(RESEARCH ARTICLE)

Enhancing Manufacturing with Artificial Intelligence: An Overview of the Present Situation, Insights, Recommended Practices, Obstacles and Future Trends

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Abstract

The industrial sector is presently experiencing a significant transformation characterized by the integration of intelligent automation fueled by advancements in Artificial Intelligence (AI). This combination significantly boosts operational efficiency and facilitates data-driven decision-making. Such improvements allow for optimal resource distribution and enhance the accuracy of production planning. This paper intends to present the latest trends and ongoing innovations within the AI domain as it pertains to the manufacturing sector. Additionally, the review examines critical applications of AI in manufacturing, including predictive maintenance, quality assurance, process optimization, supply chain management, robotics and automation, as well as intelligent decision support systems. It also addresses the challenges faced by the manufacturing industry while exploring how AI can help alleviate these issues. Moreover, this study provides an in-depth analysis of recent developments in AI technologies such as explainable AI, collaboration between humans and robots, edge computing, and integration with the Internet of Things (IoT). The review concludes with recommendations that underscore best practices and identify potential collaborative opportunities.

1. Introduction

Artificial Intelligence (AI) is drastically reshaping traditional manufacturing methods by introducing a fundamental change throughout the entire production lifecycle and its management. This shift is fueled by AI's capability to analyze vast amounts of data, make informed decisions, and adapt in real-time, leading to significant and impactful transformations.

The incorporation of AI within manufacturing entails the integration of sophisticated technologies and algorithms that enable machines and systems to perform tasks typically carried out by humans. This results in improved efficiency, accuracy, and automation. By leveraging AI technology, factories can optimize their operations, enhance product quality while reduce costs, and increasing their overall productivity.

AI is driving the development of smart factories, also referred to as Industry 4.0, where interconnected systems, IoT devices, and AI algorithms work together to create a highly automated and intelligent manufacturing setting. The integration of AI in these smart factories leads to enhanced productivity, real-time monitoring of manufacturing processes, and data-informed decision-making.

Industry 5.0, promoted by the European Commission, aims for a sustainable, human-centered industrial landscape [1]. Conversely, Society 5.0 from Japan seeks to harmonize economic progress with social issues resolution. Predictive

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maintenance has emerged as a key area where AI is transforming the industrial landscape. Traditional maintenance practices are often based on fixed schedules that can lead to unnecessary downtime and inefficient resource usage. In contrast, AI-driven predictive maintenance systems analyze real-time data from sensors and equipment through machine learning algorithms to forecast potential failures or necessary maintenance actions [2]. These AI systems can identify trends and anomalies while alerting operators for proactive maintenance measures that help minimize unplanned downtime.

Quality control is another crucial application of AI in manufacturing. Algorithms can process large datasets—comprising images, sensor readings, and historical information—to detect defects or deviations from specified standards. This capability enables manufacturers to address quality issues promptly before products reach the market; AI-driven quality control solutions can reduce errors and waste significantly while enhancing customer satisfaction.

Objectives of the review

- Our analysis indicates a significant gap in the literature regarding studies on smart manufacturing that incorporates artificial intelligence. This underscores the necessity for a thorough examination of this topic. Consequently, the objectives of this paper are as follows:
- To present a detailed overview of AI applications across various facets of manufacturing, including production planning, quality control, predictive maintenance, supply chain management, and other pertinent areas.
- To conduct an in-depth analysis of recent advancements in AI within manufacturing, along with the challenges it faces, potential opportunities, and future trajectories. This resource is designed for researchers, practitioners, and decision-makers interested in leveraging AI techniques to enhance manufacturing processes and outcomes. [3]
- To explore the integration of AI methodologies with current manufacturing systems and technologies while offering practical insights into implementing AI solutions in real-world manufacturing settings.
- To address critical factors related to AI implementation such as regulatory considerations, workforce reskilling initiatives, data governance issues, and the significance of collaboration among academia, industry stakeholders, and government entities.
- Thus, this study seeks to provide clarity on the current advancements in the field, connect various subtopics within it, and outline promising avenues for future research.

Scope and organization of the paper

This paper examines various AI technologies utilized in manufacturing and their advantages for industry. It highlights recent research developments and practical applications of AI within manufacturing contexts. Furthermore, it addresses both challenges and opportunities linked to integrating AI into existing processes while exploring its implications for the future landscape of manufacturing [15]. The target leadership includes researchers, developers and engineers specializing in AI technology, technology enthusiasts, policymakers, consultants, as well as professionals operating within the manufacturing sector.

- The study makes several contributions to advancing knowledge about AI's role in manufacturing.
- It offers a comprehensive review of current cutting-edge applications of AI in areas such as predictive maintenance, quality assurance, and process optimization [14].
- The analysis identifies key challenges faced by industry such as merging new technologies with pre-existing infrastructure and concerns surrounding data privacy—and discusses how AI could help mitigate these issues.
- Insights into recent innovations like explainable AI and human-robot collaboration are provided alongside suggestions for future research directions [4].
- Additionally, best practices are highlighted along with recommendations for collaborative opportunities between academia, industry leaders, and government bodies aimed at promoting progress in applying AI within manufacturing environments.
- These contributions aspire to improve efficiency, accuracy, and automation levels within the sector while addressing prevailing challenges and paving a way toward future innovations.

2. Literature Review

The organization of this paper is as follows: Section I introduces the background, objectives, and scope of the study. Section II explores AI methods and algorithms relevant to manufacturing. In Section III, we discuss data collection and storage practices. Section IV highlights various applications of AI within the manufacturing domain. Section V offers insights into the adoption of AI within the manufacturing ecosystem. Recommendations and best practices are

presented in Section VI. Section VII summarizes key findings, while Section VIII addresses challenges and potential future directions. Finally, Section IX concludes the paper [5].

2.1. AI Methods and Algorithms in Manufacturing

This section examines a wide range of Artificial Intelligence (AI) techniques and algorithms that are transforming the manufacturing sector. Ranging from established machine learning approaches to advanced deep learning networks, these technologies significantly enhance operational efficiency, accuracy, and automation for manufacturers. Additionally, it investigates the strengths and practical uses of different AI methodologies such as computer vision, reinforcement learning, and active learning, detailing their contributions to promoting intelligent manufacturing practices. The role of Artificial Intelligence (AI) and automation has gained notable attention due to their capacity to effect change across various sectors. (Fig. 1) illustrates several technologies associated with AI in the context of manufacturing.
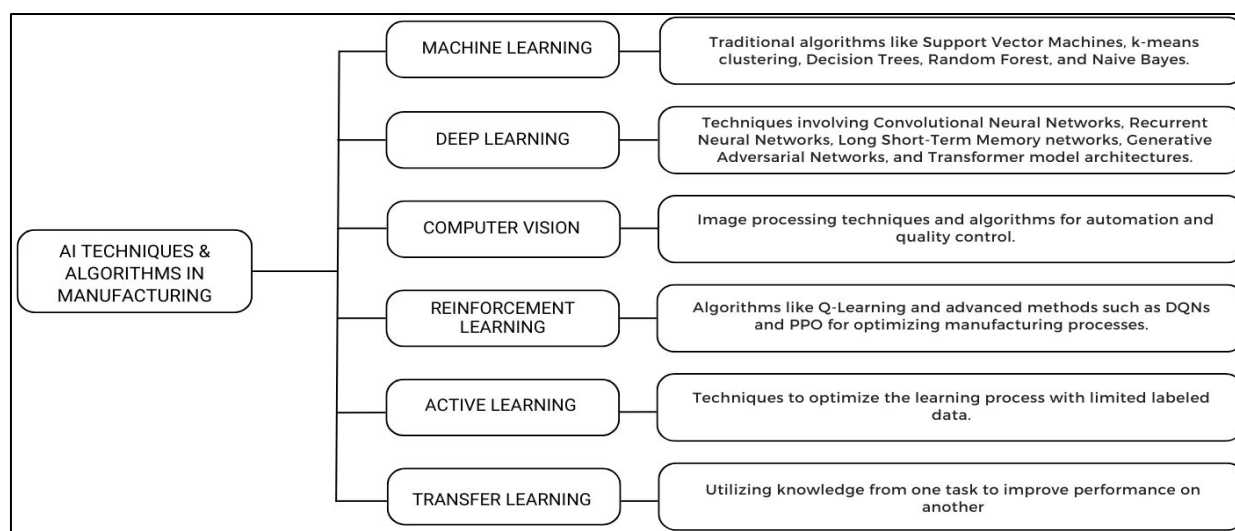

Figure 1 AI techniques and algorithms in manufacturing.

2.2. Traditional Machine Learning

Traditional machine learning algorithms serve as adaptable tools for tasks involving data analysis, pattern recognition, and modeling. Each algorithm possesses unique strengths and weaknesses, making them appropriate for particular applications [6]. For example, Support Vector Machines are known for their effective binary classification abilities, while k-means clustering is adept at organizing data points efficiently. Decision trees are valued for their transparency and interoperability. Conversely, in a random forest setup, each tree is trained using a random selection of both the data and features, which helps mitigate overfitting of the training dataset and enhances overall accuracy [7].

In the realm of machine learning, libraries like scikit-learn and XGBoost deliver a robust suite of user-friendly tools that facilitate seamless implementation. At the same time, cloud platforms such as Google Cloud, Azure, Amazon SageMaker, OpenAI, and IBM Watson have expanded opportunities for users by enabling access to scalable and flexible cloud-based solutions that leverage machine learning algorithms. Within this evolving environment, the AI4EU platform has emerged as a collaborative space housing advanced algorithms including IoT data analysis models and the Markov Decision Process—both poised to foster significant advancements in machine learning applications.

2.3. Deep Learning and Neural Networks

Deep learning encompasses a wide array of techniques that utilize neural networks to tackle complex tasks effectively. Convolutional Neural Networks shine in image analysis, Recurrent Neural Networks excel at handling sequential data , while Long Short-Term Memory Networks effectively manage long-term dependencies. These methodologies are catalyzing transformative changes across multiple fields.

Generative Adversarial Networks enable the creation of realistic synthetic data , whereas Autoencoders and Variational Autoencoders serve as powerful tools for unsupervised learning and data reconstruction purposes. Originally developed for natural language processing applications, transformer model architecture exhibits remarkable versatility

across various contexts. Additionally, Deep Reinforcement Learning facilitates intelligent decision-making within dynamic environments.

Deep learning's ability to autonomously learn hierarchical features from unprocessed data significantly reduces reliance on extensive manual feature engineering efforts. Moreover, its proficiency in managing large-scale complex datasets allows it to achieve leading performance levels across numerous domains. The widespread adoption of libraries like TensorFlow, Keras, and PyTorch [6] has accelerated the deployment of deep learning models profoundly impacting diverse sectors. These libraries also integrate effortlessly with platforms such as Google Cloud; Azure; Amazon SageMaker; and IBM Watson , fostering development in cloud-based solutions.

2.4. Computer Vision and Image processing

The manufacturing sector depends on various Computer Vision and Image Processing techniques to support automation processes such as quality control; defect detection, and process optimization. Ranging from traditional methods like histogram equalization; edge detection; or Hough Transform through state-of-the-art deep learning techniques like CNNs; GANs; or YOLO, these tools form integral components within diverse applications including object recognition; defect detection; motion analysis; or 3D reconstruction—all essential for enhancing efficiency and accuracy in manufacturing workflows amid ongoing technological advancements.

2.5. Reinforcement Learning

Reinforcement Learning (RL) has the potential to transform manufacturing processes by allowing agents to learn and make decisions through interaction with their environment, receiving feedback in the form of rewards. RL encompasses a range of algorithms, from foundational methods like Q-Learning to more sophisticated deep learning techniques such as DQNs, DDPG, and PPO. These approaches provide effective solutions for optimizing intricate processes, managing robotic systems, and improving overall efficiency within the manufacturing sector. As RL technology advances, it offers promising pathways for enhancing automation and optimization, enabling manufacturers to achieve greater productivity and improved operational performance. Various libraries like Gym, Keras-rl, Pyqlearning, and Tensor force [8]are available for building RL solutions, offering essential tools for developing efficient RL agents. Furthermore, platforms such as SageMaker RL and DeepMind Lab have been specifically created to facilitate the implementation of RL algorithms, simplifying practical applications of this technology.

2.6. Active Learning

Active learning serves as an effective strategy for overcoming the limitations posed by scarce labeled data in the manufacturing sector. By intelligently selecting the most informative samples for annotation, active learning optimizes educational outcomes significantly [8]. A variety of techniques exist within this framework, including uncertainty sampling, query by committee, density-based sampling, expected model change analysis, query by bagging approaches, information density sampling methods, margin sampling strategies, and diversity sampling initiatives aimed at improving model performance and generalization capabilities.

2.7. Edge AI

In contrast to conventional centralized data processing systems, there is an increasing demand for developing models that can be deployed directly on devices for real-time decision-making—this concept is referred to as Edge AI. This approach is critical when devices lack consistent network access or when central server processing is slow or impractical. Kubiak et al. investigate potential investigation of edge computing within manufacturing industries and reveal its wide array of use cases along with associated benefits. Key benefits of Edge AI include expedited processing speed and enhanced privacy since computations occur locally on devices without necessitating constant communication with a central server—this approach reduces latency while bolstering data privacy [8] .

2.8. Explainable AI

The intricate nature of features derived from different machine learning methodologies often results in models functioning as black boxes; thus, rendering intuitive interpretation of their decisions difficult. This challenge has become increasingly important due regulatory requirements surrounding trustworthiness in AI systems. In response, various explainable artificial intelligence (XAI) techniques have emerged—including Local Interpretable Model-Agnostic Explanations (LIME), Shapley Additive explanations (SHAP), Partial Dependence Plots (PDP), feature importance assessments, rule-based frameworks, Layer-wise Relevance Propagation (LRP) , counterfactual reasoning mechanisms, and anchors—that aim at facilitating user understanding regarding how models operate during decision-making

processes. Such advancements empower stakeholders justifying actions based upon algorithmic recommendations thereby enhancing confidence towards generated outcomes.

2.9. Transfer Learning

Transfer Learning has surfaced as a crucial component across machine-learning endeavors facilitating knowledge transition acquired through one task into another closely related endeavor ultimately enhancing overall productivity while conserving computational resources. By addressing issues stemming from insufficient data sets coupled with reducing requisite training durations transfer-learning empowers manufacturers constructing proficient models utilizing minimal annotated examples. Techniques involving meaningful extractions from pre-trained architectures subsequently fine-tuning them targeted towards specific industrial assignments whilst capitalizing upon generalized patterns observed across differing domains yield heightened efficacy concerning numerous objectives encompassing defect identification process enhancement outcome forecasting etc.. Moreover, this methodology cultivates generalizability robustness equipping algorithms adeptly tackling noise variations prevalent throughout industrial workflows.

3. Data collection and storage

In the context of Industry 4.0, data collection and storage form essential components that underline the extensive realm of AI-driven manufacturing. This section examines the complex array of technologies and strategies that facilitate the efficient gathering and retention of crucial data. It discusses the implementation of advanced Internet of Things (IoT) sensors alongside sophisticated Manufacturing Execution Systems (MES), highlighting various methods that extract valuable insights from all areas of the manufacturing floor. Additionally, it investigates robust storage solutions— ranging from conventional databases to contemporary data lakes—that maintain both the integrity and accessibility of this information, thus enabling intelligent analysis and informed decision-making within innovative factory settings.

3.1. Data collection

3.1.1. Internet of things (IoT) sensors

Within manufacturing environments, IoT sensors are instrumental in transforming data collection processes, significantly enhancing monitoring and optimization across production operations. These intelligent sensors are strategically positioned throughout the facility to collect real-time data from machines, devices, and various operational parameters[9]. They consistently monitor aspects such as temperature, pressure, humidity, machinery performance, energy use, among others. The resulting data provides manufacturers with critical insights into their workflows, allowing for well-informed decisions regarding process enhancements, predictive maintenance strategies, and quality assurance measures. The integration of IoT sensors leads to improved efficiency, minimized downtime, enhanced product quality, ultimately driving cost reductions and a competitive advantage within the sector. While FIWARE facilitates easier management and connectivity of IoT devices, a direct link remains necessary for accessing generated data.

3.1.2. Supervisory Control And Data Acquisition (SCADA) Systems

SCADA systems are vital in manufacturing due to their effectiveness in collecting, monitoring, and controlling operational data. These systems continuously acquire real-time information from a wide range of sensors and devices, facilitating quick identification of issues as well as production optimization efforts. Furthermore, SCADA systems archive historical data which supports trend analysis over time. Configurable alerts and event notifications quickly address any irregularities encountered during operations. In addition to enhancing productivity through comprehensive data collection capabilities, SCADA systems also play a crucial role in ensuring compliance within industries subject to strict regulatory frameworks by assisting in necessary data collection and reporting required for audits.

Libraries such as Ignition allow Python to connect with SCADA systems, which usually keep data in a database for straightforward retrieval.

Figure 2 Illustration of MES functions and their interconnections with other systems. The extent of these linkages can vary depending on the specific application. Source: [9]

3.2. Manufacturing Execution Systems (MES)

The implementation of a Manufacturing Execution System (MES) has become increasingly common, as highlighted by . This system supports two-way communication across the enterprise by linking data from various production sites. Fig. 2 illustrates the functionalities of an MES. Research has investigated optimal strategies for data extraction from these systems.
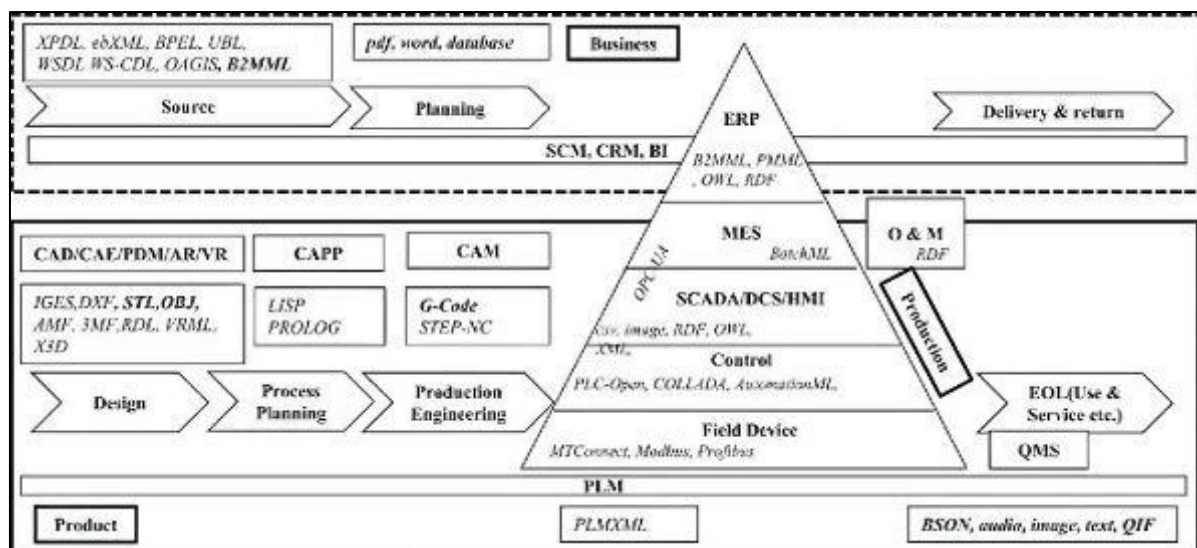

Figure 3 Depicts the diverse range of data formats encountered within smart manufacturing systems. Source: [71]

Adopting an MES offers a centralized platform that enhances continuous improvement efforts and operational excellence in contemporary manufacturing settings. By integrating with other enterprise systems such as Enterprise Resource Planning (ERP) and Supply Chain Management (SCM), [10]MES facilitates smooth information flow and improved decision-making throughout the organization. These systems are vital to the manufacturing sector's success and significantly impact various manufacturing facets, including production planning and scheduling, real-time monitoring, quality control, inventory management, traceability, equipment upkeep, workforce optimization, and data analytics.

The extensive range of data available within intelligent manufacturing systems is depicted in Fig. 3 from the review by Cui et al., which summarizes cutting-edge research on big data applications in manufacturing.

4. Data storage

4.1. Relational and NOSQL databases

The use of both relational and NoSQL databases within manufacturing environments presents significant benefits since each type is optimized for managing different kinds of data effectively. Relational databases like MySQL, PostgreSQL, Microsoft SQL Server, and Oracle are adept at handling structured data while ensuring integrity and offering advanced querying capabilities—making them suitable for critical information like product specifications and inventory levels. Conversely, NoSQL databases such as MongoDB, Cassandra, and Amazon DynamoDB manage unstructured or semi-structured data efficiently; they provide scalability, flexibility, and high performance—ideal for input from sensors or computer vision systems along with IoT devices. Moreover, databases like Influx DB have gained popularity for their efficiency in storing time series data; this makes them particularly suitable for real-time monitoring applications. By utilizing both types of databases effectively, manufacturing companies can achieve optimal storage solutions that maintain integrity while scaling according to diverse requirements from their various data sources and applications.

4.2. Data lakes and warehouses

Data lakes serve as adaptable repositories capable of holding various types of information from multiple sources while delivering an integrated perspective on the manufacturing process through effective data integration. They enable manufacturers to store raw data without modification so that analysis can occur, when necessary, later on. Furthermore, they facilitate real-time monitoring alongside analytics derived from connected devices—offering a cost-effective option for long-term storage solutions. In contrast to this approach are data warehouses designed specifically for housing structured or processed datasets ready for querying or reporting purposes. They provide an organized method for storing information that allows managers and executives within manufacturing organizations to produce reports easily while gaining insights into overall company performance metrics including key performance indicators.

4.3. Cloud Storage

Cloud storage presents a versatile solution for the manufacturing sector, enabling seamless scalability in data storage to handle the substantial amounts of information generated from sensors, machinery, IoT devices, and other systems. This approach eliminates the need for on-premises hardware and maintenance, resulting in significant cost reductions while providing strong security measures such as encryption and access controls to ensure data privacy. Furthermore, cloud storage integrates effortlessly with AI platforms, allowing manufacturers to leverage AI and machine learning algorithms for enhanced data analysis and modeling.

4.4. File Systems

File systems play an essential role in the manufacturing sector by efficiently storing and managing a wide range of data types—from images and videos to structured formats like JSON and CSV. Manufacturers utilize this information derived from sensors, cameras, and machines to enhance operational efficiency, maintain quality control, and make well-informed decisions. By effectively employing specialized libraries and technologies to extract meaningful insights from their data, manufacturers can significantly improve their production processes. With careful attention to security protocols and compliance standards, file systems establish a solid foundation for unlocking the full potential of data-driven practices in manufacturing.

4.5. Data Security, Backup, and Recovery

Data security is critical within the manufacturing industry due to the sensitive nature of information handled—including production processes and customer details. Implementing stringent measures such as encryption protocols, access controls, and user authentication helps protect against unauthorized access and cyber threats while ensuring confidentiality and integrity of data[11]. Moreover, robust data security safeguards valuable intellectual property against theft or unauthorized disclosure that could undermine a company's competitive edge. Regular backups alongside off-site recovery options enable rapid restoration of vital information during disruptions caused by data loss—facilitating swift resumption of production activities. Proactively testing recovery procedures enhances resilience against cybersecurity threats or hardware failures while promoting effective risk management strategies within manufacturing operations[12].

4.6. AI Applications in Manufacturing

The integration of artificial intelligence (AI) into the manufacturing landscape has heralded a transformative era termed Industry 4.0. This section delves into AI applications within the sector where traditional methodologies are being

redefined through automation; advanced analytics; as well as machine learning techniques. From predictive maintenance improvements; enhanced quality control measures; optimized supply chain logistics; down-to human-robot collaboration initiatives—AI significantly boosts both efficiency levels alongside productivity metrics throughout modern-day manufacturing environments[14].
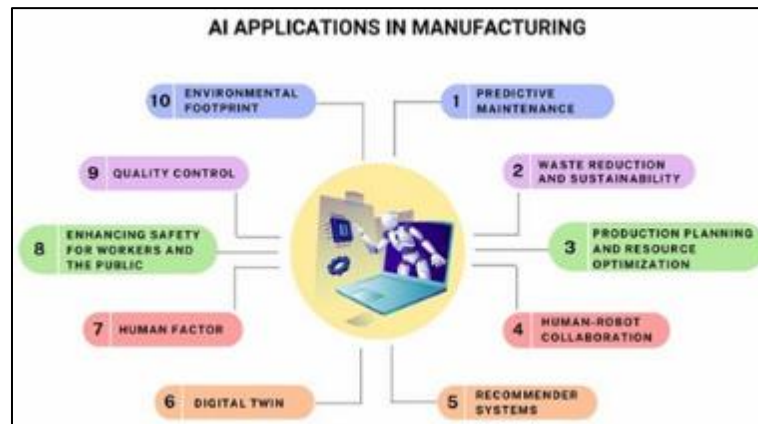

Figure 4 Applications of AI in manufacturing

5. Recommendation and Best Practices

Recent years have witnessed significant transformations around advancements driven technological evolution relentless pursuit excellence shaping contemporary practices seen various sectors recognizing immense potentials inherent Artificial Intelligence optimizing operational capacities[18]. As we approach accelerated adoption journeys realizing relevance developing comprehensive understandings curated guidelines reinforce positive trajectories underpinning transformations imperative navigate intricacies involved fully leveraging benefits available amid transitions hereunder provide key recommendations/best-practice considerations pertinent organizations embarking implementations:

- Ensure access to high-quality reliable relevant datasets underpinning models concurrently instituting management protocols uphold integrity preserving accuracy standards
- Encourage collaborative interdisciplinary engagements involving experts' researchers, domain-specific professionals ensure thorough comprehension of specific requirements inherent integrations
- Prioritize securing safeguarding sensitive information against breaches emphasizing robust measures uphold privacy standards guiding ethical conducts [15].
- Commence small-scale pilot projects gradually scaling integration glean valuable insights assessing impacts minimalizing risks associated broadened implementations
- Facilitate upskilling training programs cultivating workforce competencies surrounding emerging technologies engender culture embodying continuous improvement innovation ethos
- Embed ethical principles developmental deployment lifecycles governing fairness responsibility transparency resonating stakeholder trust values
- Remain cognizant prevailing regulatory landscapes prioritizing adherence compliance mandates pertaining existing safety quality assurances regarding system operability
- Consider hybridized computing paradigms balancing cloud edge demands computational power real-time processing requisites accentuating efficacy responsiveness needed contextual scenarios.

6. Findings

This section delineates primary discoveries prevailing trends notable advancements witnessed applications harnessed through Artificial Intelligence prevalent realms operating under auspices Manufacturing Industries encapsulating concise summaries key insights illuminating pathways currently informing directions steer future research pragmatic implementations serving guidance readers decision-makers traversing dynamic fields alike:

- Notable increases observed regarding productivity efficiency operational performances resulting from widespread adoptions occurring respective sectors globally affirmatively impacting bottom lines positively

elevating outputs commensurate profitability margins realized businesses striving thrive amidst competition heightened stakes precipitated transitions underway [16].

- Smart Manufacturing Systems leveraging IoT integrate seamlessly communication networks empowering informed decisions harnessed actuated dynamically responding to changing marketplace conditions swiftly aptly executing adaptations required promptly meeting demands anticipated consumers expectations readily satisfying evolving preferences crafting bespoke offerings tailored precisely meeting desires expressed vis-vis engagement mechanisms deployed cross-channel touchpoints!

- Machine Learning Algorithms extensively utilized optimizing varied facets enhancing productive outcomes notably decreasing downtimes ameliorated quality control measures substantially increasing throughput ratios attainable accomplished expediently systematically progressively iteratively aligning continuous improvement imperatives ingrained cultures fostering excellence defining new norms setting benchmarks industry-wide reshaping identities redefining paradigms established norms shifting perspectives altogether illuminating paths otherwise obscured long overdue reevaluations warranted[17].

- Predictive Maintenance techniques fortified powered enhanced robustness utilizing AIs analytical prowess demonstrating unprecedented abilities forecast impending failures preemptively generating substantial savings diminishing unexpected interruptions proactively transitioning activities sustains uninterrupted flow uniformly cascading benefits felt ripple effects downstream amplifying efficiencies realized upstream consequently invigorating entire ecosystems broadly universally beneficially impacted profoundly positively engendered trust building revered reputations cultivated nurtured relationships forged lasting legacies memorable milestones achieved collaboratively paving ways brighter horizons beckoning enticing potentials await exploration promising ventures fruitful moments ahead surely worthwhile indeed[18].

- Supply Chain Optimization bolstered significantly enhanced reliability rotational inventories reduced lead times improved forecasting accuracy enriching holistic view supply chain dynamics facilitated transparent communications foster collaboration partners empowered resilient adaptable structures emergent exceed expectations manage contingencies deftly proficient henceforth poised leverage advantages garnered maintain relevance amidst swirling currents fluctuating tides surging unpredictability's confronting emerging realities dynamically adjusting calibration responses ensuring stability sustained continuity paramount paramountcy prioritized diligently ceaseless vigilance maintained unwavering commitments follow-through engender enduring trust forged alliances.

7. Conclusion

The influence of artificial intelligence (AI) on the future landscape of manufacturing is significant, ushering in a substantial transformation within the sector that impacts economic growth, sustainability, and competitiveness across multiple fronts. The incorporation of AI into manufacturing processes has the potential to significantly enhance economic development [19]. By improving production efficiency and product quality through AI technologies, manufacturers can achieve higher output levels while simultaneously lowering costs. This foster increased competitiveness and greater profitability for companies within the manufacturing realm. Moreover, innovations driven by AI pave the way for new avenues in product creation and market growth, thereby supporting broader economic advancement.

AI also plays an essential role in promoting sustainability in manufacturing. As organizations encounter increasing demands to implement eco-friendly practices, AI presents solutions that facilitate more efficient resource management. Utilizing data analytics, AI optimizes energy consumption, reduces waste, and supports principles of a circular economy, ultimately decreasing the environmental impact of the industry. Adopting sustainable practices driven by AI not only aligns with global environmental objectives but also enhances a company's image among environmentally conscious consumers[20].

Additionally, AI boosts competitiveness by revolutionizing conventional manufacturing paradigms. Its capacity to process extensive datasets and forecast trends enables businesses to make informed decisions and maintain a competitive edge. By allowing manufacturers to respond swiftly to evolving market conditions and consumer preferences, AI helps ensure their ongoing relevance in an increasingly volatile business environment. The insights derived from AI can also inspire the development of innovative products and services, providing companies with distinctive advantages in their respective markets.

As the manufacturing sector increasingly integrates AI technologies, collaboration and knowledge-sharing become crucial for sustainable advancement. It is essential for companies, researchers, and policymakers to join forces in establishing best practices while addressing ethical considerations surrounding this technology. Responsible adoption

of AI will help ensure equitable distribution of its benefits while proactively tackling potential challenges such as job displacement.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

Statement of ethical approval

Ethical approval was not required for this study as it did not involve human or animal participants. The research utilized publicly available and anonymized data.

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References

[1] Bokrantz, J., Henningsson, S., & Rönnqvist, M. (2017). Challenges of industrial AI: A literature survey. Journal of Manufacturing Technology Management, 28(7), 974-991. https://doi.org/10.1108/JMTM-01-2017-0011

[2] Bousdekis, A., & Daskalaki, N. (2021). Artificial Intelligence applications in manufacturing: A systematic literature review. International Journal of Production Research, 59(24), 7493-7526. https://doi.org/10.1080/00207543.2021.1975398

[3] Haseeb, M., Shafique, M. F., & Ghani, U. (2020). The Industrial Internet of Things (IIoT) in Smart Manufacturing: Impact and challenges. International Journal of Advanced Manufacturing Technology, 107, 1733-1744. https://doi.org/10.1007/s00170-020-05899-2

[4] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for smart manufacturing. CIRP Annals, 64(1), 101-104. https://doi.org/10.1016/j.cirp.2015.04.002

[5] Thangavel, K., & Bijaya, S. (2020). Review on artificial intelligence techniques used for managing manufacturing. Materials Today: Proceedings, 33, 4741-4745. https://doi.org/10.1016/j.matpr.2020.03.233

[6] Yang, Y., & Wu, X. (2020). AI-driven smart manufacturing: The future of manufacturing in the Industry 4.0 era. Future Generation Computer Systems, 108, 153-161. https://doi.org/10.1016/j.future.2018.03.014

[7] Zheng, P., & Xu, C. (2018). The roles of artificial intelligence in Industry 4.0: A review. Journal of Industrial Information Integration, 13, 1-12. https://doi.org/10.1016/j.jii.2018.06.001

[8] Xu, C., & Xu, Y. (2019). Intelligent manufacturing: A "digital twin" approach. Journal of Manufacturing Systems, 51, 158-169. https://doi.org/10.1016/j.jmsy.2019.05.008

[9] Son, Y. J., & Kim, Y. D. (2017). The role of artificial intelligence in smart manufacturing. International Journal of Production Research, 55(15), 4291-4305. https://doi.org/10.1080/00207543.2017.1304660

[10] Zhao, R., Riff, J., & Xu, S. (2020). Artificial intelligence in manufacturing: A review of progress and prospects. Cirp Journal of Manufacturing Science and Technology, 29, 168-188. https://doi.org/10.1016/j.cirpj.2020.08.007

[11] Kadir, M. H. A., & Khedhaouria, A. (2020). The impact of artificial intelligence on manufacturing performance: A review and future research directions. Computers in Industry, 123, 103288. https://doi.org/10.1016/j.compind.2020.103288

[12] Teo, T. S. H., & C. L. E. K. (2020). AI in manufacturing: A technological and managerial overview. International Journal of Production Research, 58(16), 4977-4993. https://doi.org/10.1080/00207543.2020.1813218

[13] Duflou, J. R., & Thoma, K. (2012). Manufacturing and production: Latest trends and future directions. International Journal of Production Research, 50(1), 3-11. https://doi.org/10.1080/00207543.2012.707730

[14] Duflou, J., & Koc, C. (2020). Smart manufacturing in the era of Industry 4.0: A survey on AI applications and challenges. Journal of Manufacturing Systems, 54, 123-132. https://doi.org/10.1016/j.jmsy.2020.01.005

[15] Luthra, S., & Mangla, S. K. (2018). Barriers to the adoption of AI in supply chain management: A review and interactions. International Journal of Production Research, 56(18), 5851-5865. https://doi.org/10.1080/00207543.2018.1484521

[16] Wang, Y., Gunasekaran, A., & Ngai, E. W. T. (2016). Big data in smart manufacturing: A review. Journal of Manufacturing Technology Management, 27(5), 629-646. https://doi.org/10.1108/JMTM-01-2015-0008

[17] Duflou, J. R., & Kagermann, H. (2018). The role of artificial intelligence for manufacturing: A comparative overview of challenges and opportunities. CIRP Working Papers, 66, 64-69. https://doi.org/10.1016/j.cirp.2018.03.010

[18] Ghadge, A., & Gohar, T. (2020). Impacts of artificial intelligence on business models in manufacturing. Artificial Intelligence Review, 53(4), 2105-2127. https://doi.org/10.1007/s10462-019-09767-3

[19] Milani, A. S., & Aghazadeh, F. (2020). AI in manufacturing and the position of human workers: A qualitative exploration. Technological Forecasting and Social Change, 158, 120182. https://doi.org/10.1016/j.techfore.2020.120182

[20] Pöppelbuß, J., & Matzner, M. (2019). Digital transformation in manufacturing: Findings from case studies and implications for future research. Computers in Industry, 104, 89-101. https://doi.org/10.1016/j.compind.2018.10.022