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IoT–AI Convergence in Smart Manufacturing: A Survey of Technologies, Applications, And Challenges

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ABSTRACT: The Internet of Things (IoT) and Artificial Intelligence (AI) is changing the conventional meaning of manufacturing to new smart, connected, and responsive manufacturing. Such integration will be possible to have live data provided by sensors, machines, production lines, and AI-based analytics as an instrument of predictive, prescriptive, and autonomous decision-making. The IoT-AI systems cater to the needs of a layered system design, industrial internet platform, and digital twin systems in order to improve the operational efficiency, scale and interoperability. Predictive maintenance, intelligent quality control, fault detection, process control, energy control, and supply chain control are the most common uses of it. Other facilitating technologies that can be used to revitalize responsiveness and smarts of systems include intelligent sensing, edge-cloud computing, big data analytics, next-generation networking (5G/TSN) and immersive technologies (AR/VR). These advantages notwithstanding, the system integration, cybersecurity, data governance, standardization, and workforce readiness issues are also a challenge. These problems are to be taken into account to realize the full potential of the IoT-AI convergence and allow building resilient, sustainable, and data-oriented manufacturing ecosystems as part of the goals of Industry 4.0.

KEYWORDS: IoT–AI Convergence, Smart Manufacturing, Industrial Internet of Things (IIoT), Digital Twin, Edge and Cloud Computing, Big Data Analytics.

I. INTRODUCTION

The industrial environment has been radically modified by Industry 4.0 due to its focus on the integration of digital and physical technologies in an effort to find more manufacturing efficiency, elasticity and smartness[1]. The manufacturing sectors contribute towards the growth and development of any economy, therefore, there is need to incorporate technological innovation in order to enhance output, quality of products and sustainability[2][3]. In this regard, smart manufacturing has been a paradigm that has made it feasible to consider having data-driven, automated and intelligent production systems, which can dynamically react to the dynamics of the market and operation dynamics.

The Internet of Things (IoT) and artificial intelligence (AI) are two of the enabling technologies of smart manufacturing that have become prominent. It is this interrelated environment that builds up the foundations of cyber-physical systems (CPS) in which physical processes are constantly monitored and controlled through the use of computational intelligence[4][5]. The recent developments in the sensing technology, lower sensor prices, and high-speed industrial communication networks have further increased the rate of adaptation of IoT in manufacturing environment such that unprecedented levels of visibility and traceability of production processes are now available.

Artificial intelligence can alleviate this need by facilitating the use of adaptive, predictive and autonomous decisions. Predictive maintenance, quality inspection, fault diagnosis, process optimization, and planning of production are some of the uses of machine learning (ML) and deep learning (DL) techniques[6]. The AI-driven analytics-based manufacturing systems can convert the reactive control that is currently in place to predictive and prescriptive control and significantly improve the efficiency of operations and resource utilization. The IoT and AI convergence is a critical turning point towards connected

manufacturing technologies which are smarter and more self-improving[7][8]. Smart factories based on IoT and AI mean that

sensor data related to machines is constantly analyzed by AI models to facilitate closed-loop control mechanisms and adaptive control. With this convergence, process parameters are dynamically optimized, anomaly is detected early and there is intelligent resource scheduling.

The nature of Industry 4.0 smart factories is highly automated and connected production systems, which embrace IoT, AI, robotics, and sophisticated analytics to increase productivity and quality. Since the industrial environment turns into Industry 5.0, the scope is broader than automation and encompasses such aspects as sustainability, collaboration between humans and machines, resilience, and mass customization[9]. The convergence of IoT-AI is critically important in this transition, as it allows human-centred decision support, energy-efficient operations and adaptable manufacturing systems that can produce to meet the requirements of many, specially designed customers[10][11].

A. Structure of the Paper

This paper is organized as follows: Section II introduces IoT–AI convergence in smart manufacturing, detailing system architectures, industrial internet platforms, and digital twin integration. Section III discusses enabling technologies for IoT–AI convergence, while Section IV presents key industrial applications and use cases. Finally, Sections V and VI highlight the summary of the literature and conclude the paper, highlighting challenges and future research directions for intelligent and sustainable manufacturing systems.

II. ARCHITECTURE OF IOT–AI CONVERGED SMART MANUFACTURING SYSTEMS

The converged smart manufacturing system IoT-AI architecture provides the basic technologies, layered system architecture, industrial internet architectures, and digital twin integration. It also introduces the significant industrial problems related to the interoperability, cybersecurity, data management, and employment readiness in realizing an intelligent, scalable manufacturing environment.

A. IoT-AI of Things in Manufacturing

IoT is the process of connecting machines, sensors, and other objects to the internet to enable transfer of data. The IoT is being utilized to create smart factories in the production industry by linking equipment, tools, and operators to centralized monitoring systems that produce and transmit real-time data on vibration, temperature, pressure, and machine performance.

Basic IoT Solutions in the Manufacturing:

- **Sensors and Actuators:** To monitor and collect production line data in real-time.
- **Edge Computing:** Edge preprocessing of data to improve decision-making and reduce delay [12].
- **Machine-to-Machine (M2M) Communication:** This facilitates machine-to-machine communication in real time without requiring humans to be involved.

A wide range of technologies that enable machines to learn, recognize patterns, and make judgments based on data are together referred to as artificial intelligence (AI). In production, AI is applicable in supply chain management, process optimization, quality control, and predictive maintenance[13]. The products can be improved with the help of AI algorithms, such as ML schedules.AI Applications in Manufacturing:

Predictive Maintenance: Predicting equipment breakdowns before they happen with AI algorithms. Using AI-based vision systems to identify product flaws during production is known as quality control. AI algorithms that optimize production schedules and machine environment to reduce waste and downtime are known as production optimization algorithms.

B. Layered Architecture for IoT–AI Smart Manufacturing

Separate a system into separate, self-contained, and logically arranged tiers or layers. Each layer accomplishes a specific duty, and these layers cooperate to achieve a common objective. This kind of design has several benefits, including understandability, scalability, modularity, and maintainability[14][15]. The many capabilities and interactions that take place in an Internet of Things system are designed and managed using layered architecture. There should be cooperation between the many devices, sensors, networks, and applications that make up an IoT system[16]. This system has been split into distinct levels according to the layered architecture principle, each of which has a distinct function and level of abstraction. There are normally four primary levels in an IoT layered architecture, including:

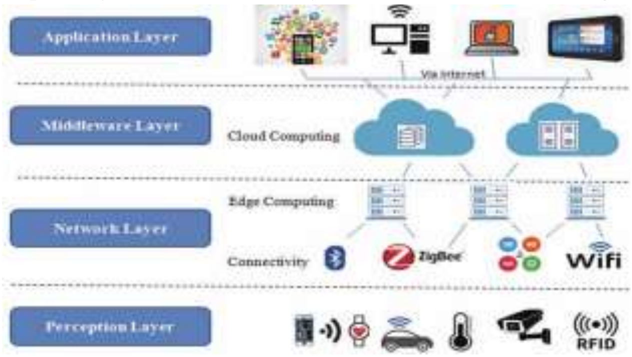

Fig. 1. Layered Architecture

- **Perception Layer:** This lowest layer is centered on the sensors and actuators. Actuators allow the system to react to the physical world, whereas sensors gather information there (as seen in figure 1). The Perception Layer is in charge of collecting the information so that it may be processed, converting, and storing raw data in digital form.
- **Network Layer:** The Network Layer sits above the Perception Layer and manages communication and data transfer. Cellular networks, Bluetooth, Wi-Fi, and other communication technologies may be the basis for communication between the central processing unit that controls IoT devices and the devices themselves.
- **Middleware Layer:** The center layer, known as the middleware layer, serves as an interface between the higher (application) and lower (perception and network) levels. Device administration, data processing, and message brokering are all under its control. This layer introduces an abstraction, simplifying communication between devices and applications.
- **Application Layer:** The Application Layer, which sits at the top of the structure, is where end users and other external systems connect to the IoT. This layer makes it easier to create IoT applications and analyze data and user interfaces.

C. Industrial Internet Platform

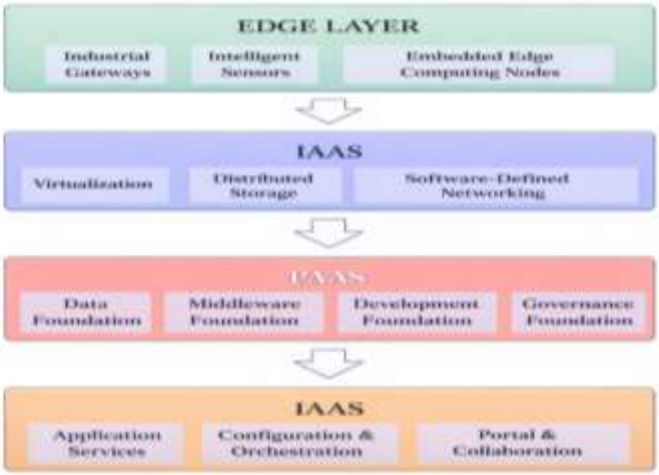

Fig. 2. **The Four-Tier Structure of the Industrial Internet Platform**

The IIP generally assumes a 4-layer architecture: The Edge, Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) Layer, as Figure 2[17].

- **Edge Layer:** Deploys gateways, sensors, and edge computing nodes to handle multi-protocol adaptation (e.g., Modbus, OPC UA, MQTT) and local AI inference, ensuring control latency of less than 10 ms. Multi-protocol convergence technologies have proven effective in improving interoperability.
- **IaaS Layer:** As the digital foundation, it orchestrates computing and storage resources via virtualization and Software-Defined Networking (SDN), achieving high reliability and elastic scalability through containerized orchestration.
- **PaaS Layer:** This layer provides time-series databases and data lakes to integrate OT and IT data, enabling large-scale real-time processing of IoT time-series data and AI model deployment. It also advocates low-code modeling, federated learning, AutoML and blockchain-based trusted cross-enterprise data exchange.
- **SaaS Layer:** This layer provides on-demand industrial software that includes Product Lifecycle Management (PLM), Manufacturing execution system (MES), and Quality Management system (QMS). Its low-code visual architecture maintains the speedy development of operations and maintenance software, which highly enhances the core efficiency of cross-department interaction.

D. Digital Twin

The Digital Twin (DT) technology in smart manufacturing systems brings about high-fidelity interactions between physical and virtual factories[18]. It aims at getting closed-loop control with real-time mapping, predictive analytics, and optimized decision-making. A common DT architecture is based on three fundamental modules, namely physical entity, virtual model, and twin data, which are maintained by security, services, and scalability modules.

- **Physical Entity:** This module gathers real-time information of equipment, robots, production lines, and warehouses, mechanical status, environmental parameter, and process indicators, to assist virtual modelling[19]. It is based on high precision sensors, industrial buses, and intelligent terminals to acquire stable data in industrial environment.
- **Virtual Model:** This encompasses geometric, multi-physics, models of dynamic simulation of physical entities that are data-driven and mechanism-based. As an example, a material-flow DT model assists in predicting, monitoring, and diagnosing the production processes, which are ensured to be applicable in industry by use of protocols including OPC UA.
- **Twin Data:** Facilitates two-way information between the physical and virtual environment, via high-performance networks and real-time computing infrastructures. It combines sensor data as well as simulation data of virtual models. Blockchain is applicable in the security and governance of data.
- **Security & Services:** The security module provides security to the data and control commands by the authentication, access control and encryption. The service module provides monitoring, predictive analysis, optimization recommendations and visualization to aid in decision-making.
- **Scalability:** Assures that the system is flexible enough to accommodate single equipment to full plants with variability of complexity.

Features and Applications: Digital Twin (DT) technology provides predictive analytics, scalability, real-time sensing, closed-loop decision-making and interoperability as well as strong security. It is implemented on equipment operation and maintenance (O&M), production scheduling, lifecycle management and energy and safety management [20]. DT minimizes the failures and downtimes in predictive maintenance (PDM). It is efficient in resource allocation in production scheduling. The performance monitoring of the lifecycle management is as well helped by DT and helps to save energy, reduce emissions and enhance safety.

E. Challenges of IoT and Ai Integration in Industry

Regardless of such great potential, there are several significant problems with the IoT and AI integration in industrial automation. Complexity of integration is one of the most notable issues; old equipment, disconnected systems require substantial transformation and interoperability systems to fit the flawless exchange of information and integrated AI control[21]. There should be standardization of inter-device, inter-protocol, and inter-data formats which are normally non-existent. One more severe issue is cybersecurity[22]. Diffused industrial resources were exposed to cyber-attacks that would disrupt the business or confidential data. It is not an easy task to secure the IoT endpoints, secure the data transmissions, and adopt the threat detection using AI. Another problem is the issue of data management because massive volumes of data require an efficient data storage process, data process and governance strategies. Another level of complication is to make sure that there is data quality and the privacy issues are met with in the event that personal or operational data is involved. Further, the workforce should be modified to equip employees with the digital capabilities and refocus the organization culture to more autonomous and even more data-driven processes. Businesses must navigate both technological and human variables to accomplish effective transformation, weighing the long-term advantages of IoT-AI adoption against the investment costs.

III. Enabling Technologies for IoT–AI Convergence

The academic and industrial worlds are becoming more interested in SM as a new paradigm. In order to create novel products more quickly and dynamically while guaranteeing real-time supply chain and production optimization, the SM has to intensify the deployment of novel intelligence approaches. There are several supporting technologies that help IoT systems develop and set up quickly[23]. The main technologies that have the potential to enhance IoT-enabled industrial services are discussed in this section:

A. Sensing and Data Acquisition Technologies

Smart sensors form the basic layer of the IoT-based manufacturing systems because they constantly gather real-time data on machines, production lines, and environmental factors. Smart sensors unlike traditional sensors combine embedded processing, self-calibration as well as communications so that local data preprocessing and contextual understanding can be made. These capabilities minimize the latency and communication overhead as well as enhance reliability of the data. Cyber-physical systems (CPS) combine the physical manufacturing processes closely with the computational intelligence to allow constant interaction of physical assets and the digital model.

B. Edge and Cloud Computing Platforms:

Edge computing also puts the computational intelligence nearer to the data sources and, thus, allows it to make low-latency inferences and minimizes communication overhead[24]. Edge intelligence would be especially appropriate in process control and safety monitoring which are latency sensitive applications. Federated learning allows to conduct cooperative learning on distributed edge nodes without exchanging raw data, which increases data privacy and decreases network load[25]. Cloud systems offer scalable data storage, machine learning, and AI model training resources. Cloud-based AI services make it easy to learn across several factories, to analyze trends in the long run and to integrate with enterprise systems like MES and ERP. Cloud scalability and AI functions allow advancing the production processes based on worldwide optimization and ongoing improvement[26].

C. Virtual Reality (VR) and Augmented Reality (AR):

Asset utilization, workforce training, root cause analysis, and maintenance are just a few of the benefits that come from integrating VR and AR with IoT systems. Virtual reality (VR) makes it possible for someone to be physically present in a virtual setting and replicates how people would interact with virtual items. Predictive maintenance, worker training, and digital design have all made extensive use of VR[27]. But augmented reality (AR) adds computer inputs including sound, video, images, and instructions to the actual, real-world environment. AR makes it possible for the real world and online world to interact closely, improving user experience and understanding of how smart things and networks are connected, as well as for human operators.

D. Networking Technologies and Communication

Communication technologies, such as 5G and the soon-to-be 6G networks, provide extremely low latency and excellent dependability, along with massive device connectivity needed for mission-critical industrial applications. Time-Sensitive Networking (TSN) is an improvement of Ethernet-based industrial networks that provides deterministic communication with a specified latency and bandwidth. Mobile robotics, 5G and TSN 5G integration are used to support real-time control, collaborative manufacturing and mobile robotics. Industrial wireless systems like WirelessHART, ISA100, and industrial Wi-Fi make it available and scalable to deploy anything in the factory and minimize the cost and complexity of wired infrastructure. The networks are made to work in difficult industrial conditions and are used in applications of mobile assets, remote monitoring and adaptive reconfigurability of manufacturing systems.

E. Big data Analytics

The features of large data via IoT sensing include high diversity, high volume, high velocity, and high veracity[28]. The variety that results from the vast array of data types used in manufacturing, each of which necessitates a distinct signal gathering parameter. They consist of cutting force signals, auditory emissions, power profiles, and machining parameters. Additionally, there is a lot of noise, uncertainty, and nonstationary elements in the production workshop environment. Since statistical models are imprecise and uncertainty cannot be quantified, accuracy is especially crucial in the context of the IoT. But as the demand for data-driven knowledge changes, the industrial sector is ill-prepared[29][30]. Big data analytics offers useful and effective techniques and resources for managing massive amounts of IoT data for information processing and industrial process control. The availability of big data technologies such as these aids in overcoming the constraints of conventional algorithms in processing large amounts of data and further extracting significant information and new patterns to help raise the intelligence level of manufacturing.

IV. APPLICATIONS OF IOT–AI CONVERGENCE IN SMART MANUFACTURING

Artificial Intelligence (AI) meeting the Industrial Internet of Things (IIoT) has become a prominent facilitator of smart manufacturing, enabling industries to take advantage of the large amounts of sensor-collected data and provide intelligent-added values through smart services. The development of communication technologies has allowed manufacturing machines to be provided with intelligent sensors that can constantly gather data about the functioning of machines. In an Industry 4.0 environment, AI techniques like ML, DL, and reinforcement learning handle this data and support automation, optimization, and wise decision-making[31]. Smart manufacturing systems are connected machines, workstations and management information systems that allow free flow of data and real-time analytics[32]. The past and live process data are used to optimize production efficiency, reliability and competitiveness. The significant uses of IoT-AI convergence in smart manufacturing are discussed below:

A. *Predictive Maintenance and Asset Health Management*

Among the most noticeable IoT to AI convergence applications in smart manufacturing is predictive maintenance (PdM)[33]. Industrial machines have smart sensors, which constantly check factors in vibration, temperature, pressure, and acoustic messages. AI models would process this condition-monitoring data to forecast machine failures and estimate the usefulness left of equipment (RUL). This is pro-active and ensures less unwarranted downtime, lower maintenance expenses, and better reliability of equipment when compared to the traditional time-based maintenance measures.

B. *Fault Detection, Diagnosis, and Alarm Management*

Smart factories use IoT to offer a real-time manufacturing process to identify anomalies and faults in the initial phase. The AI-based fault identification models are used to conduct time-series analysis in order to detect abnormal patterns, issue alarms and prescribe corrective measures[34]. AI-based perception and decision-making in collision avoidance systems of automated production lines also guarantee operation safety and ensure a lack of equipment damage.

C. *Intelligent Quality Prediction and Inspection*

Another important area of application is quality prediction where AI uses sensor data, machine parameters and past production history to predict the quality outcomes of a product. Cameras equipped with the IoT and powered by AI computer vision systems allow automatic inspection and detection of defects in real-time. These minimize human error, enhance consistency, and adherence to quality standards.

D. *Process Selection and Optimization*

The AI algorithms are applied to the data produced by IoT to select the manufacturing process and tune its parameters. AI models suggest the best ways to follow through processes, production schedules and machine configurations Through analyzing both current and historical data. This increases the throughput, minimizes material waste and improves the overall production.

E. *Smart Factory Monitoring and Control*

Smart factories are made by machines that are linked to each other utilizing sensors and computer systems that are capable of continually gathering and storing data about the machine operations on central databases or cloud storage. IoT also provides the possibility of remote monitoring and control of manufacturing processes, and the operators can monitor the conditions in production and make suitable decisions[35]. AI-driven analytics help in making decisions in real time and also making adaptive control strategies which help in making manufacturing environments flexible and autonomous.

F. *Inventory, Warehouse, and Supply Chain Management*

RFID, smart meters and wireless sensors are examples of IoT that enhance inventory visibility and management of the warehouse by offering real time data of materials and products. This information is processed by AI models which can predict the change in demand, identify bottlenecks, and optimize inventory levels. IoT-AI convergence can create smart supply chains that anticipate any delay and suggest corrective measures and reduce production disturbances.Inventory, Warehouse, and Supply Chain Management

G. *Energy Management and Operational Efficiency*

Smart meters based on IoT and its variants track consumption trends of energy in manufacturing plants. The AI algorithm evaluates the data on energy usage to optimize power consumption, minimize the operational costs, and facilitate the sustainable manufacturing process[36]. Smart energy management systems result in a higher efficiency and lower environmental impact.

H. *Decision Support and Business Intelligence*

The Industrial IoT produces huge amounts of information associated with the volume of production, rates of defects, labor productivity, and the performance of equipment[37]. Business intelligence and decision-support systems made by AI can convert this data into actionable insights, which can be used to improve strategic planning efforts, operational optimization, and unceasing improvement initiatives.

V. Literature Review

As summarized in Table I, the reviewed literature reveals the increasing utilization of the IoT-driven predictive maintenance, real-time monitoring, and intelligent decision-support structures in smart manufacturing to improve productivity, quality, and system reliability. Nevertheless, issues of data quality and availability, complex integration of systems, and scalability constraints and scanty large scale industrial validation are some of the obstacles. These results show that there is a need to have generalized, scalable, and secure IoT-AI systems that can be properly deployed in different manufacturing environments.

Rakholia et al. (2025) Proactive management enables timely repair of machinery and equipment, reduces unplanned downtime, extends equipment life, and increases system reliability, all of which contribute to more inexpensive and efficient operations. Time-consuming, ineffective, and resource-intensive, periodic manual inspections, human observations, and monitoring are often the foundation of traditional machinery and equipment maintenance techniques. Therefore, it is crucial to optimize machinery and equipment maintenance by utilizing automation systems with predictive models based on IoT and ML. The purpose of this research is to come up with predictive maintenance models, including the prediction of the temperature and vibration of the electric motors, using machine learning methods and the production data provided by the ERP systems and current sensor networks[38].

Dmitrieva et al. (2024) provides a factual analysis of the revolution in smart manufacturing's integration of IoT and AI. Based on the data, the post-treatment temperature increases to 36.2 o C and the 44.8% humidity reduction resulted in a significant 1.52% gain in production efficiency. Decreases in the defects found (2) resulted in a 0.76% improvement in the quality control's quality scores (93.1). Because there was less downtime (52 minutes) and maintenance hours (2.3), the procedures were more effective. In addition to making smart manufacturing the leader in the radical landscape of Industry 5.0 and enhancing efficiency, quality, and maintenance, it emphasizes the useful benefits of combining IoT and AI[39].

Nehete et al. (2024) discusses the way these technologies are combined and the way production systems are affected. The research study is devoted to the architecture, advantages, difficulties, and the opportunities of the future that have emerged with optimizing industrial processes with the use of cloud computing, AI, and the IoT. The following case studies reveal how these technologies can be applied in practice to optimize the process and make decisions in real time. To improve decision-making, operational efficiency, and productivity, manufacturing industries are implementing the newest technology. A useful platform to improve industrial processes in real time may be provided by combining IoT, cloud computing, and AI[40].

Haricha et al. (2023) explains the latest advancements in SM research in detail. The unresolved challenges are also addressed in this study and an effort made to give a logical and comprehensive review of the existing smart manufacturing initiatives. With the increasing evidence on smart processes with advanced technology, one would want to know whether manufacturing systems can be made to manage complexity and flexibility to enhance smart factory monitoring. As a continuation of traditional manufacturing, smart manufacturing (SM) showcases the power and potential of smart technologies like AI and the IoT. The extensive use of these technologies is bringing critical changes in all industries[41].

Jain (2022) discusses the process of gathering granular data on the production using IoT-enabled devices and running AI models to optimize the scheduling, reduce downtime, and decrease the number of defects. A mid-size electronics assembly factory is given, to show statistical betterment: The average throughput rose by 18%, the defect rate decreased by 15%, and downtime decreased by 22%. Descriptive analytics and supervised learning models are used in the methodological framework to detect abnormalities. It demonstrates that the combination of IoT and AI generates significant benefits regarding the existing technology limits through 2022[42].

Xu et al. (2022) provides a non-expert executive summary of AI methods with a focus on DL. Then discussed are the outstanding issues with AI safety, data security, and data quality that are critical for fully automated industrial AI systems. Present the state-of-the-art methods for every problem that offer strong foundations for comprehensive industrial AI solutions, together with the associated industrial use cases from various industries to give a more tangible picture of these methods. To support the increasing complexity of industrial processes, data-driven AI approaches have gained prominence due to low-cost computer and storage infrastructures[43].

TABLE I. SUMMARY OF RELATED LITERATURE ON IOT–AI CONVERGENCE IN SMART MANUFACTURING

Authors	Focus Area	Key Findings	Challenges	Limitations	Key Contribution
Rakholia et al. (2025)	Predictive maintenance using IoT and machine learning	Demonstrated that ML-based predictive maintenance extends the life of equipment and decreases unscheduled downtime, and enhances system reliability through temperature and vibration prediction of electric motors	Dependence on continuous sensor data availability and integration with ERP systems	Model performance may vary across different machine types and industrial environments	Developed IoT–ML–based predictive maintenance models leveraging sensor networks and ERP data
Dmitrieva et al. (2024)	IoT–AI integration for efficiency, quality, and maintenance	Reported a 1.52% increase in production efficiency, 0.76% improvement in quality score, and reduced maintenance time and downtime through AI-driven monitoring	Environmental sensitivity of sensor-based systems and data calibration issues	Results are based on a specific manufacturing setup with limited generalizability	Provided quantitative evidence of operational gains from IoT–AI adoption aligned with Industry 5.0
Nehete et al. (2024)	IoT, cloud computing, and AI architecture for	Highlighted real-time decision-making, process optimization, and improved productivity	Complexity of system integration and interoperability	Lack of large-scale empirical validation	Proposed a feasible architectural framework

	manufacturing optimization	through integrated IoT–cloud–AI frameworks	across heterogeneous platforms	across industries	supported by industrial case studies
Haricha et al. (2023)	Survey of smart manufacturing technologies and trends	Identified key research trends, benefits, and open challenges in AI- and IoT-enabled smart manufacturing	Managing flexibility, scalability, and complexity in smart factory environments	Primarily conceptual and survey-based without experimental validation	Offered a comprehensive taxonomy and research outlook for AI–IoT–driven smart manufacturing
Jain (2022)	IoT–AI synergy for production optimization	Achieved 18% throughput improvement, 22% downtime reduction, and 15% defect reduction using supervised ML in an electronics assembly plant	Data quality and dependency on domain-specific feature engineering	Case study limited to a single mid-scale manufacturing facility	Demonstrated practical benefits of IoT–AI integration with statistical performance gains
Xu et al. (2022)	AI techniques and challenges in industrial automation	Emphasized the role of deep learning and data-driven AI for complex manufacturing processes	Data quality, data privacy, AI safety, and explainability	Limited discussion on real-time IoT integration and deployment constraints	Provided a non-expert overview of industrial AI challenges and state-of-the-art solutions

VI. CONCLUSION AND FUTURE WORK

IoT and AI convergence have become a pillar of smart manufacturing industries can transform the most reactive and isolated type of operations into intelligent and connected manufacturing spaces and autonomous ones. IoT -AI systems help improve operational visibility, predictive maintenance, quality assurance, process optimization, and energy efficiency by combining real-time sensing, edge -cloud computing, industrial internet platforms, and digital twin technologies. The discussed layered architectures and industrial platforms are scalable, interoperable, and make data-driven decisions throughout the manufacturing lifecycle. The integration with the legacy system, the absence of standardization, the problems of cybersecurity, the complexity of data management and the skill gap among the workforce remain, however, the challenges preventing widespread adoption. The only way to overcome these barriers is to have a coordinated technological innovation, strong governance structures, and organizational preparedness. When properly used, the IoT and AI convergence can enhance the productivity and reliability and also make the manufacturing systems more sustainable, resilient, and competitive in line with the Industry 4.0.

The future studies must concentrate on standardized IoT-AI systems, safe and clear AI models, and massive implementation of digital twins. The next generation of smart manufacturing systems will be even more autonomous, more cybersecure, more sustainable, and promote collaboration between humans and AI due to further advancements in federated learning, 6G-enabled industrial networks, and human-cantered AI.

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