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AI-Driven Real-time Quality Monitoring and Process Optimization for Enhanced Manufacturing Performance

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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Abstract

The integration of artificial intelligence (AI) into manufacturing processes has revolutionized quality control and process optimization. This paper focuses on AI-driven real-time monitoring and process optimization, exploring its potential to enhance manufacturing performance. The study reviews recent advancements in AI technologies, emphasizing their application in manufacturing environments. Utilizing machine learning algorithms, sensor data, and IoT connectivity, the proposed system facilitates continuous monitoring of production parameters. The AI-driven framework enables early fault prognosis, minimizing disruptions and the likelihood of substandard output. The paper further explores AI's role in dynamically optimizing manufacturing through real-time analytics, adaptive control, predictive maintenance, and intelligent decision-making, enhancing efficiency, resource utilization, and product quality. Drawing on a comprehensive review of literature, case studies, and experimental results by Wan et al. (2021), Kleven Maritime AS, and Ekornes collectively demonstrate how AI-assisted Computer-aided Manufacturing (CM) enhances production efficiency and customization through real-time data analysis, modularization, ERP system implementation,

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and Industry 4.0 readiness, thereby enabling concurrent processing of multiple tasks tailored to customer preferences. This paper provides a valuable resource for researchers, practitioners, and industry professionals aiming to harness the full potential of AI to propel manufacturing performance to new heights.

Keywords: AI integration; process optimization; fault prognosis; efficiency enhancement; machine learning algorithms; industry 5.0.

1 Introduction

The manufacturing industry is undergoing a profound transformation with the integration of artificial intelligence (AI) into its core processes. The pursuit of efficiency, quality, and overall performance has spurred a paradigm shift towards AI-driven solutions with the fusion of manufacturing technology. Li et al. [1]. This will impact diverse industry characterised by many challenges in terms of material availability, production capability, and demand forecasting. Olanrewaju, O. [2].

With AI driven automation, the manufacturing industry is faced with new challenges of demand and competition leading to a radical change with a need for industry 4.0 integration of AI with recent emerging technologies. Lee et al. [3].

One of the key contributions of AI in manufacturing lies in predictive maintenance. In a study by Zonta et al. [4], AI algorithms can analyse vast amounts of data from sensors and machinery to predict potential equipment failures before they occur. Additionally, AI-driven asset optimization ensures that resources are used efficiently, reducing costs, and improving overall operational performance. Lee et al. [5] explored the vital role of key enabling technologies in Industrial AI within the manufacturing industry. No doubt AI plays a pivotal role in revolutionizing supply chain management in manufacturing through predictive analytics that assists in demand forecasting, inventory management, and logistics optimization.

Historically, manufacturing operations relied on conventional quality control methods and static process optimization strategies, often leading to inefficiencies, disruptions, and suboptimal output. The advent of AI technologies, encompassing advanced machine learning algorithms, sensor data utilization, and Internet of Things (IoT) connectivity, presents an unprecedented opportunity to revolutionize these traditional approaches. Gupta et al. [6].

The synergy of AI and robotics has propelled automation in manufacturing, with AI-driven robots enhancing production efficiency through precision and speed [7]. Collaborative robots work alongside human operators, elevating safety, and productivity. AI empowers manufacturers to meet dynamic consumer demands by enabling mass customization through the analysis of preferences and market trends, enhancing customer satisfaction and competitiveness. Instead of job displacement, AI in manufacturing fosters human-machine collaboration [8], allowing human workers to concentrate on creative and complex aspects, fostering productivity and innovation in manufacturing.

The primary objective of this research is to explore the potential of AI in real-time quality monitoring, emphasizing its role in the early detection of defects, deviations, and inefficiencies. Leveraging the capabilities of machine learning, our proposed system continuously monitors production parameters, enabling swift and precise fault prognosis. The aim is to minimize production disruptions and reduce the likelihood of substandard output, addressing critical challenges in contemporary manufacturing.

In presenting this research, we present a comprehensive review of recent advancements in AI technologies, relevant literature, case studies, and experimental results. With insights from diverse sources, this paper seeks to provide a comprehensive understanding of the practical implications and benefits associated with AI-driven real-time quality monitoring and process optimization in manufacturing. As we navigate through the subsequent sections, the paper will give insights to the proposed framework and present findings that contribute to the ongoing discourse on the transformative potential of AI in manufacturing processes. Fig. 1 shows the evolution of industry 4.0.

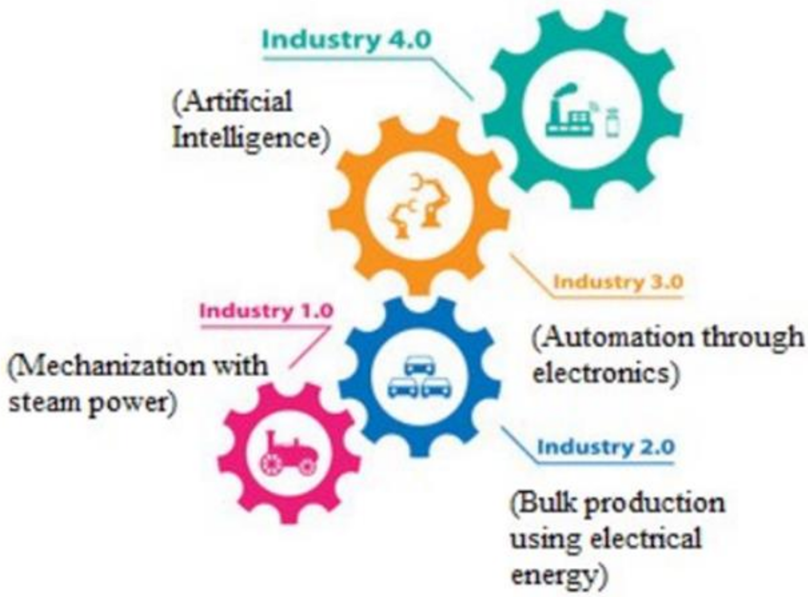

Fig. 1. Evolution of industry 4.0 [9]

2 Materials and Methods

The adoption of artificial intelligence (AI) in manufacturing has gained significant traction, promising to revolutionize conventional processes. Scholars such as Tao et al. [10] and Zhong et al. [11] underscore the pivotal role of AI in enhancing decision-making processes, reducing defects, and optimizing production efficiency. Their research underscores the necessity for AI-driven systems capable of real-time monitoring and optimization of manufacturing processes.

Zhou et al. [12] shed light on the critical role of the human-cyber-physical system (HCPS) within the technological framework of intelligent manufacturing. Their work outlines the evolution of this system to new-generation intelligent manufacturing (NGIM), seamlessly integrating advanced manufacturing and new-generation AI, thus propelling the ongoing industrial revolution. The study also addresses challenges in optimizing human-machine collaboration, maximizing intelligence synergies, achieving hybrid-augmented intelligence, and addressing safety, privacy, and ethical concerns in AI and intelligent manufacturing.

In the realm of manufacturing, real-time quality monitoring is paramount. Research by Zheng et al. [13] and Avola et al. [14] delves into real-time quality monitoring systems employing AI techniques like machine learning and computer vision. By integrating sensors and IoT devices, these systems collect real-time data, enabling swift decision-making to promptly address quality issues during production.

Sharma et al. [15] contributes insights into the challenges of AI implementation within India's Project Management System (PMS). Their study, utilizing the DEMATEL method, identifies interconnected factors such as data quality issues, limited managerial understanding of cognitive technologies, data privacy concerns, integration challenges with cognitive projects, and high costs. The research recommends the DEMATEL model for informed decision-making by industrial leaders, especially in developing intelligent AI systems for manufacturing in emerging economies.

Efficient and cost-effective manufacturing processes are integral to success. Research by Lee [16] and Wan et al. [17] explores AI-driven process optimization techniques that dynamically adjust parameters based on real-time data. These studies showcase AI's potential to adapt manufacturing processes in real time, minimizing waste and maximizing output.

The Industrial Internet of Things (IIoT) serves as a crucial connector of devices and sensors on the manufacturing floor. Investigations by Bu et al. [18] highlight the synergy between AI and IIoT, emphasizing the importance of seamless data exchange for effective real-time quality monitoring and process optimization. The integration of AI algorithms with IIoT offers a holistic approach to enhancing manufacturing processes.

Leesakul et al. [19] employ mixed methods to delve into challenges and acceptance factors in adopting human-robot collaboration (HRC) and digital manufacturing technologies. The study considers perspectives from diverse stakeholders, addressing key issues such as job displacement and privacy concerns. The research emphasizes the need to understand broader human factors for effective technology adoption and proposes specific interventions for responsible implementation, contributing to a roadmap for nurturing a sustainable workforce in digital manufacturing.

Despite significant progress, challenges persist in the implementation of AI-driven solutions for manufacturing. Research by Jagatheesaperumal et al. [20] identifies issues related to data security, scalability, and the demand for skilled personnel. Thus, there is an imperative to develop more robust AI algorithms, address ethical considerations, and foster interdisciplinary collaborations to effectively tackle complex manufacturing challenges. Subsequent sections will delve deeper into the role of AI in manufacturing, with a specific focus on real-time quality monitoring and process optimization.

3 Artificial Intelligence Use Cases

3.1 AI in manufacturing

AI applications in manufacturing span a wide range of processes, from design and production to quality control and maintenance. One significant area is the use of AI-driven design tools that optimize product development and enhance overall product performance. According to Rane, Choudhary and Rane [21], the research explores how 4D/5D/6D Printing accelerates prototype development and how IoT enhances product functionality through real-time monitoring and data-driven design improvements.

In production, AI plays a crucial role in process optimization, predictive maintenance, and supply chain management. Robotics and automation powered by AI are transforming factory floors, leading to increased precision and speed in manufacturing processes. Improved efficiency and productivity are among the foremost advantages of AI in manufacturing, as AI-powered systems can analyse vast amounts of data to optimize production processes and resource utilization. Predictive maintenance, enabled by AI algorithms, helps reduce downtime and extend the lifespan of equipment, leading to cost savings [22]. Quality control is another area where AI excels, ensuring that products meet stringent standards and reducing the likelihood of defects.

Furthermore, AI elevates decision-making by furnishing real-time insights through data analytics, empowering manufacturers to optimize inventory management, demand forecasting, and resource allocation. Additionally, the integration of collaborative robots, or cobots, alongside human operators promote safer and more ergonomic work environments, highlighting the harmonious convergence of AI and human labor.

3.2 Real time quality monitoring

Real-time quality monitoring, facilitated by artificial intelligence (AI), revolutionizes efficiency, defect mitigation, and production refinement. AI-driven systems automate quality monitoring, surpassing human capabilities for precision and accuracy. Machine learning algorithms adeptly analyze extensive real-time data, detecting subtle deviations in product quality. By continuously scrutinizing data from various sensors, AI systems identify deviations early, minimizing waste and rework. Leveraging historical data, AI predicts equipment failures proactively, optimizing machinery operation and reducing downtime. This approach is supported by Sundaram and Zeid [23], who emphasize data-driven techniques and IoT-enabled real-time tracking, highlighting the efficacy of AI-based quality control measures like Deep Learning (DL). Their custom Convolutional Neural Network (CNN) achieves a remarkable 99.86% accuracy in visual inspection of casting products, illustrating the tangible benefits of AI in manufacturing quality assurance.

AI is instrumental in enabling adaptive manufacturing, dynamically adjusting production parameters based on real-time quality data. This adaptability empowers manufacturers to swiftly respond to evolving conditions, ensuring consistent product quality in dynamic environments. The integration of AI in quality monitoring not only minimizes defects and reduces downtime but also optimizes processes, leading to significant cost savings and enhanced operational efficiency. These streamlined production processes contribute to a more competitive and sustainable manufacturing operation. Moreover, AI's influence extends beyond the factory floor, facilitating collaboration among manufacturers, suppliers, and partners to implement standardized quality measures throughout the supply chain. This seamless integration ensures a continuous flow of high-quality materials and components, underscoring AI's overarching impact in enhancing manufacturing quality across the entire production ecosystem.

3.3 Process optimization with AI

AI's role in manufacturing process optimization is exemplified through predictive maintenance, a paradigm shifts from reactive to proactive equipment management. By analysing historical and real-time data, AI algorithms forecast equipment failures, enabling pre-emptive maintenance interventions. This not only reduces unplanned downtime but also extends machinery lifespan, ultimately optimizing the entire production process. Real-time quality monitoring is another facet where AI showcases its capabilities. By continuously analysing production data, AI systems identify deviations from established quality standards early in the manufacturing process. This proactive approach minimizes defects and rework, ensuring the delivery of high-quality products and bolstering customer satisfaction.

AI influences production planning and inventory management, offering intelligent solutions that forecast demand, adjust production schedules, and optimize resource utilization. This ensures efficient resource allocation, minimizes waste, and provides manufacturers with the agility to respond promptly to market fluctuations. Energy efficiency and environmental sustainability are further areas where AI contributes to process optimization. By identifying energy-intensive operations and recommending efficient alternatives, AI enhances energy management, resulting in cost savings and a reduced environmental footprint.

In supply chain management, AI's analytical capabilities are indispensable. By processing extensive datasets encompassing logistics, procurement, and demand forecasting, AI empowers manufacturers to make informed decisions, streamline operations, and boost overall efficiency. The integration of AI redefines adaptive manufacturing, enabling production processes to dynamically adjust to changing conditions, thus optimizing resource utilization in real-time and enhancing responsiveness to market demands.

Moreover, AI's influence transcends operational aspects, extending to innovation and product development. Through the analysis of market trends, consumer preferences, and feedback, AI furnishes manufacturers with valuable insights to design products aligned with market demands, ensuring sustained relevance and competitiveness. These insights derived from AI analytics aid manufacturers in making informed decisions regarding process enhancements, resource allocation, and strategic planning.

As Helo and Hao [24] elucidate, AI's impact on supply chain management is profound. Their research offers a comprehensive overview of AI and SCM, delving into the timely and critical analysis of AI-driven supply chain research and applications. Through an exploratory examination of various case companies, their study evaluates the emerging AI-based business models and their significance, thus identifying several areas of value creation in AI application within the supply chain.

4 Case Study Analysis

The evolving role of AI technologies in manufacturing is evident in their capacity to enhance adaptability, environmental understanding, and critical process knowledge. This includes advanced business models like intelligent production, networked collaboration, and extended service models. Wan et al. [17] presented a case study on customized packaging, demonstrating that AI-assisted Computer-aided Manufacturing (CM) can significantly increase production flexibility and efficiency. The case study focuses on a prototype platform, utilizing AI for big data analysis in preventive maintenance, and implementing cloud-assisted customization services.

The prototype platform, designed for customized candy-wrapping, integrates CM devices, an industrial network (OPC Unified Architecture and data distribution service), a conveyor, and a cyber-physical system. The candy packing line, catering to small-batch production, tailors' candies to customer preferences, utilizing industrial IoT and four interconnected layers with diverse link functions.

The device layer, featuring five robots, two AGVs, a conveyor system, and a warehouse, handles essential functions in the intelligent production line. The industrial network in the second layer facilitates intelligent connection and information interaction. The third layer focuses on big data analysis, computing, and knowledge mining. The fourth layer, the service layer, stores manufacturing resources in the cloud platform, offering various AI services such as pattern recognition, accurate modelling, knowledge discovery, reasoning, and decision-making.Customers select candy preferences through an AI recommender, initiating order creation, decomposition into steps, and task completion using autonomous agents. Collaborative groups of devices conclude the process with candy wrapping.

Sensor data is analysed in the cloud during manufacturing, informing product monitoring and process adjustments for improved quality and efficiency. A model-driven method ensures interoperability and knowledge sharing across platforms. Manufacturing resource reconstruction aids production scheduling for multiple tasks. The cloud-based manufacturing semantic model guides task construction and matching. In the AI-assisted platform, three candy-wrapping tasks with ten different candies were concurrently processed, employing the first-in-first-out (FIFO) scheme. Fig. 2(a) and Fig. 2(b) shows the integration of AI and Customized Manufacturing.

Some key findings from Kleven Maritime AS were recorded according to Strandhagen et al. [25]. Production at the shipyards were characterised by ETO production where ships were designed based on client's preference. Kleven was focused on achieving production efficiency through modularization. These enhanced process control, production quality, and minimize lead times. In recent times, an ERP system has been implemented by Kleven to digitalise work operations.

A furniture production company called Ekornes was equally researched on by Strandhagen et al. [25]. The company provided a combination of MTO and ATO strategy for production where products are finalized upon receiving customer orders, which include customization preferences such as skin type and colour. Upon order reception, the skin is cut, sewn, and then assembled onto the chair. Survey response suggests Industry 4.0 is a realistic and promising goal for the company [26].

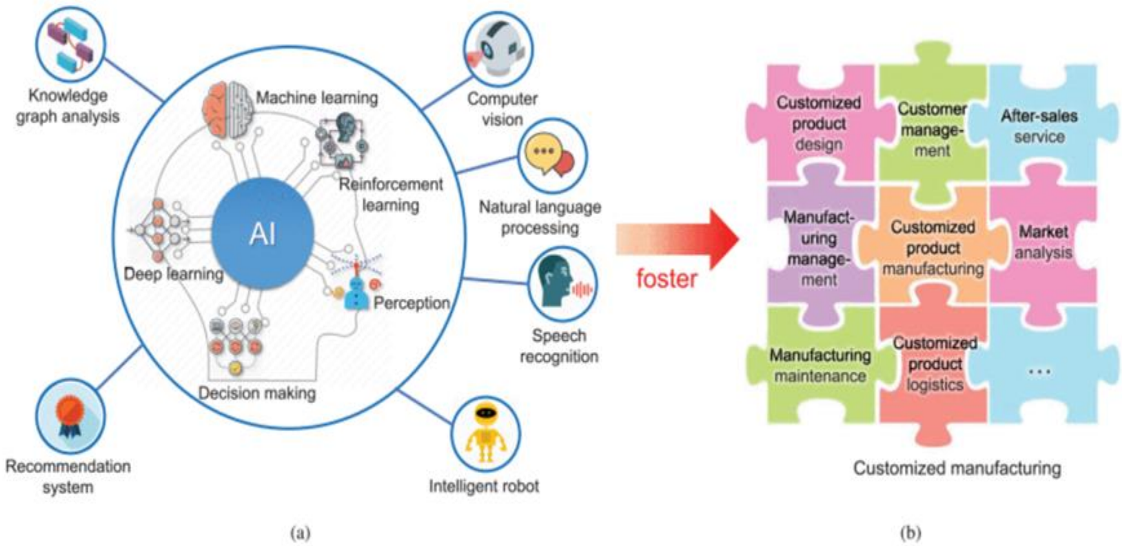

Fig. 2. Integration of AI and Customized Manufacturing [17]

5 Conclusion

While AI presents significant advantages in manufacturing, challenges such as implementation costs, workforce retraining, and data security are prevalent. The initial financial investment may hinder widespread AI integration, particularly for smaller enterprises, necessitating continuous workforce training to ensure a smooth transition. Ethical concerns, including job displacement and AI algorithm bias, require careful consideration to strike a balance between automation and preserving human jobs. As AI technologies reshape traditional processes, addressing challenges related to costs, workforce adaptation, and ethics is crucial for a sustainable manufacturing ecosystem.

In the realm of AI-driven real-time quality monitoring in manufacturing, significant advancements are underway, from early defect detection to adaptive manufacturing, enhancing product quality, cost reduction, operational efficiency, and competitiveness. As manufacturers embrace these innovations, they position themselves for sustained success in a dynamic global market.

In conclusion, the integration of AI-driven real-time quality monitoring and process optimization represents a transformative advancement in manufacturing. These systems not only streamline processes but also drive precision, efficiency, and innovation. With the emergence of Industry 5.0, future directions may focus on enhancing human-machine collaboration, improving workforce well-being and skills, and integrating advanced technologies for increased efficiency and productivity.

However, it's important to acknowledge the limitations of the study, such as potential biases in the data collected and the scope of the research. Future research could explore more deeply the impacts of AI integration on specific industries within manufacturing, address broader ethical considerations, and investigate novel approaches to mitigating implementation challenges.

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Competing Interests

Authors have declared that no competing interests exist.

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