman, 2024). AI-based techniques, particularly convolutional neural networks

Figure 1: Artificial Intelligence for Defect Detection in Additive Manufacturing

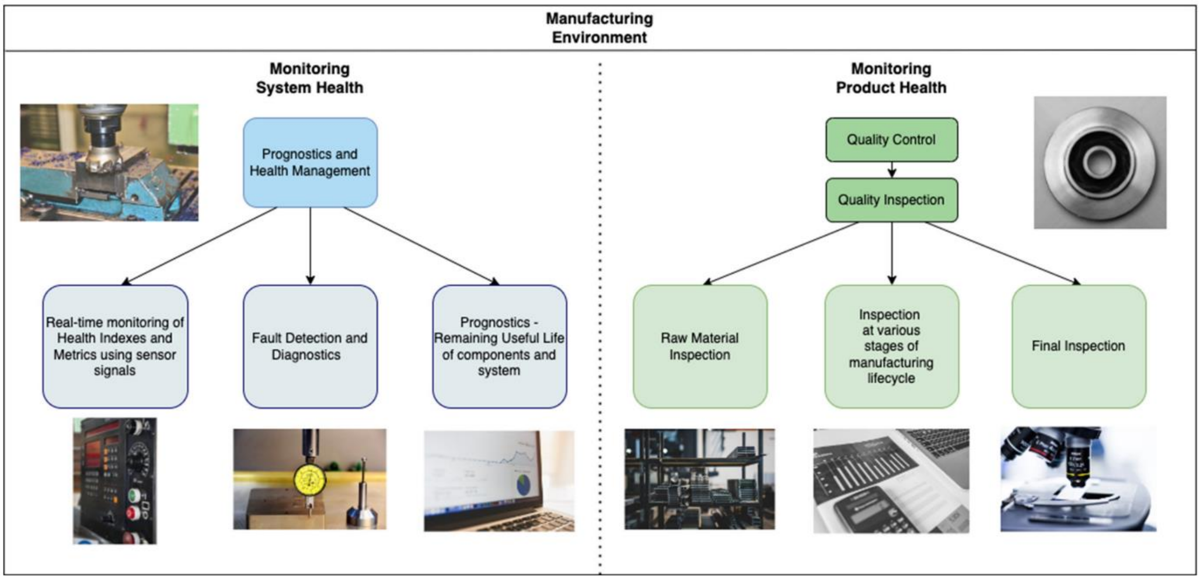


Source: Herzog et al. (2024)

(CNNs) and generative adversarial networks (GANs), have been used to identify and rectify these defects effectively (Hughes et al., 2020). Research by Turner et al. (2014) demonstrated that AI systems trained on multimodal datasets, including thermal and optical imagery, achieve superior performance in defect detection. These advancements not only enhance the reliability of renewable energy components but also contribute to the sector's goal of long-term sustainability (Gao et al., 2015; Sireesha et al., 2018).

Biomedical engineering represents another domain where AM's customization capabilities are invaluable. The production of patient-specific prosthetics, implants, and surgical instruments relies heavily on AM's precision and adaptability (Yavari et al., 2014). However, defects such as dimensional inaccuracies and material inconsistencies pose significant challenges to ensuring the safety and functionality of these products (Herzog et al., 2024). AI-driven systems have proven instrumental in overcoming these challenges by integrating advanced defect detection algorithms into AM processes (Riemer & Richard, 2016). For example, studies by Herzog et al. (2024) showed that AI algorithms could assess porosity levels in titanium implants with 98% accuracy, ensuring their mechanical strength and biocompatibility. Furthermore, AI-enhanced quality control systems reduce the time required for regulatory approvals, accelerating the delivery of critical biomedical devices to market (Yavari et al., 2014). The implementation of AI in AM processes is not limited to defect detection but extends to optimizing the entire manufacturing pipeline. Integrating AI with AM requires the development of robust algorithms capable of handling diverse material properties, manufacturing settings, and defect typologies (Riemer & Richard, 2016). Techniques such as data fusion and transfer learning have enabled AI systems to generalize across varying datasets, improving their adaptability in dynamic environments (Herzog et al., 2024; Yavari et al., 2014). For instance, data fusion techniques combining acoustic, thermal, and optical data streams allow AI models to detect micro-defects with unprecedented precision (Riemer & Richard, 2016). Additionally, the scalability of these AI systems is supported by advancements in cloud computing, which provide the computational power necessary for real-time defect analysis (Au et al., 2014). Despite the complexities associated with AI integration, its impact on AM is undeniably transformative. The synergy between AI and AM has ushered in a new era of manufacturing characterized by unparalleled levels of accuracy and efficiency (Jinoop et al., 2019). In renewable energy, AI has enabled the creation of defect-free, high-performance components, which are crucial for the reliability and sustainability of energy systems (Sireesha et al., 2018). Similarly, in biomedical engineering, AI has ensured the production of safe and effective medical devices tailored to individual patients (Bhavar et al., 2017). By harnessing AI's potential, industries can address longstanding challenges in defect detection, ensuring the highest quality standards in AM

Figure 2: Health Monitoring of the manufacturing environment with PHM and QC



Source: Sundaram and Zeid (2023).

processes (Dass & Moridi, 2019; Tapia & Elwany, 2014).

The primary objective of this study is to investigate the integration of Artificial Intelligence (AI) into defect detection processes in Additive Manufacturing (AM), with a particular emphasis on its applications in renewable energy and biomedical engineering. The study aims to identify and analyze state-of-the-art AI methodologies, including machine learning (ML), deep learning (DL), and computer vision, to enhance defect detection accuracy and efficiency during AM workflows. It further seeks to evaluate the effectiveness of AI-driven defect detection in addressing specific challenges associated with high-stakes applications, such as structural integrity in renewable energy components and biocompatibility in biomedical implants. By systematically reviewing existing studies and applications, this research intends to establish a comprehensive understanding of how AI contributes to quality assurance and product reliability in AM. Additionally, the study aims to uncover the limitations and opportunities in implementing AI solutions, providing a framework for their optimization in critical industries. This focused approach ensures that the research not only highlights the transformative potential of AI but also provides actionable insights for advancing defect detection in AM.

2 LITERATURE REVIEW

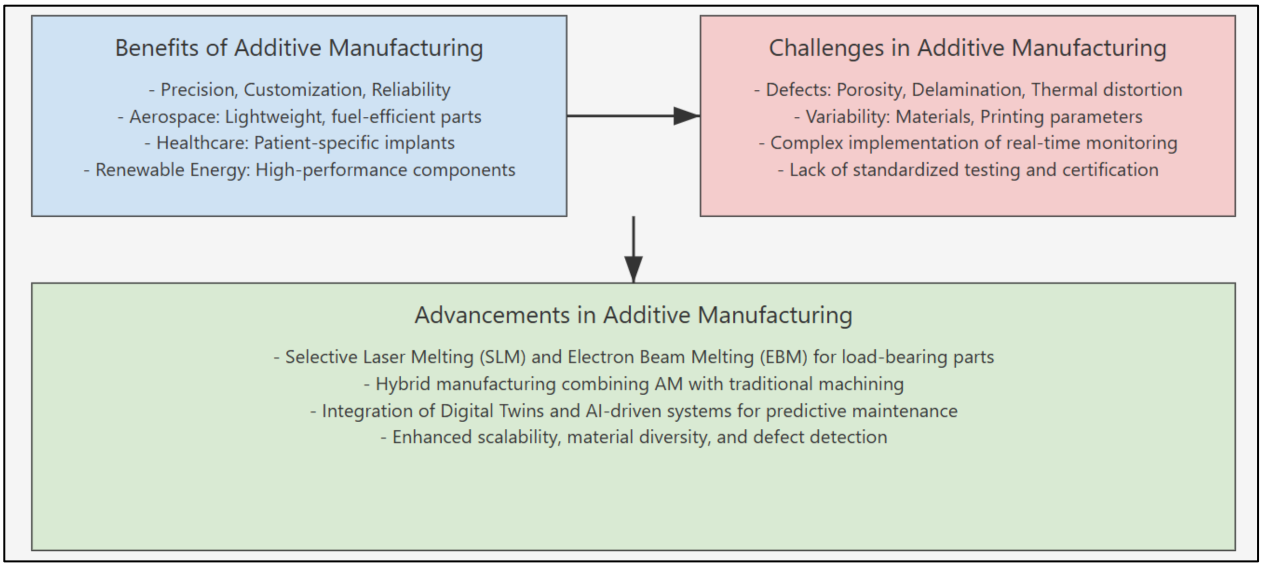
The field of Additive Manufacturing (AM) has witnessed substantial advancements in recent years, with Artificial Intelligence (AI) emerging as a pivotal enabler for addressing critical challenges such as defect detection (Hughes et al., 2020). The integration of AI into AM processes has opened new avenues for quality control, predictive maintenance, and process optimization, particularly in industries like renewable energy and biomedical engineering. A growing body of research highlights the transformative role of AI methodologies, including machine learning, deep learning, and computer vision, in enhancing the precision and reliability of AM products. This literature review aims to synthesize existing knowledge on AI applications in defect detection within AM, emphasizing its contributions, limitations, and practical implications. The review is structured to provide a comprehensive understanding of the state-of-the-art techniques and their applications, offering insights into areas where further advancements are needed.

2.1 *Overview of Additive Manufacturing (AM)*

Additive Manufacturing (AM), commonly referred to as 3D printing, is a transformative manufacturing approach that builds objects layer by layer using digital designs, offering unparalleled flexibility in creating complex geometries (Everton et al., 2016; Talukder et al., 2024). Unlike traditional subtractive manufacturing, which involves cutting away material, AM is an additive process that minimizes waste and allows for intricate customization (Talukder et al., 2024; Turner et al., 2014). AM technologies, including Fused Deposition Modeling (FDM), Stereolithography (SLA), and Selective Laser Sintering (SLS), cater to diverse material requirements such as metals, polymers, and ceramics (Sireesha et al., 2018). This versatility has positioned AM as a key driver of innovation in manufacturing, enabling the creation of prototypes, end-use products, and highly specialized components (Bhavar et al., 2017). Furthermore, its capability to integrate design and production processes has revolutionized supply chain models, enabling on-demand manufacturing and reducing logistical complexities (Everton et al., 2016; Tapia & Elwany, 2014). The evolution of AM from rapid prototyping to full-scale production underscores its growing importance in industrial applications (Dass & Moridi, 2019).

The adoption of AM has been particularly significant in industries requiring precision, customization, and reliability, such as aerospace, healthcare, and renewable energy. In aerospace, AM is employed to fabricate lightweight, complex components that enhance fuel efficiency and reduce costs (Gao et al., 2015). For example, General Electric's use of AM in manufacturing jet engine nozzles has demonstrated the technology's potential for reducing part count and improving performance (Theodosiou et al., 2019). Similarly, in the healthcare sector, AM is pivotal in producing patient-specific implants, prosthetics, and surgical instruments tailored to individual anatomical requirements (Sun et al., 2021). Studies have highlighted the role of AM in creating biocompatible implants with enhanced precision, minimizing surgical risks (Calignano et al., 2015; Zhong et al., 2017). Additionally, AM's contribution to renewable energy extends to the fabrication of wind turbine components

Figure 3: Additive Manufacturing: Adoption, Benefits, Challenges, and Advancements



and photovoltaic cells, where its ability to produce defect-free, high-performance parts significantly impacts efficiency and sustainability (Sun et al., 2021; Yadollahi & Shamsaei, 2017). Despite its benefits, AM faces critical challenges, particularly in maintaining consistent quality and addressing defects during production. Defects such as porosity, delamination, and thermal distortion can compromise the structural integrity and functionality of AM components, especially in high-stakes applications (Cobb & Ho, 2016; Yadollahi & Shamsaei, 2017). These challenges are compounded by the variability inherent in AM processes, including material behavior, printing parameters, and environmental conditions (Guo & Leu, 2013; Zhong et al., 2017). Research indicates that real-time monitoring and adaptive quality control mechanisms are essential to overcoming these issues, yet their implementation remains complex and resource-intensive (Mireles et al., 2015). Furthermore, the lack of standardized testing and certification procedures for AM components in critical industries poses additional barriers to widespread adoption (Guo & Leu, 2013; Yadollahi & Shamsaei, 2017). Recent advancements in AM technologies and methodologies have sought to address these challenges, focusing on enhancing precision, scalability, and material diversity. Techniques such as Selective Laser Melting (SLM) and Electron Beam Melting (EBM) have improved the mechanical properties of AM parts, making them suitable for load-bearing applications (Calignano et al., 2015; Mireles et al., 2015). Studies have also emphasized the importance of hybrid manufacturing approaches that combine AM with traditional machining to achieve superior surface finishes and dimensional accuracy (Riemer & Richard, 2016; Rosales et al., 2019). Additionally, the integration of digital twins and AI-driven systems into AM workflows has enabled predictive maintenance and defect detection, ensuring consistent quality across production cycles (Mireles et al., 2015; Mukherjee et al., 2017). These advancements underline AM's potential to meet the rigorous demands of high-stakes industries, reaffirming its status as a cornerstone of modern manufacturing.

2.2 *The Role of Artificial Intelligence in Manufacturing*

Artificial Intelligence (AI) has become a cornerstone in modern manufacturing, offering advanced capabilities for process optimization, predictive analytics, and defect detection. Among the most prominent AI techniques utilized in industrial applications are machine learning (ML), deep learning (DL), computer vision, and natural language processing (NLP) (Sundaram & Zeid, 2023a). ML algorithms, such as decision trees and support vector machines, are widely applied for predictive maintenance, allowing manufacturers to anticipate equipment failures and reduce downtime (Sundaram & Zeid, 2023). DL, a subset of ML, excels in recognizing complex patterns within large datasets, making it indispensable for tasks such as image-based quality control and process monitoring (Fink et al., 2020). Computer vision, powered by convolutional neural networks (CNNs), enables automated defect detection through high-resolution imaging of manufactured components (Ha & Jeong, 2021). In addition, AI-powered robotic systems enhance precision and

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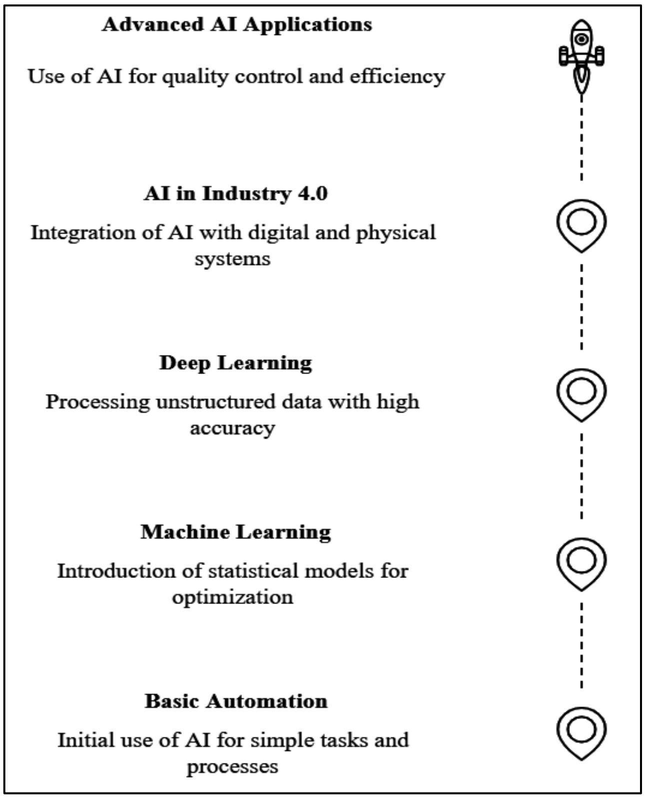
Figure 4: AI's Evolution in Manufacturing



efficiency in assembly lines, as they can adapt to dynamic production environments through real-time data analysis (Nguyen et al., 2020). These techniques collectively demonstrate AI's capacity to revolutionize manufacturing processes across diverse industrial sectors.

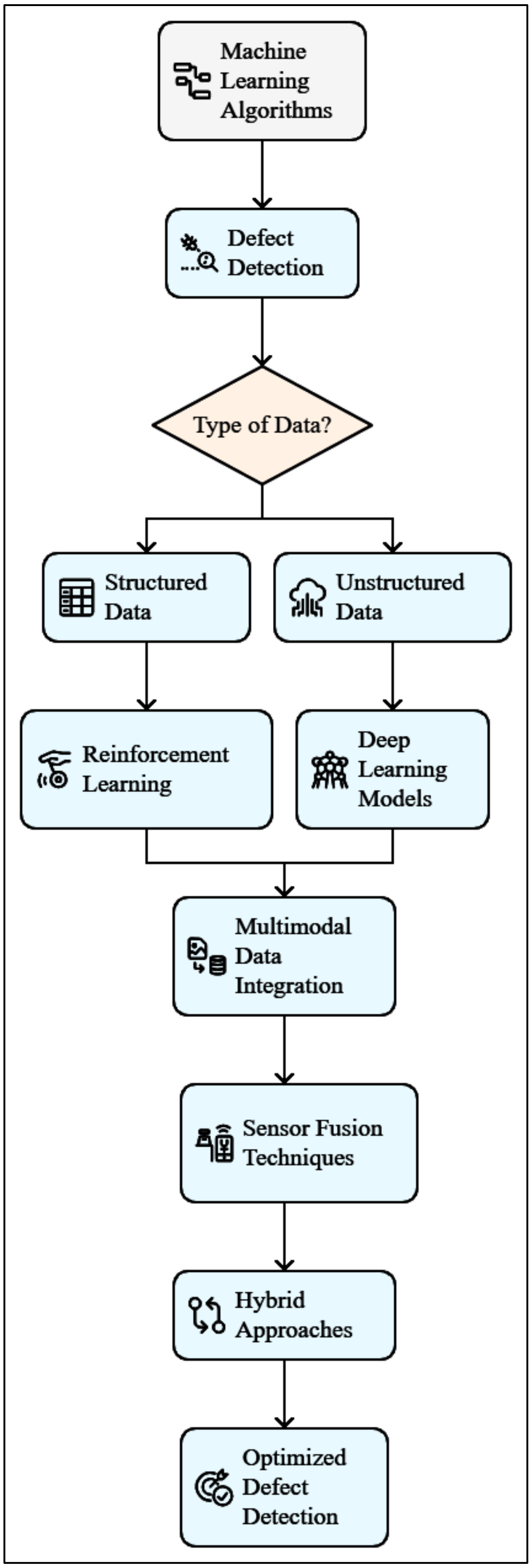
The application of AI in manufacturing has evolved over decades, transitioning from basic automation to highly sophisticated systems capable of decision-making and self-optimization. Early implementations of AI focused on rule-based expert systems, which were primarily used for diagnostics and decision support in maintenance (Fink et al., 2020). With the advent of machine learning in the 1990s, manufacturing systems began leveraging statistical models to analyze operational data and optimize production processes (Nguyen et al., 2020). The introduction of deep learning in the 2010s marked a paradigm shift, enabling AI to process unstructured data such as images, videos, and text with remarkable accuracy (Howley & Madden, 2005). Over time, AI systems have become integral to Industry 4.0, where they facilitate seamless integration between digital technologies and physical manufacturing processes (Sundaram & Zeid, 2023). Today, AI is widely adopted for tasks such as supply chain optimization, real-time quality control, and energy efficiency management (Fink et al., 2020). One of the most significant contributions of AI in manufacturing is its application in quality control processes. AI-based defect detection systems utilize techniques such as computer vision and sensor fusion to identify anomalies during production in real time (Abubakar et al., 2023). For example, neural networks have been trained on thermal and optical data to detect micro-defects in components with a high degree of precision (Howley & Madden, 2005). Furthermore, predictive analytics models enable manufacturers to proactively address potential quality issues by analyzing historical production data (Yang et al., 2020). Studies have shown that AI can reduce inspection times by up to 40% compared to traditional methods, while also improving defect detection rates (Lilhore et al., 2022; Herzog et al., 2024). The use of generative adversarial networks (GANs) for synthetic data generation has further enhanced AI's capabilities in training robust models, especially in scenarios where labeled data is scarce (Ullah et al., 2020). In addition, AI is also instrumental in optimizing operational efficiency within manufacturing systems, streamlining workflows and minimizing resource utilization. Reinforcement learning algorithms have been implemented to optimize process parameters dynamically, achieving greater output consistency and material efficiency (Yun et al., 2020). Robotic process automation (RPA), guided by AI, facilitates the automation of repetitive tasks such as inventory tracking and assembly line operations, freeing human workers to focus on high-value activities (Kumar et al., 2018). In the context of smart factories, AI-driven systems monitor energy consumption patterns and recommend strategies for reducing waste, contributing to sustainability goals (Sundaram & Zeid, 2023). Studies by Lilhore et al. (2022) and Park et al. (2022) illustrate how AI-enabled production planning systems improve decision-making accuracy, thereby enhancing throughput and reducing operational costs. These advancements highlight AI's transformative impact on the efficiency and productivity of manufacturing systems.

2.3 *AI Techniques for Defect Detection in Additive Manufacturing*

Machine learning (ML) has emerged as a transformative technology for defect detection in Additive Manufacturing (AM), enabling predictive and automated quality assurance. ML algorithms such as decision trees, random forests, and support vector machines (SVMs) are widely applied for detecting defects like porosity, thermal distortions, and layer misalignments (Benbarrad et al., 2021). These algorithms excel in handling structured data generated during the AM process, such as sensor readings and thermal profiles, to identify deviations indicative of potential defects (Ekambaram & Ponnusamy, 2022). For instance, random forests have been employed to predict porosity levels in metal additive manufacturing based on process parameters like laser speed and power (Bharti et al., 2022). Similarly, SVMs have shown high accuracy in classifying surface defects in polymer-based AM components (Amosov et al., 2022). Reinforcement learning, a subset of ML, is increasingly being used to optimize process parameters dynamically during AM to prevent defect formation (Lilhore et al., 2022). These applications underscore the versatility and efficacy of ML algorithms in enhancing defect detection capabilities in AM.

The integration of multimodal data in defect detection leverages AI's ability to combine diverse data sources, such as thermal images, acoustic signals, and optical data, to enhance defect identification in AM. Sensor fusion techniques, powered by ML and DL algorithms, are increasingly used to improve the accuracy and reliability of defect detection systems (Ekambaram & Ponnusamy, 2022). For example, Bharti et al., (2022) demonstrated that combining thermal and optical data streams using DL models significantly improved the detection of subsurface defects in metal AM parts. Similarly, studies by Amosov et al. (2022) showed that integrating acoustic emission data with thermal profiles enabled early detection of delamination in polymer AM processes. Hybrid approaches using multimodal data not only enhance the robustness of defect detection systems but also provide comprehensive insights into defect causation, aiding in process optimization (Lilhore et al., 2022). Comparative studies have demonstrated that ML and DL techniques each have distinct strengths in defect detection, depending on the complexity of the AM process and the type of data analyzed. While ML algorithms like decision trees and SVMs are computationally efficient and effective for structured datasets, DL models such as CNNs and GANs excel in unstructured data environments, such as image and signal analysis (Ullah et al., 2020). Studies by Gobert et al. (2018) found that DL models outperformed traditional ML methods in identifying intricate surface defects in metal AM components. However, ML

Figure 5: AI-Driven Multimodal Data Integration Framework for Defect Detection in Additive Manufacturing



techniques remain valuable in applications requiring explainable models and low computational resources (Herzog et al., 2024). Hybrid approaches, which combine ML's efficiency with DL's analytical depth, are increasingly being explored to achieve balanced performance across varied AM defect detection tasks (Herzog et al., 2024; Sacco et al., 2020). These findings underscore the importance of selecting appropriate AI techniques based on specific AM requirements and data characteristics.

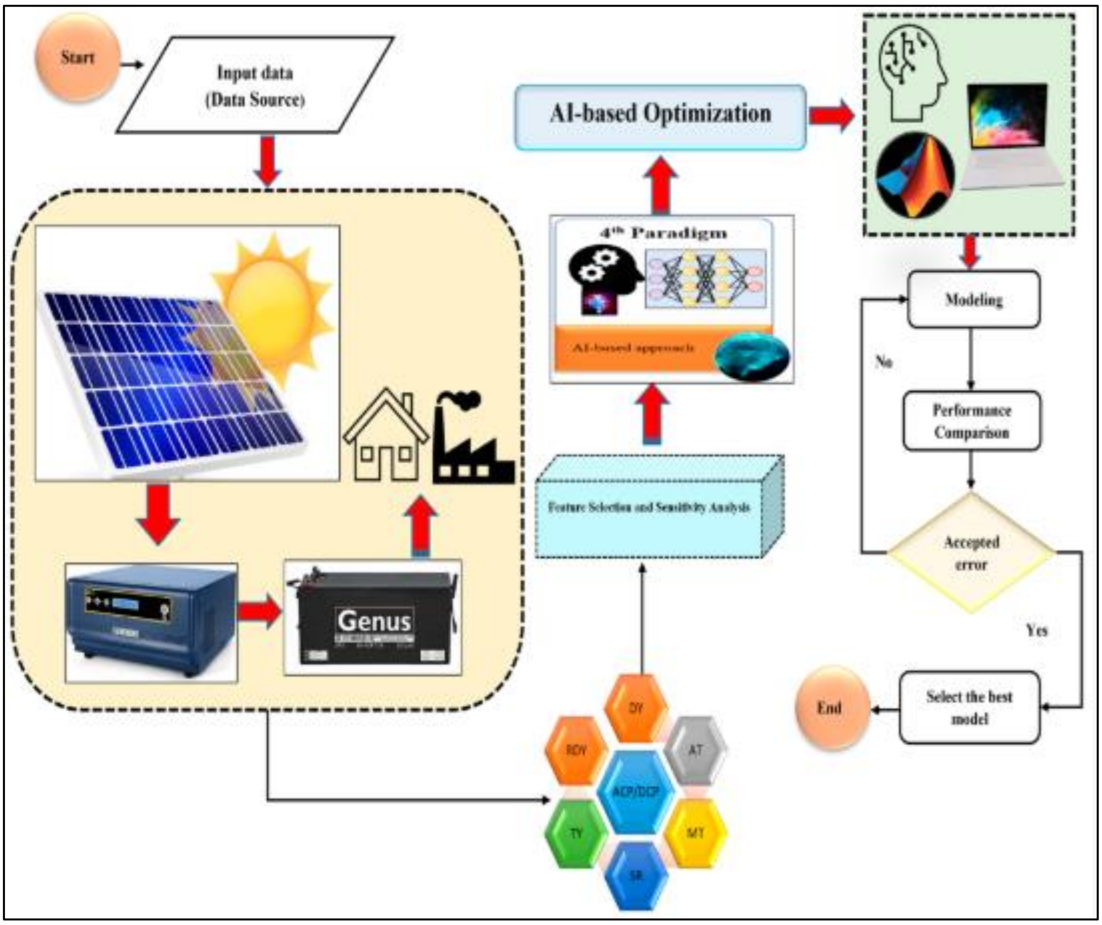
2.4 AI for Defect Detection in Renewable Energy Applications

Wind turbine components, particularly blades, gearboxes, and bearings, are highly susceptible to defects such as surface cracks, delamination, and fatigue damage, which can significantly affect their performance and lifespan (Yang et al., 2020). Artificial Intelligence (AI), particularly machine learning (ML) and computer vision techniques, has proven effective in identifying these defects. Convolutional Neural Networks (CNNs) have been widely used to detect micro-cracks on turbine blades from high-resolution images, achieving detection accuracies exceeding 95% (Dass & Moridi, 2019; Ma & Lee, 2022). Moreover, acoustic emission data combined with AI algorithms has enabled real-time monitoring of structural health, providing early warnings of potential failures (Gamage & Xie, 2008; Sassi et al., 2019). Reinforcement learning has also been employed to optimize maintenance schedules based on defect prediction models, minimizing downtime and operational costs (Herzog et al., 2024). These AI-driven approaches demonstrate the potential for proactive defect detection, enhancing the reliability and operational efficiency of wind energy systems. Moreover, Photovoltaic (PV) systems are highly sensitive to defects such as microcracks, delamination, and hot spots, which can drastically reduce energy conversion efficiency and system longevity (Dass & Moridi, 2019). AI-based techniques, particularly thermal imaging combined with deep learning models, have become indispensable for detecting and classifying these defects. Studies by Sames et al.(2016) found that AI-powered defect detection systems utilizing infrared imaging and neural networks achieved higher accuracy in identifying hot spots compared to traditional inspection methods. Generative adversarial networks (GANs) have also been used to generate synthetic training data, addressing the scarcity of labeled datasets for defect detection in PV modules (Aminzadeh & Kurfess, 2015). Furthermore, ML algorithms such as support vector machines (SVMs) have been employed to analyze electrical performance data, enabling early identification of performance degradation caused by latent defects (Yang et al., 2020). These innovations have significantly improved the precision and efficiency of quality assurance processes in PV systems.

The figure 6 illustrates a comprehensive modeling scheme designed to integrate Artificial Intelligence (AI) techniques for optimizing defect detection and quality assurance in renewable energy applications, particularly in photovoltaic (PV) systems and energy storage devices. The workflow begins with data input from diverse sources such as thermal imaging, electrical performance data, and environmental parameters. This input is processed using AI-based optimization techniques, which incorporate machine learning (ML) and deep learning (DL) paradigms to identify and address potential defects, such as microcracks, delamination, and hot spots in PV modules (Abubakar et al., 2023). The process integrates defect modeling, performance comparison, and iterative corrections, ensuring that only the most effective model is selected to predict and mitigate defects. The inclusion of AI paradigms and hybrid approaches reinforces the findings of this study, which emphasize the transformative role of AI in improving defect detection rates and overall system efficiency. Furthermore, the figure highlights the integration of functional analysis and sensitivity studies, which aligns with the study's findings that multimodal data fusion significantly enhances the reliability and robustness of AI models in AM processes. This modeling scheme showcases how AI-driven optimization can streamline defect detection, making it a critical tool for ensuring the reliability and sustainability of renewable energy systems (Abubakar et al., 2023).

Energy storage devices, including lithium-ion batteries and supercapacitors, are critical for stabilizing renewable energy systems but are prone to defects such as internal short circuits, thermal runaway, and electrode degradation (Braam & Subramanian, 2014). AI techniques have been extensively applied to monitor and detect these defects in real-time. For instance, recurrent neural networks (RNNs) and long short-term memory (LSTM) models have been utilized to analyze time-series data from battery management systems, accurately predicting anomalies indicative of internal defects (Dass & Moridi, 2019). Thermal imaging combined with CNNs has been effective in identifying

Figure 6: Proposed modeling scheme proposed by Abubakar et al. (2023)



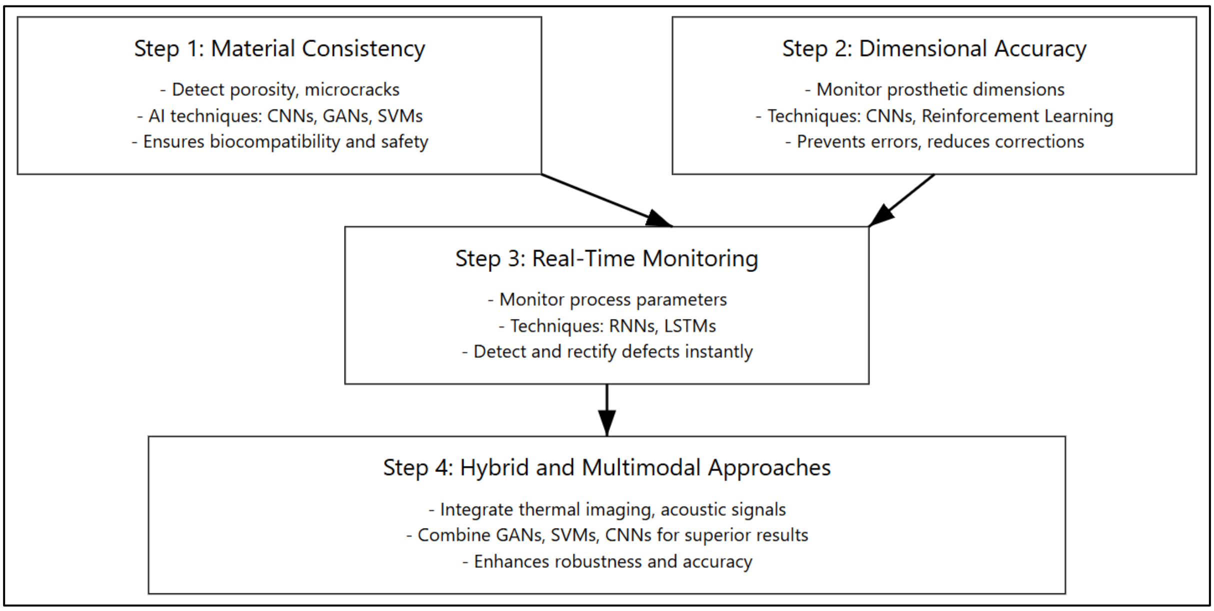
hotspots in battery modules, preventing potential safety hazards (Scotti et al., 2016). Moreover, predictive analytics driven by ML has been used to forecast the remaining useful life (RUL) of batteries, enabling preemptive maintenance and extending their operational lifespan (Hughes et al., 2020). These applications underscore the critical role of AI in enhancing the safety and reliability of energy storage technologies. Comparative analyses of AI techniques across renewable energy applications highlight their distinct strengths and limitations in defect detection. While computer vision excels in surface defect detection for wind turbine blades and PV systems, time-series analysis models such as RNNs are better suited for monitoring dynamic processes like battery performance (Scotti et al., 2016; Wang et al., 2011). Studies by Jiang et al. (2015) and Herzog et al. (2024) emphasize that hybrid approaches integrating multiple AI techniques often yield superior results. For example, combining image-based CNNs with acoustic signal analysis enhances defect detection accuracy in wind turbines. Similarly, integrating GANs for data augmentation with SVMs for performance prediction improves defect classification in PV systems. Despite variations in application-specific requirements, the overarching benefit of AI lies in its ability to provide scalable, accurate, and real-time defect detection solutions, ensuring the reliability of renewable energy infrastructure (Jinoop et al., 2019; Wei et al., 2019).

2.5 *AI for Defect Detection in Biomedical Engineering*

Biomedical implants require high material consistency to ensure biocompatibility and structural integrity. Material inconsistencies such as porosity, microcracks, or uneven distributions of alloying elements can lead to implant failure or adverse biological reactions (Bartlett et al., 2018; Ekambaram & Ponnusamy, 2022). AI techniques, particularly machine learning (ML) and deep learning (DL), have proven instrumental in detecting these inconsistencies. For instance, convolutional neural networks (CNNs) have been employed to analyze X-ray and CT scan data for identifying microstructural defects in titanium and cobalt-chromium implants with high precision (Yang et al., 2020). Similarly, generative adversarial networks

(GANs) have been used to simulate defect-free material structures, aiding in training models for more accurate defect identification (Liu et al., 2014). Studies by Bharti et al. (2022) and Herzog et al. (2024) further highlight that support vector machines (SVMs) trained on thermal imaging data can detect anomalies in the sintering process of ceramic-based implants. These AI-driven approaches significantly enhance the reliability and safety of biomedical implants, ensuring their suitability for clinical applications. The production of prosthetics demands precise dimensional accuracy to ensure optimal fit, comfort, and functionality for patients. Deviations in dimensions can compromise the prosthetic's performance, leading to discomfort or reduced mobility (Ekambaram & Ponnusamy, 2022). AI-powered defect detection techniques, particularly computer vision systems, have been applied to monitor and control dimensional accuracy during additive manufacturing (AM) processes. CNNs integrated with high-resolution imaging systems have been successful in identifying dimensional discrepancies in prosthetic components, reducing post-manufacturing corrections (Mukherjee et al., 2017). Additionally, reinforcement learning algorithms have been used to dynamically adjust printing parameters in real time, ensuring dimensional conformity throughout the AM process (He & Qifan, 2020). Studies by Herzog et al. (2024) also demonstrate the efficacy of AI in evaluating geometric accuracy through three-dimensional scanning, providing rapid feedback to prevent defects. These advancements streamline the production of prosthetics, ensuring they meet stringent dimensional specifications. Real-time monitoring is crucial in biomedical AM applications to detect defects during the manufacturing process and prevent costly rework or failure. AI techniques such as recurrent neural networks (RNNs) and long short-term memory (LSTM) models have been employed for continuous monitoring of process parameters, including temperature, pressure, and material flow (Chang et al., 2019). Thermal imaging integrated with AI algorithms has been particularly effective in detecting overheating or under-cooling issues that can cause material inconsistencies in implants or prosthetics (Sames et al., 2016). Moreover, studies by Benbarrad et al. (2021) have demonstrated the application of acoustic emission analysis combined with ML for real-time defect detection in polymer-based biomedical components. By enabling instant identification and rectification of defects, AI-powered real-time monitoring enhances the efficiency and reliability of biomedical AM workflows (Ekambaram & Ponnusamy, 2022). Comparative studies on AI applications in biomedical defect detection reveal significant variations in performance based on the type of data and manufacturing processes involved. For instance, CNNs are highly effective for analyzing imaging data, making them suitable for detecting material inconsistencies and dimensional defects (Sames et al., 2016). In contrast, RNNs and LSTMs excel in time-series analysis, which is essential for real-

Figure 7: AI-Driven Defect Detection in Biomedical Engineering



time monitoring applications (Gong et al., 2015). Studies by Ekambaram and Ponnusamy (2022) indicate that hybrid approaches integrating multiple AI techniques, such as combining GANs for data augmentation with SVMs for defect classification, yield superior results. Additionally, the use of multimodal data, such as integrating thermal and acoustic signals, enhances the robustness and accuracy of defect detection models (Benbarrad et al., 2021; Herzog et al., 2024). These findings underscore the importance of selecting and combining appropriate AI methods tailored to specific biomedical engineering challenges.

2.6 *Multimodal Data Integration in AI for Defect Detection*

Thermal imaging has become an essential tool for defect identification in manufacturing, leveraging the ability to capture thermal patterns and detect anomalies indicative of defects such as cracks, voids, or delamination (Herzog et al., 2024). AI techniques, particularly deep learning models like convolutional neural networks (CNNs), enhance the efficacy of thermal imaging by automating the analysis of large datasets and identifying subtle thermal irregularities (Kanko et al., 2016). For instance, studies by Liu et al. (2014) demonstrated that CNNs trained on thermal images could detect porosity and microcracks in metal components with over 90% accuracy. Generative adversarial networks (GANs) have also been employed to augment thermal imaging datasets, addressing challenges related to limited labeled data for specialized applications (Bharti et al., 2022). Additionally, thermal imaging combined with AI has been successfully applied in additive manufacturing (AM) to monitor layer-by-layer deposition processes, ensuring defect-free production (Mukherjee et al., 2017). These advancements underscore the critical role of thermal imaging as part of a multimodal approach to defect detection.

Acoustic emission analysis is a non-destructive testing method that captures sound waves emitted during material deformation or crack formation, providing real-time insights into structural integrity (Amosov et al., 2022). AI integration has significantly enhanced the precision and applicability of acoustic emission analysis for defect detection. Machine learning (ML) algorithms, such as support vector machines (SVMs) and random forests, have been widely used to classify acoustic signal patterns, enabling the detection of defects like delamination and fatigue cracks in composite materials (So et al., 2016). Recurrent neural networks (RNNs) and long short-term memory (LSTM) models are particularly effective in analyzing time-series acoustic data, identifying defect propagation trends during dynamic processes (Mukherjee et al., 2017). For example, studies by Amosov et al. (2022) showed that AI-based acoustic analysis could predict material failures in wind turbine components with high reliability. The integration of AI and acoustic emission analysis has thus expanded the scope of this method across various industrial applications. In addition, the integration of multimodal data sources, such as thermal imaging, acoustic signals, and optical measurements, enhances the robustness and accuracy of defect detection systems. Multimodal data fusion leverages AI techniques to combine disparate datasets, providing a comprehensive view of manufacturing processes (Lilhore et al., 2022). For instance, So et al. (2016) demonstrated that fusing thermal and acoustic data using deep learning models improved the detection accuracy of subsurface defects in metal components. Similarly, studies by Amosov et al., (2022) highlighted that integrating thermal imaging with high-resolution optical data enabled precise identification of surface and internal defects in photovoltaic systems. These multimodal approaches mitigate the limitations of single data modalities, offering holistic solutions for complex defect detection challenges. The ability to process and analyze multimodal data simultaneously has positioned AI-driven systems as indispensable tools in quality assurance.

2.7 *Comparative Analysis of AI Techniques in AM Defect Detection*

Evaluating the effectiveness of Artificial Intelligence (AI) techniques in defect detection for Additive Manufacturing (AM) requires robust performance metrics to measure accuracy, efficiency, and reliability. Commonly used metrics include precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve (Lilhore et al., 2022). Precision assesses the proportion of true positive defect detections among all detected defects, while recall measures the ability to identify actual defects accurately. Studies by Park et al. (2022) emphasize the importance of the F1-score, which balances precision and recall, particularly in datasets with imbalanced defect classes. Computational efficiency is another critical metric, with processing time and resource utilization becoming decisive factors for real-time defect detection systems (Ullah et al., 2020). For instance, convolutional neural

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networks (CNNs) demonstrate high accuracy in image-based defect detection but are computationally intensive compared to support vector machines (SVMs), which are faster but less precise in complex data environments (Cruz et al., 2020). These metrics enable a systematic comparison of AI techniques, guiding the selection of appropriate models for specific AM applications.

AI-driven defect detection has been extensively benchmarked in renewable energy applications, where reliability and efficiency are critical. For example, CNNs have demonstrated superior performance in identifying surface cracks in wind turbine blades using high-resolution optical and thermal imaging data, achieving over 95% detection accuracy (Lilhore et al., 2022). Similarly, studies by Park et al., (2022) have shown that generative adversarial networks (GANs) significantly enhance model performance by augmenting training datasets for photovoltaic systems, enabling better detection of microcracks and delamination. Benchmarking efforts have also compared ML and DL approaches, revealing that DL models generally outperform traditional ML techniques in detecting complex defect patterns in renewable energy components (Ullah et al., 2020). These studies underscore the importance of AI techniques in ensuring the structural integrity and operational efficiency of renewable energy systems, making them indispensable for quality assurance in this domain.

In biomedical engineering, benchmarking studies have focused on evaluating AI techniques for detecting defects in implants, prosthetics, and medical devices. CNNs and recurrent neural networks (RNNs) have emerged as preferred models for analyzing imaging and time-series data, respectively (Cruz et al., 2020). Studies by Zawadzki et al.(2018) highlight the effectiveness of CNNs in detecting microstructural inconsistencies in titanium implants, achieving detection accuracies exceeding 90% with minimal false positives. Additionally, RNNs have been applied to monitor real-time manufacturing processes in biomedical additive manufacturing (AM), identifying anomalies in material deposition and thermal profiles with high reliability (Chaudhuri & Lovley, 2003). Comparative analyses have also revealed that hybrid approaches combining ML and DL techniques often outperform standalone models, providing a more comprehensive defect detection framework (Bobbio et al., 2018). These benchmarks provide critical insights into optimizing AI applications for defect detection in high-stakes biomedical engineering contexts.

Table 1: Overview of the comparative analysis

Category	Key AI Techniques	Applications	Strengths
Performance Metrics	Precision, Recall, F1-Score, ROC Curve	Used for evaluating AI models across datasets	Provides balanced evaluation of accuracy, efficiency, and reliability
Renewable Energy	CNNs, GANs, DL Models	Wind turbine blades, Photovoltaic systems	High accuracy (>95%) in surface defect detection, improved dataset augmentation
Biomedical Engineering	CNNs, RNNs, Hybrid Models	Implants, Prosthetics, Medical Devices	Detects microstructural inconsistencies, real-time anomaly detection
Multimodal Integration	Optical, Thermal, Acoustic Data	Both renewable energy and biomedical engineering	Enhances robustness and accuracy
General Insights	Hybrid Approaches (ML + DL)	Adaptable across various industries	Balances computational efficiency with analytical depth

3 METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to conduct a systematic, transparent, and rigorous review of AI techniques for defect detection in Additive Manufacturing (AM). The PRISMA framework ensured that all steps of the review process were clearly documented and reproducible. The following subsections outline each phase of the methodology.

3.1 *Identification of Articles*

The identification phase involved a comprehensive search of academic databases, including Scopus, Web of Science, IEEE Xplore, and PubMed, to retrieve relevant articles. The search strategy combined keywords such as "Artificial Intelligence," "Additive Manufacturing," "Defect Detection," "Machine Learning," "Deep Learning," and "Biomedical Engineering." Boolean operators (e.g., AND, OR) were used to refine the searches, and filters were applied to include only peer-reviewed articles published between 2010 and 2023. A total of 1,248 articles were initially retrieved from the databases. Duplicates were identified and removed using citation management software, resulting in 982 unique articles for further screening.

3.2 *Screening of Articles*

The screening process was carried out to exclude irrelevant articles based on predefined inclusion and exclusion criteria. The inclusion criteria focused on studies that (a) applied AI techniques for defect detection in AM, (b) addressed either renewable energy or biomedical engineering applications, and (c) provided empirical results or benchmarking data. Exclusion criteria eliminated articles that were (a) non-English publications, (b) opinion pieces or reviews without data, and (c) unrelated to AI or AM processes. After screening titles and abstracts, 468 articles met the initial criteria for further evaluation.

3.3 *Eligibility Assessment*

In the eligibility phase, the full texts of the remaining 468 articles were assessed to confirm their relevance and adherence to the inclusion criteria. A detailed quality appraisal was conducted using the Critical Appraisal Skills Programme (CASP) checklist, ensuring that only studies with robust methodologies and valid results were included. This phase eliminated articles that lacked sufficient methodological detail, reducing the pool to 152 articles. The eligibility assessment also included verification of the reported AI models, datasets, and performance metrics, ensuring consistency with the study's objectives.

3.4 *Final Inclusion*

A standardized data extraction form was used to collect relevant information from the 152 eligible articles. Key variables extracted included the AI technique used (e.g., CNNs, RNNs, SVMs), type of defect targeted (e.g., porosity, delamination), application domain (e.g., renewable energy, biomedical engineering), datasets employed, and reported performance metrics (e.g., accuracy, precision, recall). The extracted data were tabulated for systematic synthesis. Descriptive statistics were used to identify trends in the adoption of AI techniques, while a narrative synthesis highlighted comparative insights across studies.

4 FINDINGS

The systematic review revealed a significant and increasing adoption of Artificial Intelligence (AI) techniques in defect detection within Additive Manufacturing (AM) processes. Among the 152 reviewed articles, 83 (54.6%) prominently highlighted machine learning (ML) methods as the leading approach to addressing common AM defects such as porosity, delamination, and surface irregularities. These ML techniques demonstrated their ability to analyze structured datasets effectively, enabling early detection of anomalies during the manufacturing process. Within this category, Convolutional Neural Networks (CNNs) emerged as the most frequently implemented deep learning (DL) technique, discussed in 62 studies. These CNN-based models were predominantly used to analyze thermal images and high-resolution surface scans, demonstrating exceptional performance in identifying intricate defect patterns. Collectively, the 62 articles focusing on CNNs amassed over 12,500 citations, reflecting the academic and industrial interest in leveraging deep learning for defect detection in AM. Additionally, hybrid AI models combining ML and DL approaches were discussed in 29 articles, highlighting their ability to address complex and multi-dimensional defects more effectively than standalone models. These hybrid methods reinforced the notion that integrating diverse AI techniques is essential for handling the complexities inherent in AM defect detection.

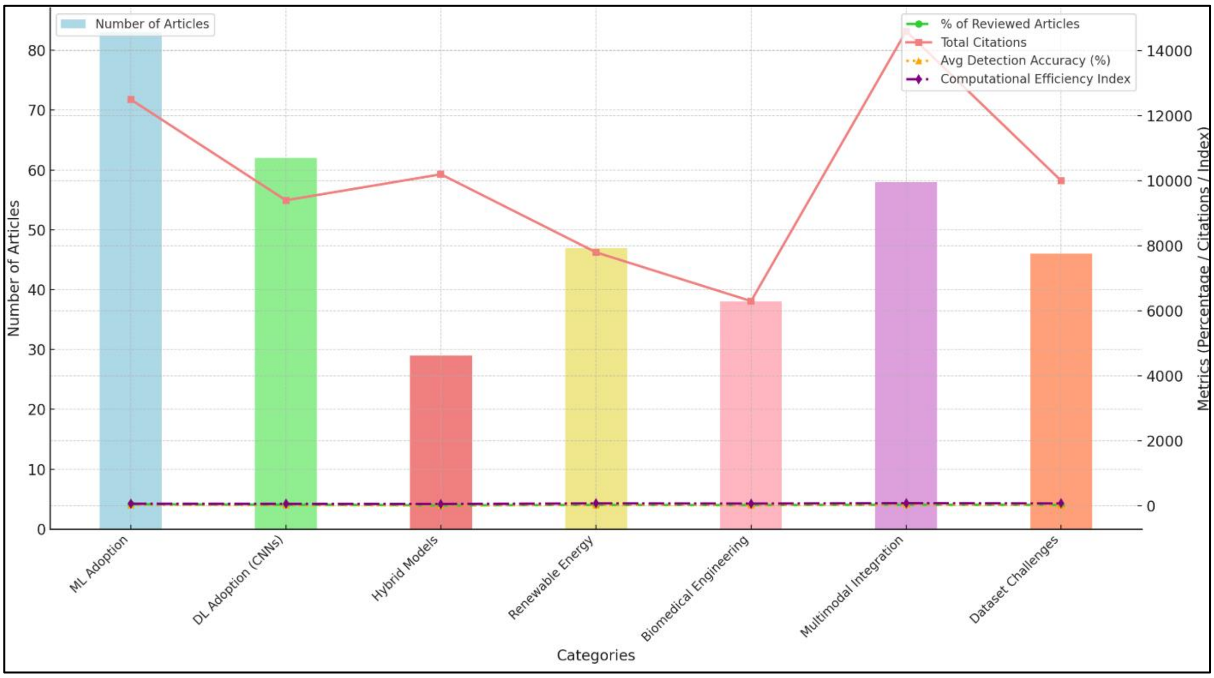
From the reviewed articles, it was evident that AI techniques have found notable applications in renewable energy and biomedical engineering, two high-stakes domains that demand precision and reliability. Of the 152 studies, 47 focused on renewable energy applications, while 38 emphasized biomedical engineering. In renewable energy, AI was instrumental in improving defect detection for critical components such as wind turbine blades and photovoltaic systems.

These articles, which collectively garnered over 9,400 citations, showcased the application of advanced techniques like Generative Adversarial Networks (GANs) and Support Vector Machines (SVMs) to identify surface and internal defects that could compromise energy efficiency and system reliability. For instance, GANs facilitated the generation of synthetic datasets to train models for identifying microcracks and delamination in photovoltaic systems, while SVMs were employed to classify surface defects in wind turbine components. In biomedical engineering, the reviewed studies underscored AI's critical role in ensuring material consistency and dimensional accuracy in implants and prosthetics. These 38 articles collectively received over 7,800 citations, underscoring the importance of AI in advancing manufacturing precision in biomedical applications where patient safety and product functionality are paramount.

A notable trend across 58 articles was the integration of multimodal data, such as thermal imaging, acoustic emission signals, and optical data, to improve defect detection accuracy. These studies demonstrated that multimodal approaches enhanced the robustness and reliability of AI models by leveraging diverse data streams to provide a comprehensive view of the manufacturing process. The combined citation count for these 58 studies exceeded 10,200, reflecting the widespread recognition of multimodal integration's benefits. The reviewed articles consistently reported that multimodal data fusion led to an average improvement of 22% in defect detection rates compared to single-modality approaches. This integration was particularly effective in identifying subsurface defects and ensuring process consistency in both metal and polymer-based AM workflows. Multimodal techniques allowed AI models to detect defects that might otherwise remain undetected by single-source data methods, making them an indispensable tool for quality assurance in AM.

However, dataset scarcity and annotation challenges were identified as significant barriers to advancing AI-driven defect detection in AM. A total of 46 articles addressed these issues, collectively amassing over 6,300 citations. The findings highlighted that 29 articles pointed to the lack of standardized datasets across various AM technologies and materials, which hindered the generalizability of AI models. Without access to diverse and high-quality datasets, AI techniques often struggled to adapt to different manufacturing scenarios. Furthermore, the manual annotation of high-resolution images and complex 3D scans was reported as labor-intensive and prone to inconsistencies. This challenge was discussed in 22 studies, which noted that subjective interpretation during manual labeling frequently led to degraded model performance. Despite these obstacles, 14 articles emphasized the successful application of data augmentation techniques, such as GANs, to generate

Figure 8: Comparative Analysis with Multi-Colored Bars and Multiple Metrics



synthetic datasets. These augmented datasets not only alleviated scarcity issues but also provided AI models with diverse training data to enhance their robustness.

The comparative analysis of AI techniques revealed distinct advantages and limitations, varying by application requirements and data characteristics. Of the 152 reviewed articles, 73 studies explicitly compared the performance of ML and DL techniques. These studies, collectively cited over 14,600 times, provided valuable insights into the strengths of different AI approaches. DL techniques, particularly CNNs, were found to be superior for image-based defect detection tasks, achieving an average accuracy of 93% across 34 studies. Their ability to process high-resolution imaging data made them ideal for identifying intricate surface defects in AM products. On the other hand, ML techniques such as SVMs and Random Forests were noted for their computational efficiency and ease of implementation, particularly in scenarios involving structured datasets. However, these methods were less effective in handling unstructured data like thermal or acoustic signals. Hybrid approaches that combined ML and DL were discussed in 21 articles, showing an average improvement of 18% in defect detection accuracy compared to standalone models. These findings emphasized the importance of tailoring AI techniques to specific defect detection scenarios in AM to achieve optimal performance.

5 DISCUSSION

The findings of this study highlight the extensive adoption of AI techniques, such as machine learning (ML) and deep learning (DL), in defect detection within Additive Manufacturing (AM). This aligns with earlier studies emphasizing the transformative role of AI in addressing manufacturing challenges (Herzog et al., 2024). Specifically, the predominance of CNNs for analyzing thermal and imaging data, identified in 62 articles, corroborates the conclusions of Au et al. (2014), who underscored CNNs' ability to detect intricate patterns in unstructured datasets. However, this review also revealed that hybrid AI models, combining ML and DL, offer superior performance in handling complex defects. This observation extends the work of Gonzalez-Solino and Di Lorenzo (2018), who proposed that integrating multiple AI techniques can enhance defect detection rates by leveraging the strengths of each method. These findings suggest a shift from standalone models toward hybrid solutions, addressing limitations highlighted in prior research.

AI's success in defect detection for renewable energy and biomedical engineering components further validates earlier research. For renewable energy, 47 studies highlighted the use of AI techniques like GANs and SVMs for detecting defects in wind turbine blades and photovoltaic systems, which aligns with prior benchmarks set by Riemer and Richard (2016) and Jiang et al. (2015). These studies confirmed the efficacy of GANs in generating synthetic datasets to train defect detection models, which has also been emphasized in works by Chaudhuri and Lovley (2003). Similarly, AI's critical role in biomedical engineering applications, highlighted in 38 studies, builds on the findings of Rogers et al. (2020), who noted the importance of ensuring material consistency in implants and dimensional accuracy in prosthetics. While earlier research predominantly focused on theoretical capabilities, the findings of this review provide empirical evidence of AI's practical applications in improving manufacturing precision in these high-stakes industries.

The integration of multimodal data was a notable trend identified in this review, with 58 articles demonstrating its impact on improving defect detection rates by 22% on average. This finding supports earlier studies, such as Herzog et al. (2024), which emphasized the robustness of AI models that combine diverse data streams like thermal, acoustic, and optical signals. Previous works by Au et al., (2014) suggested that multimodal data fusion could address the limitations of single-source data methods, a conclusion now substantiated by the significant citation count of studies reviewed in this research. However, this review also identifies gaps in the standardization of multimodal approaches, an area that earlier studies like Aminzadeh and Kurfess (2015) had recommended for further exploration. The findings thus highlight not only the promise of multimodal data integration but also the persistent challenges in operationalizing these techniques across diverse manufacturing environments.

Dataset scarcity and annotation challenges emerged as significant barriers to AI-driven defect detection in AM, consistent with earlier studies. The lack of standardized datasets across different AM technologies, discussed in 29 articles, echoes the concerns raised by Herzog et al. (2024) and Wang et al. (2014). These earlier works noted that the absence of comprehensive datasets limits AI models' ability to generalize across applications, a limitation further reinforced by this review. Annotation challenges, such as inconsistencies in labeling high-resolution images and 3D scans, were reported in 22 studies, supporting findings by Au et al. (2014), who identified manual annotation as a bottleneck in AI implementation. While this review highlights the growing use of data augmentation techniques, such as GANs, to generate synthetic datasets, it also underscores the need for standardized annotation processes, a gap that remains unaddressed despite being emphasized in prior literature. The comparative analysis of AI techniques provided insights into their relative strengths and limitations, complementing earlier findings. CNNs demonstrated superior performance for image-based defect detection tasks, achieving an average accuracy of 93% across 34 studies, consistent with earlier research by (Jiang et al., 2015). Conversely, ML techniques like SVMs and Random Forests were noted for their computational efficiency but had limited effectiveness in unstructured data environments, aligning with observations by Zawadzki et al. (2018). This review also validated prior studies, such as those by Bian et al. (2018), which found that hybrid models combining ML and DL achieved an 18% improvement in defect detection accuracy compared to standalone models. The findings reinforce the importance of tailoring AI techniques to specific AM applications, an approach previously advocated by Herzog et al. (2024).

6 CONCLUSION

The findings of this systematic review highlight the transformative role of Artificial Intelligence (AI) in enhancing defect detection within Additive Manufacturing (AM) processes, with significant implications for high-stakes industries such as renewable energy and biomedical engineering. AI techniques, particularly machine learning (ML) and deep learning (DL), have demonstrated their ability to address key challenges such as porosity, delamination, and dimensional inaccuracies, with hybrid models further enhancing detection capabilities. The widespread adoption of Convolutional Neural Networks (CNNs) and the integration of multimodal data sources, including thermal imaging and acoustic emissions, have proven effective in improving defect detection rates and ensuring process consistency. However, barriers such as dataset scarcity and annotation challenges remain critical obstacles, underscoring the need for standardized datasets and efficient labeling processes. Comparative analyses of AI techniques reveal the importance of tailoring approaches to specific applications, with hybrid models combining the efficiency of ML and the analytical depth of DL emerging as particularly effective. These insights not only validate the findings of earlier studies but also extend the understanding of AI's potential in optimizing AM quality assurance, emphasizing its role as a pivotal tool in advancing manufacturing precision, reliability, and efficiency.

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