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Machine Learning and IoT-Driven Solutions for Smart Manufacturing in Industrial Applications

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Abstract:

The Internet of Things (IoT) has transformed the industrial sector by enabling seamless integration of diverse systems, devices, and technologies within manufacturing environments. IoT has significantly contributed to various aspects of manufacturing, including remote monitoring and control of industrial operations, improved energy efficiency, optimized resource utilization, and reduced operational costs, thereby supporting the evolution of smart manufacturing under the industry 4.0 paradigm. This review presents a comprehensive and up-to-date examination of IoT technologies and machine learning (ML) techniques employed in smart manufacturing. It focuses on four key application domains: industrial security, predictive maintenance, process control, and additive manufacturing. The study also provides a detailed overview and comparison of the ML algorithms most adopted in smart manufacturing environments. Furthermore, it critically evaluates recent IoT-based solutions reported in the literature, examining their architectural frameworks, sensing technologies, data analytics approaches, communication protocols, performance metrics, and other distinguishing characteristics. By comparing these solutions, the review identifies their respective strengths and limitations. Finally, the paper discusses emerging trends and highlights the essential features and capabilities expected in future IoT-driven systems for advanced smart manufacturing applications.

Keywords — **machine learning; IoT, smart manufacturing, Industry 4.0, additive manufacturing, predictive maintenance, industrial process control, worker's health, data safety**

I. Introduction

The industrial manufacturing sector has experienced substantial growth driven by continuous technological advancements aimed at streamlining production processes while improving product quality, efficiency, and output. The adoption of interconnected digital technologies has enabled the real-time integration of all components involved in manufacturing operations, resulting in enhanced product quality, improved plant safety, and more effective monitoring of operational conditions through predictive maintenance (PdM). Additionally, these technologies contribute to protecting workers' health by continuously tracking physiological indicators and workplace environmental conditions.

A key enabler of this transformation is the Internet of Things (IoT), which facilitates the collection, storage, and analysis of data generated by sensors distributed throughout industrial environments. The information derived from this data supports informed decision-making regarding production performance, equipment status, workplace safety, and environmental monitoring.

The application of IoT extends far beyond manufacturing. In the healthcare sector, wearable IoT devices have been developed to monitor and collect physiological data such as electrocardiogram (ECG), electroencephalogram (EEG), body temperature, and photoplethysmography (PPG) signals for diagnostic and monitoring purposes. For instance, IoT-enabled systems have been implemented to acquire clinical data and detect cardiac abnormalities such as atrial fibrillation through ECG analysis. In agriculture, IoT has given rise to Smart Agriculture 4.0, which enhances the precision and efficiency of farming operations. Technologies such as drones and robotic systems support weed detection, crop monitoring, livestock management, and automated agricultural tasks. Furthermore, IoT-based monitoring systems optimize irrigation, soil conditions, pesticide and fertilizer application, greenhouse management, and environmental control, ultimately increasing productivity while reducing operational costs.

More broadly, IoT technologies have significantly improved logistics and warehouse management by enhancing operational efficiency, productivity, safety, and responsiveness. They also help mitigate labor shortages, lower operational expenses, and reduce environmental impacts. Since order-picking activities account for a major portion of warehouse operating costs, IoT-enabled visibility and traceability systems play a crucial role in improving inventory management and increasing picking efficiency.

Another important application of IoT is predictive maintenance, a proactive maintenance strategy that relies on continuous equipment monitoring and data analysis to predict potential failures before they occur. As industrial facilities become increasingly critical to economic stability and productivity, predictive maintenance helps maintain high equipment reliability and operational efficiency while reducing maintenance expenses. By detecting early signs of equipment degradation, organizations can minimize unexpected downtime, decrease the frequency of unplanned maintenance actions, and significantly reduce the risk of system failures.

The emergence of Industry 4.0 represents the fusion of manufacturing digitalization with IoT-enabled technologies and smart connected devices. Often referred to as the Fourth Industrial Revolution, Industry 4.0 envisions highly adaptive and intelligent production environments in which manufacturing systems can autonomously optimize operations and respond dynamically to changing conditions. Numerous IoT-based applications support manufacturers in their digital transformation efforts by improving operational efficiency, automation, competitiveness, and customer-centric production strategies. Moreover, data generated across the production value chain can be leveraged to create new business opportunities and revenue streams.

The primary objective of Industry 4.0 is to move beyond the mass-production automation characteristic of the Third Industrial Revolution toward more flexible, intelligent, and resource-efficient manufacturing systems. This technological transformation emphasizes greater industrial automation, connectivity, and digital integration. As a result, Smart Manufacturing (SM) has emerged as a key outcome of industrial digitalization, combining advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Cloud Computing, and Cyber-Physical Systems (CPS) to create intelligent, data-driven manufacturing environments capable of optimizing performance, productivity, and sustainability.

Figure 1. Information Flow within the IoT Paradigm. Data collected by sensing devices installed throughout industrial facilities or used for worker monitoring are transmitted through wired or wireless communication technologies to a centralized data-processing platform. The collected information is then analysed to generate valuable insights related to production quality, equipment condition, operational progress, energy consumption, environmental pollution, and worker well-being.

Cyber-Physical Systems (CPS) play a fundamental role in Industry 4.0 by bridging the gap between the physical and digital domains through advanced information and communication technologies. These systems integrate software, hardware, and physical components to continuously monitor, analyze, and control real-world industrial processes, enabling seamless interaction between physical assets and digital environments. The primary objective of Industry 4.0 is to modernize and optimize manufacturing operations through sustainable, intelligent, and highly connected production systems. This transformation relies on advanced technologies such as the Internet of Things (IoT), robotics, and additive manufacturing.

Security remains a critical concern within industrial environments because it helps prevent operational disruptions, reduce workplace accidents, and improve employee training and safety management. The integration of sensing technologies and machine learning (ML) algorithms has led to the development of smart personal protective equipment (PPE) capable of monitoring workers' health conditions and verifying the correct use of safety gear. Current research in this area focuses on developing devices that are smaller, more ergonomic, user-friendly, and capable of self-powering or self-recharging. However, industrial digitalization has also introduced new challenges, including cybersecurity threats such as data breaches, data manipulation, and attacks targeting industrial automation systems. Consequently, modern IoT-based security solutions must address issues related to technological complexity, large-scale data management, evolving cyber threats, and effective threat classification.

Additive Manufacturing (AM) represents one of the key technological pillars of digital manufacturing and has significantly transformed conventional production methods. Unlike traditional subtractive manufacturing techniques, additive manufacturing creates components by depositing material layer by layer according to digital design specifications. This approach eliminates many steps associated with conventional manufacturing processes, including complex machining cycle planning, the use of large machining centers, chip disposal procedures, and extensive maintenance operations. Originally developed for rapid prototyping applications, additive manufacturing has evolved into a viable production technology through the advancement of various AM techniques.

Among the most widely adopted additive manufacturing technologies are stereolithography (SLA), selective laser sintering (SLS), three-dimensional printing (3DP), laminated object fabrication (LOF), and fused deposition modeling (FDM). Within smart manufacturing environments, IoT technologies are increasingly employed to monitor and optimize additive manufacturing processes, helping to detect and minimize production defects. For example, digital twins and augmented reality interfaces enable real-time process monitoring and early identification of manufacturing anomalies, thereby improving process reliability and predictability.

A notable industrial example is Fast Radius, now part of SyBridge Technologies, which successfully implemented an IoT-based manufacturing platform that gathers and analyzes data from digitally stored component designs and production activities. This capability allows engineers to identify suitable applications for 3D printing while evaluating the technical and economic feasibility of manufacturing specific parts. In recognition of its innovative approach, the company's Chicago facility was named one of the world's leading smart factories by the World Economic Forum in 2018.

Another example is the Geico Taikisha Group, a global provider of automated automotive paint-shop solutions. The company leverages IoT-enabled digital twin technology to provide customers with real-time access to detailed production and operational data. This connectivity enables continuous monitoring of equipment performance, identification of recurring issues, and optimization of paint-shop operations. Furthermore, digital twin capabilities allow customers to conduct live simulations to evaluate process improvements, identify vulnerabilities, and reduce operational costs. These technologies also support predictive maintenance strategies and smart energy management, leading to reduced downtime, greater resource efficiency, enhanced sustainability, and significant cost savings.

Strengthened clarity while preserving the original technical meaning and references to Industry 4.0 and smart manufacturing.

While Industry 4.0 primarily emphasizes the integration of intelligent technologies into manufacturing systems and supply chains, the emerging concept of Industry 5.0 seeks to advance this transformation by promoting stronger collaboration between humans and machines within interconnected digital environments. This new paradigm combines the speed, accuracy, and efficiency of automated systems with human creativity, innovation, and critical thinking, resulting in more effective and value-driven industrial processes. Rather than replacing human workers, Industry 5.0 aims to complement and enhance human capabilities through advanced technological support.

Industry 5.0 should not be viewed as a completely new industrial revolution but rather as an evolution of Industry 4.0. It builds upon existing technologies, including additive manufacturing, augmented reality, autonomous robots, big data analytics, cloud computing, cybersecurity, system integration, the Internet of Things (IoT), and digital twins, while placing greater emphasis on human well-being, creativity, and sustainable development. The objective is to achieve a harmonious balance between machine efficiency and human ingenuity, leveraging the strengths of both to improve industrial outcomes.

Three fundamental principles define the Industry 5.0 framework. The first is human-centricity, which prioritizes the needs, skills, and well-being of workers within industrial environments. Instead of requiring employees to adapt to technological advancements, Industry 5.0 focuses on designing technologies that support and empower people. Although machines and robots excel in precision, consistency, and endurance, they cannot replicate the creativity, intuition, and problem-solving abilities inherent to humans.

The second principle is resilience, which refers to the ability of industrial systems to withstand disruptions, adapt to changing conditions, and maintain stable operations during crises. Recent global challenges, particularly the COVID-19 pandemic, revealed significant vulnerabilities in manufacturing processes and supply chains, underscoring the need for more agile and robust production systems capable of responding effectively to unexpected events.

The third principle is sustainability, which aims to minimize environmental impacts through responsible resource utilization and circular economy practices. Key sustainability initiatives include reducing energy consumption, greenhouse gas emissions, and industrial waste while preserving natural resources and promoting environmentally responsible production methods. By embracing these principles, organizations can achieve long-term benefits such as improved energy efficiency, increased operational resilience, enhanced competitiveness, and greater attractiveness to skilled talent.

Ultimately, Industry 5.0 advocates for technology that serves human needs and enhances workers' contributions to production processes. Emerging software solutions provide valuable insights that improve manufacturing performance while supporting sustainable operations. In particular, artificial intelligence (AI)-based soft sensors can reduce excessive consumption of raw materials and energy by delivering real-time information about product quality, thereby enabling more efficient decision-making and process optimization.

Based on these developments, this review provides a comprehensive overview of IoT applications in industrial environments, examining the various approaches proposed in the scientific literature and their corresponding outcomes. To facilitate analysis, the discussion is organized into four major application domains, as illustrated in Figure 2:

- Safety: This area addresses both workplace safety and cybersecurity. It focuses on protecting workers' health and well-being while safeguarding industrial systems from cyber threats and attacks.
- Predictive Maintenance: Various IoT-enabled approaches for anticipating equipment failures are examined. These solutions aim to reduce maintenance costs, prevent unexpected downtime, and extend machinery lifespan.
- Process Control: IoT techniques used for monitoring and controlling industrial processes are explored, with the objective of maintaining operational stability and preventing process deviations or failures.
- Additive Manufacturing: The integration of IoT technologies with 3D-printing and additive manufacturing processes is analyzed, highlighting their role in improving production monitoring, quality assurance, and manufacturing efficiency.

Figure 2. Overview of the Topics Covered in This Review.

To strengthen the scientific contribution and practical relevance of this review, each section provides the following:

- A comparative analysis of the studies examined, highlighting and contrasting the key features, advantages, and contributions of each research work.
- A comprehensive summary table outlining the main characteristics and technical aspects of the reviewed studies, facilitating a clear comparison of the different approaches and solutions.

This review is organized into several sections. Section 1 introduces the main topics addressed in the paper and describes the methodology used for selecting the scientific articles included in the review. Specifically, the systematic identification and selection of publications related to machine learning (ML) and Internet of Things (IoT)-based solutions for smart manufacturing are conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

Section 2 presents an overview and comparative evaluation of the machine learning algorithms most commonly applied within smart manufacturing environments. Section 3 focuses on security issues in smart manufacturing, covering both worker safety and cybersecurity measures designed to protect industrial systems and data. Section 4 examines predictive maintenance applications, emphasizing IoT technologies that enable the prediction of equipment failures and support effective maintenance planning to minimize unexpected downtime. Section 5 discusses IoT-based process control approaches used to monitor manufacturing operations and detect process deviations before they lead to failures. Section 6 reviews recent developments in IoT-enabled additive manufacturing (AM), highlighting technologies that improve process monitoring and production quality. Finally, Section 7 presents the overall conclusions and key findings of the study.

At the end of each section, a summary table is provided to present the principal components of the IoT solutions adopted in the reviewed studies. In addition, a comparative assessment identifies the strengths, limitations, and distinguishing characteristics of the analyzed approaches.

Selection Method for the Analyzed Articles Based on the PRISMA Framework

Before examining the selected studies, it is essential to establish the criteria used for article inclusion and exclusion. These criteria were carefully defined to ensure the selection of the most relevant and high-quality scientific literature. Factors considered during the selection process include the relevance of the study to the research topic, practical applicability, publication date, scientific significance, and the avoidance of redundant or overlapping contributions.

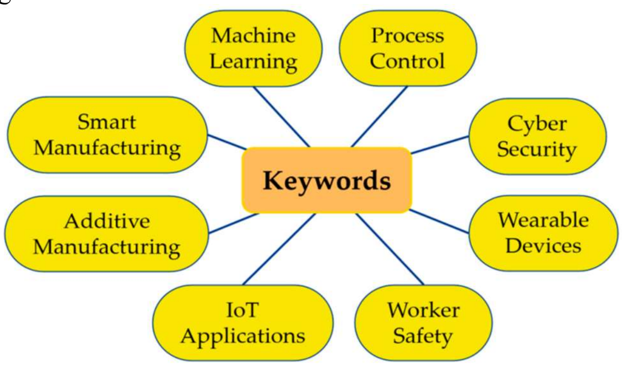
The primary objective of this review is to provide a comprehensive and up-to-date overview of the state of the art of IoT applications in smart manufacturing. To achieve this objective, the selection of publications related to machine learning and IoT-based solutions was conducted according to the PRISMA methodology, a widely recognized framework that enhances the transparency, reliability, and reproducibility of systematic literature reviews.

The selection process was carried out in several stages. Initially, the titles of identified publications were screened to determine their relevance to the scope of this review. Subsequently, the abstracts were examined to evaluate the alignment of the research content with the topics under investigation. Finally, the full-text articles were reviewed in detail to assess their suitability and contribution to the study. In cases where the content of a publication lacked clarity or required further verification, additional sources were consulted to obtain a more complete understanding of the research.

The document selection procedure is illustrated in Figure 3, which outlines the sequential screening stages, including:

1. Title Relevance Assessment – Evaluation of whether the article title reflects topics related to IoT, machine learning, and smart manufacturing.
2. Abstract Screening – Examination of the abstract to determine the study's relevance and potential contribution.
3. Full-Text Review – Detailed analysis of the complete article to evaluate its scientific value, applicability, and alignment with the objectives of the review.

This systematic selection approach was consistently applied across all thematic areas covered in this paper, ensuring a rigorous and unbiased review of the literature



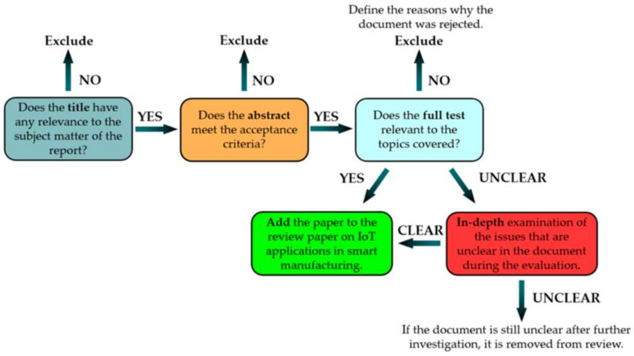
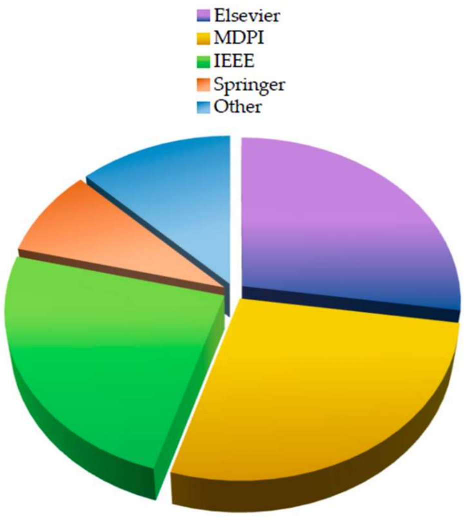
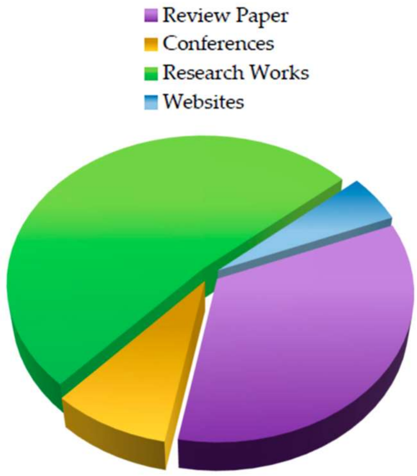


Figure 3 presents the document selection process employed in this review. Figure 3(a) illustrates the primary keywords used to identify and filter relevant literature, while Figure 3(b) outlines the article selection procedure for identifying studies aligned with the topics addressed in this review. To provide a comprehensive analysis of smart manufacturing applications enabled by the Internet of Things (IoT) across the domains, a total of 135 documents were examined. These documents comprised review papers, conference proceedings, research articles, and relevant web-based sources. The literature was primarily collected from major academic publishers and databases, including Elsevier, MDPI, IEEE, and Springer, supplemented by a limited number of publications from other sources. The distributions of the selected sources and document types are illustrated in Figure 4, where Figure 4(a) presents the distribution of publication sources and Figure 4(b) shows the distribution of the analyzed document categories.



(a)



(b)

Figure 4. Diagrams related to the publishers of identified documents (a) and scientific articles' typology (b).

II. OVERVIEW AND COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR DATA PROCESSING IN SMART MANUFACTURING

This section presents an overview of machine learning (ML) algorithms employed for data processing in smart manufacturing, with a particular focus on the most adopted techniques reported in the literature. The documents considered for this section were selected through a comprehensive review of research articles and review papers that primarily address the application of ML in manufacturing environments.

Smart manufacturing integrates traditional manufacturing principles with advanced data analytics to enhance decision-making capabilities and improve overall system performance. The widespread adoption of sensors, cyber-physical systems, and the Internet of Things (IoT) has led to the generation of vast amounts of industrial data, creating a growing demand for rapid data processing, real-time analytics, and the effective management of diverse data sources.

The integration of ML into manufacturing processes has significantly contributed to improving operational efficiency, productivity, and product quality. As a branch of artificial intelligence (AI), ML enables computer systems to learn from historical and real-time data using statistical and computational methods, eliminating the need for explicit programming. ML techniques support a wide range of applications, including prediction, classification, clustering, anomaly detection, and process optimization.

In smart manufacturing environments, ML algorithms analyze production data to identify patterns, detect inefficiencies, and provide actionable insights for process improvement. Data collected from machines, sensors, and production systems are used to train learning models capable of recognizing complex relationships and making informed decisions. Once deployed, these models can continuously adapt and improve their performance as new data becomes available, reducing dependence on manual intervention and enhancing operational autonomy. By leveraging insights derived from ML-driven analytics, manufacturers can make more informed production decisions, optimize resource utilization, improve machine performance, and foster continuous business growth and innovation

Machine learning (ML) algorithms have demonstrated significant benefits across various smart manufacturing applications, particularly by enabling the automation of tasks that traditionally require human involvement. One notable example is predictive maintenance (PdM), where ML techniques are utilized to overcome the limitations of conventional maintenance schedules. By analyzing historical and real-time operational data, ML models can detect early signs of equipment degradation and predict potential failures before they occur, thereby reducing downtime and maintenance costs. In addition, ML has been successfully applied in areas such as inspection, condition monitoring, and process control, where data acquired from sensors, cameras, and industrial systems are processed to facilitate rapid and accurate quality assessment, fault detection, and production monitoring.

Based on their learning mechanisms, ML algorithms can be broadly categorized into four main groups: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, as illustrated in Figure 5. Each category differs in the way data are utilized during the learning process and is suited to specific manufacturing applications, ranging from quality prediction and fault classification to anomaly detection and autonomous decision-making

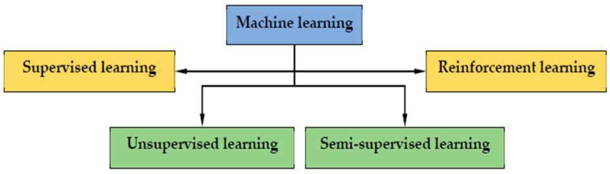


Figure 5: Classification of the machine learning algorithms.

A. *Supervised Learning*

Supervised learning is a machine learning approach that relies on labelled datasets, where each input instance is associated with a known output or target value. By learning from these input-output relationships, the algorithm develops a model capable of predicting outcomes for new, unseen data. The primary objective of supervised learning is to establish a mapping function that accurately relates input variables to their corresponding outputs.

Supervised learning techniques are generally divided into classification and regression tasks. Classification algorithms assign data instances to predefined categories or classes, producing discrete outputs that indicate class membership. In contrast, regression algorithms predict continuous numerical values, making them suitable for applications such as performance forecasting and process parameter estimation. Common supervised learning algorithms include linear regression, logistic regression, Naïve Bayes, K-nearest neighbors (KNN), decision trees, random forests, and Extreme Gradient Boosting (XGBoost). These methods have been widely adopted in smart manufacturing for tasks such as quality prediction, fault diagnosis, demand forecasting, and predictive maintenance.

B. *Unsupervised Learning*

Unsupervised learning refers to machine learning techniques that analyze data without relying on labeled outputs or predefined target variables. The primary goal is to discover hidden patterns, structures, or relationships within the dataset by examining the inherent characteristics of the data. This approach is particularly valuable when labeled data are unavailable or difficult to obtain.

Unsupervised learning encompasses several key tasks, including clustering, dimensionality reduction, density estimation, and anomaly detection. Clustering techniques group similar data points based on shared characteristics, enabling the identification of meaningful patterns and operational states. Dimensionality-reduction methods reduce the number of variables in a dataset while retaining the most relevant information, thereby improving computational efficiency and visualization. Density estimation techniques seek to model the underlying probability distribution of the data, whereas anomaly detection algorithms identify observations that significantly deviate from normal behavior, often indicating faults or abnormal operating conditions.

Popular unsupervised learning algorithms applied in smart manufacturing include stacked autoencoders (SAE), k-means clustering, k-medoids clustering, and fuzzy c-means clustering. These techniques are commonly used for condition monitoring, fault detection, process optimization, pattern recognition, and data exploration in complex manufacturing environments.

C. *Semi-Supervised Learning*

Semi-supervised learning is a machine learning paradigm that integrates the principles of both supervised and unsupervised learning by utilizing a combination of labelled and unlabelled data during the training process. This approach is particularly advantageous in situations where obtaining labelled data is costly, time-consuming, or impractical, while large volumes of unlabelled data are readily available.

By leveraging the information contained in both data types, semi-supervised learning algorithms can achieve higher predictive accuracy and better generalization performance than models trained solely on limited labelled datasets. The labelled data provide guidance for learning the target task, while the unlabelled data help the model capture the underlying structure and distribution of the dataset. As a result, semi-supervised learning offers an effective balance between the accuracy of supervised learning and the scalability of unsupervised learning.

In smart manufacturing applications, semi-supervised learning is widely employed for tasks such as fault diagnosis, predictive maintenance, quality control, and anomaly detection, where only a small portion of the collected industrial data may be labeled. By exploiting both labeled and unlabeled data, these methods enhance model reliability, reduce annotation costs, and improve overall decision-making performance in industrial environments

III. CONCLUSIONS

Over the past decade, the Internet of Things (IoT) has emerged as a transformative technology across numerous sectors, including manufacturing, agriculture, healthcare, logistics, and construction. In particular, its adoption within industrial environments has resulted in significant improvements in operational efficiency, maintenance planning, worker safety, and cybersecurity. Within the context of Industry 4.0, IoT technologies have enabled more comprehensive and intelligent process control through advanced architectures capable of supporting real-time monitoring and decision-making. Such capabilities facilitate the early detection of process deviations, helping manufacturers maintain consistent product quality and optimize operational performance.

A fundamental characteristic of IoT-enabled smart manufacturing is the extensive deployment of sensing devices throughout production facilities. These devices continuously generate large volumes of operational data, which can be analyzed using machine learning (ML) algorithms to identify patterns, detect anomalies, predict failures, and assess potential risk conditions. However, the increasing reliance on connected devices and data-driven decision-making also introduces challenges related to data privacy and security. Since industrial data often contain sensitive information, robust cybersecurity frameworks are essential to protect systems from cyberattacks, unauthorized access, and data breaches.

This review has provided a comprehensive examination of IoT applications across key domains of smart manufacturing. Following a systematic literature selection process based on the PRISMA methodology, the study explored IoT-driven solutions in manufacturing process control, predictive maintenance, data security, occupational safety, and additive manufacturing. For each application area, a comparative analysis was conducted with emphasis on system architectures, data-processing approaches, communication technologies, and application-specific characteristics. The strengths, limitations, and practical implications of existing solutions were critically evaluated to provide a clear understanding of the role of IoT in modern manufacturing environments.

Looking ahead, further advancements in smart manufacturing will depend on stronger integration between IoT technologies and ML techniques. Future research should focus on improving data integration mechanisms capable of combining information from multiple sources, including IoT sensors, enterprise resource planning (ERP) systems, and production management platforms. Enhancing data quality and reliability will also be crucial for improving the accuracy and effectiveness of ML-based analytical models. Additionally, the development of standardized communication protocols and interoperability frameworks will facilitate seamless interaction among diverse IoT devices and systems. The adoption of advanced ML methods, including deep learning and intelligent predictive analytics, is expected to further enhance decision-making capabilities and operational efficiency.

From a security perspective, future efforts should prioritize the design of advanced encryption schemes, secure communication protocols, and robust access-control mechanisms to strengthen privacy protection and ensure data integrity. Moreover, the successful implementation of IoT and ML technologies requires multidisciplinary expertise spanning manufacturing, data science, cybersecurity, and information technology. Consequently, organizations must invest in workforce training and professional development to equip personnel with the skills necessary to manage increasingly intelligent production systems.

As technological innovation continues to accelerate, improvements in computing capabilities, data-processing platforms, and machine learning algorithms will enable the analysis of larger and more complex datasets with greater speed and accuracy. These developments will support more responsive, autonomous, and efficient manufacturing operations. Ultimately, the IoT paradigm is expected to remain a foundational pillar of future industrial ecosystems, driving the evolution of smart factories and shaping the next generation of manufacturing technologies.

REFERENCES:

[1] Sahoo, S.; Lo, C.-Y. Smart Manufacturing Powered by Recent Technological Advancements: A Review. J. Manuf. Syst. 2022, 64, 236–250. [CrossRef]

[2] Khanna, A.; Selvaraj, P.; Gupta, D.; Sheikh, T.H.; Pareek, P.K.; Shankar, V. Internet of Things and Deep Learning Enabled Healthcare Disease Diagnosis Using Biomedical Electrocardiogram Signals. Expert Syst. 2023, 40, 12864. [CrossRef]

[3] Bonfanti, S.B.; Crocioni, G.; Cunsolo, F.; Gruosso, G. Implementation of an IoT Node for Biomedical Applications. In Proceedings of the 4th International Forum on Research and Technology for Society and Industry (RTSI), Palermo, Italy, 10–13 September 2018; IEEE: New York, NY, USA, 2018; pp. 1–6. [CrossRef]

[4] Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Enhancing Smart Farming through the Applications of Agriculture 4.0 Technologies. Int. J. Intell. Netw. 2022, 3, 150–164. [CrossRef]

[5] Prakash, C.; Singh, L.P.; Gupta, A.; Lohan, S.K. Advancements in Smart Farming: A Comprehensive Review of IoT, Wireless Communication, Sensors, and Hardware for Agricultural Automation. Sens. Actuators A Phys. 2023, 362, 114605. [CrossRef]

[6] Kumar, D.; Kr Singh, R.; Mishra, R.; FossoWamba, S. Applications of the Internet of Things for Optimizing Warehousing and Logistics Operations: A Systematic Literature Review and Future Research Directions. Comput. Ind. Eng. 2022, 171, 108455. [CrossRef]

[7] Liu, C.; Zhu, H.; Tang, D.; Nie, Q.; Zhou, T.; Wang, L.; Song, Y. Probing an Intelligent Predictive Maintenance Approach with Deep Learning and

Augmented Reality for Machine Tools in IoT-Enabled Manufacturing. Robot. Comput.-Integr. Manuf. 2022, 77, 102357. [CrossRef]
[8] Saravanan, G.; Parkhe, S.S.; Thakar, C.M.; Kulkarni, V.V.; Mishra, H.G.; Gulothungan, G. Implementation of IoT in Production and Manufacturing: An Industry 4.0 Approach. Mater. Today Proc. 2022, 51, 2427–2430. [CrossRef]
[9] Del Real Torres, A.; Andreiana, D.S.; Ojeda Roldán, Á.; Hernández Bustos, A.; Acevedo Galicia, L.E. A Review of Deep Reinforcement Learning Approaches for Smart Manufacturing in Industry 4.0 and 5.0 Framework. Appl. Sci. 2022, 12, 12377. [CrossRef]
[10] Keerthi, C.K.; Jabbar, M.A.; Seetharamulu, B. Cyber Physical Systems (CPS): Security Issues, Challenges and Solutions. In Proceedings of the International Conference on Computational Intelligence and Computing Research (ICCIC), Coimbatore, India, 14–16 December 2017; IEEE: New York, NY, USA, 2017; pp. 1–4. [CrossRef]
[11] Ryalat, M.; ElMoaqet, H.; AlFaouri, M. Design of a Smart Factory Based on Cyber-Physical Systems and Internet of Things towards Industry 4.0. Appl. Sci. 2023, 13, 2156. [CrossRef]
[12] Ghimire, T.; Joshi, A.; Sen, S.; Kapruan, C.; Chadha, U.; Selvaraj, S.K. Blockchain in Additive Manufacturing Processes: Recent Trends & Its Future Possibilities. Mater. Today Proc. 2022, 50, 2170–2180. [CrossRef]
[13] Gallo, G.; Rienzo, F.D.; Garzelli, F.; Ducange, P.; Vallati, C. A Smart System for Personal Protective Equipment Detection in Industrial Environments Based on Deep Learning at the Edge. IEEE Access 2024, 10, 110862–110878. [CrossRef]