Journal of
Mechatronics and Automation
https://journals.stmjournals.com/joma
ISSN: 2455-1988
Volume 12, Issue 3, 2025
September–December
DOI (Journal): 10.37591/JoMA

Review JoMA

Automation and Robotics for Quality Control in Manufacturing: A Review of Technologies and Applications

Prithviraj Singh Rathore*

Abstract

Automation and robotics technologies have rapidly evolved, transforming modern manufacturing processes by improving productivity, quality, and operational efficiency. This review examines key advancements such as cloud robotics, machine vision, Industry 4.0 robotics, Building Information Modeling (BIM) combined with Computer Numerical Control (CNC), joystick-controlled automation, and intelligent manufacturing systems. These technologies utilize artificial intelligence (AI), machine learning (ML), digital twins, collaborative robots, programmable logic controllers (PLCs), and cyber-physical systems (CPS) to enable flexible, adaptive, and precise industrial operations. Despite their benefits, challenges like system interoperability, data security, shortage of skilled personnel, and safety concerns remain. The integration of blockchain technology further enhances supply chain traceability and transparency by enabling decentralized and tamper-proof record-keeping. This study highlights the need for standardized frameworks and interoperable platforms to support seamless integration. It focuses on advancing human-robot collaboration (cobots), bridging simulation-to-reality gaps, improving cybersecurity, and expanding adoption to small and medium-sized enterprises (SMEs). Incorporating sustainability metrics will be essential for responsible and inclusive industrial growth in the Industry 4.0 era. The study examines the integration of machine vision, artificial intelligence (AI), the Internet of Things (IoT), and sensor-based systems that enhance defect detection, process monitoring, and real-time decision-making. Various robotic inspection systems—such as automated optical inspection (AOI), robotic non-destructive testing (NDT), and collaborative robots for in-line quality assurance—are discussed in terms of their design, accuracy, and adaptability across diverse manufacturing environments. Furthermore, the review highlights the benefits of these technologies, including improved reliability, reduced human error, and increased production throughput, while also addressing implementation challenges such as high initial costs, data management, and system integration. The paper concludes with insights into emerging trends, including AI-driven predictive quality control and digital twins, outlining future directions for fully automated, intelligent manufacturing systems.

Keywords: Automation, robotics, cloud robotics, machine vision, industry 4.0, BIM-CNC Integration, intelligent manufacturing, blockchain, supply chain traceability, human-robot collaboration, cyber-physical systems, smart manufacturing

***Author for Correspondence**
Prithviraj Singh Rathore
E-mail: prathviraj.rathore@meu.edu.in

Assistant Professor, Department of Computer Sciences and Applications Mandsaur University, Mandsaur, Madhya Pradesh, India

Received Date: July 11, 2025
Accepted Date: October 10, 2025
Published Date: October 22, 2025

Citation: Prithviraj Singh Rathore. Automation and Robotics for Quality Control in Manufacturing: A Review of Technologies and Applications. Journal of Mechatronics and Automation. 2025; 12(3): 36–48p.

INTRODUCTION

In the manufacturing industry, quality control represents a critical aspect that is being significantly enhanced through the integration of ML technologies [1]. Quality control encompasses the processes and procedures organizations use to guarantee that their goods and services meet predefined standards and customer expectations. This includes activities such as inspection, conducting tests and keeping tabs on manufacturing to identify and address defects or deviations from established quality standards [2]. The primary objective is to deliver consistent, reliable, and high-quality products. Human error, subjectivity, and the passage of time are the main problems with manual inspection, which is still used in many traditional quality control procedures. On the other hand, errors may be detected via the analysis of visual, aural, and sensor data made possible by ML algorithms with high speed and precision.

Automation plays a crucial role in advancing manufacturing processes, particularly within the automotive industry [3]. The evolution of automation technologies continues to reshape the sector, especially in the context of Industry 4.0 [4]. This latest industrial revolution introduces significant opportunities and challenges that are driving major transformations in manufacturing systems [5]. The history of industrial development is generally categorized into four major phases. The First Industrial Revolution, beginning in the 1760s, introduced steam engines as a new source of energy. The Second Industrial Revolution brought electricity and assembly lines, revolutionizing production efficiency. The Third Industrial Revolution incorporated computer technologies, including the use of PLCs. The ongoing Fourth Industrial Revolution is characterized by the adoption of advanced robotics, 3D printing, IoT, and fully automated production systems [6].

Robotic inspection systems have emerged as essential tools for enhancing quality assurance processes. These systems are typically designed to scan target surfaces from multiple viewpoints and poses, ensuring thorough inspection coverage [7]. The planning of inspection paths is framed as a Coverage Path Planning (CPP) problem, which involves determining an optimal route that allows the robot to visit all key measurement points (MPs) on a surface while avoiding obstacles [8]. The automation of inspection tasks through robotics has become a strategic priority in the industry, aimed at accelerating inspection workflows within the production line [9]. A robot arm constitutes just one component of comprehensive robotic systems employed in non-destructive testing (NDT) during manufacturing. However, the integration of these systems poses significant challenges, particularly during the system integration phase, which can hinder the adoption and scaling of robotic sensing solutions. Furthermore, a growing skills gap among workers in operating advanced robotized NDT systems remains a pressing concern within the manufacturing sector.

Structure of the Study

This study is organized in the following way: The next Section provides an overview of quality control in manufacturing; the Sections after that display the robotic systems for quality control; discuss key technologies; outline major challenges; present a detailed literature review; and the last Section concludes the study and suggests future work directions.

FUNDAMENTALS OF QUALITY CONTROL IN MANUFACTURING

Quality control is an essential part as it ensures that products meet both customer expectations and regulatory requirements. Pulp and paper manufacturing is a multi-step process involving numerous stages of production, beginning with the procurement of the raw materials and ending with the distribution of the finished goods [10]. Robotics in manufacturing involves industrial and collaborative robots made to handle tasks in an accurate, reliable and safe way. Human-robot interchange in the workplace is possible thanks to collaborative robots, letting people and robots contribute to both flexible and productive workplaces. AI and new safety systems help robots react well to changes in their environment, which improves how automation is used in smart factories [11].

KEY APPLICATIONS OF ROBOTICS-AUTOMATION IN MANUFACTURING

The mentioned applications at the level of motion and the level of tasks, taking into account the definition of action: For an application to be considered as operating at the motion level, action space must be a perfect reflection of either the robot's joint space or the tool's Cartesian configuration; summed up, the field of robotic process control is now home to robot learning, with many of these systems aimed at production and industry [12].

Inspection and Quality Control

Inspection and Quality Control (QC) in robotics integrates machine vision and automation to compare real-time measurements, such as those from Vision2D, with nominal standards like CMM data within defined tolerances [13]. These systems use AI, sensors, and vision technologies to detect defects, ensure dimensional accuracy, and maintain product reliability with minimal human involvement.

Material Handling

Material handling in robotics and automation involves using automated manipulators, conveyors, and autonomous mobile robots (AMRs) to transport, sort, load, and unload materials within manufacturing facilities. This improves operating efficiency, cuts down on labor expenses, and makes sure everyone is safe [14]. This aids in accurate handling of goods throughout the production process. This project aims to automate material handling by including mobile robots, automating the labelling process, and modifying the feeding system for production cells, sorting area, receiving/shipping area, and warehouse.

Adaptive Manufacturing (3D Printing)

A 3D printer is used in additive manufacturing, which is also called layered manufacturing or just printing layers of material. "The process of mixing materials to manufacture things using 3D model data, generally in a layer-by-layer method", according to ASTM, is in contrast to methods that rely on subtractive manufacturing [15].

Additive manufacturing integrates robotics for precise 3D printing, enabling complex part fabrication, and customization. Figure 1 shows a general process flow for Additive manufacturing, and automation in modern production systems.

Machine Tending

Machine tending to use robots to load, operate, and unload CNC machines, improving productivity, safety, and consistency in manufacturing operations. Automated machine tending uses robotic systems to handle machines like CNCs, enhancing efficiency, reducing downtime, and minimizing manual labor needs.

In quality control, machine tending ensures consistent part handling, enabling precise inspections and reducing variability in testing and measurement processes (Figure 2).

Smart Manufacturing for Quality Assurance (QA)

The term “smart manufacturing” refers to a more recent term for the practice of integrating technology into the production system [16]. It shares a practical way to measure smart factory performance, assess a company's strengths and weaknesses across four dimensions, and create personalized business setup roadmaps. It also suggests a new way to use robots for intelligent inspection and quality control system corrections during production [17]. The injection molding technique is used to create electromechanical components, and quality assurance is an enhancement of inspection in this process, along with bringing attention to how standards might pave the way for the subsequent wave of industrial automation.

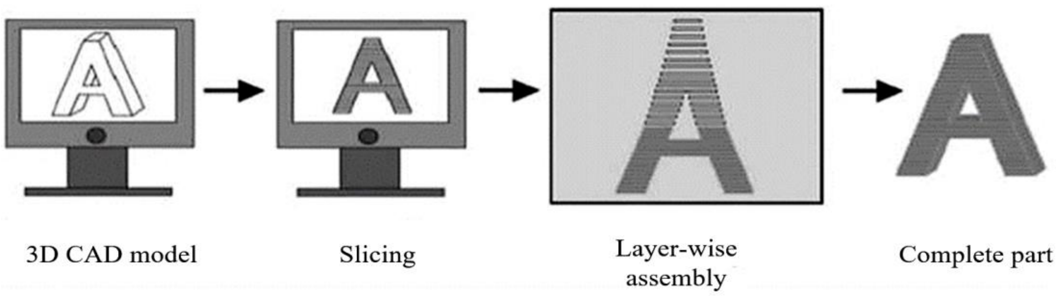

Figure 1. Flow for additive manufacturing [15].

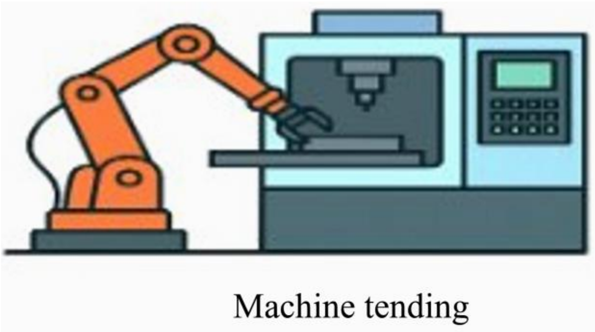

Figure 2. Machine tending in robotics automation.

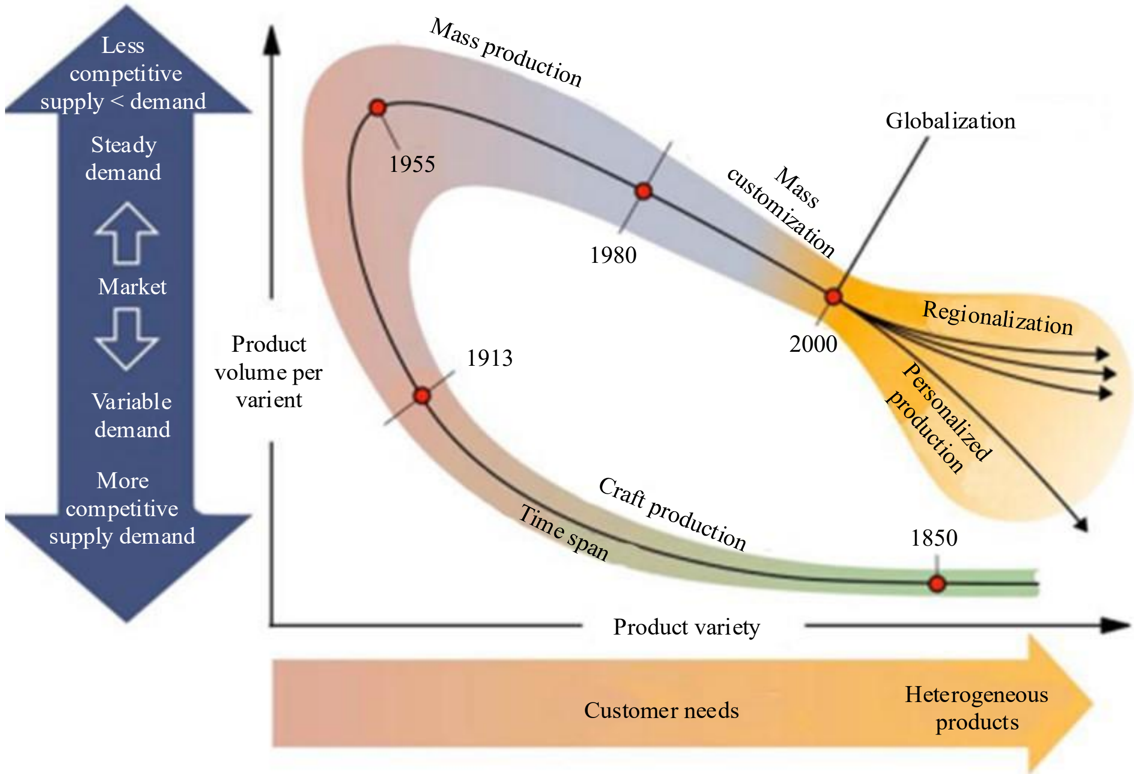

Figure 3. Manufacturing paradigm shifts and the drivers [18].

Drivers

The persistent need for customized goods in the market is a key factor propelling changes in the production paradigm [18]. Figure 3 shows the tremendous transition from mass customization to mass personalization, as well as the unprecedented rate of advancement in the underlying technologies for manufacturing automation. The market has never stopped seeking out personalized products, and manufacturers want to be able to produce highly personalized products at dynamic batch sizes while still taking advantage of mass production efficiencies.

The shift has been from craft production to mass production, then to mass customization and personalized production, driven by globalization and changing customer needs (Figure 3). Over time, manufacturing has evolved to offer higher product variety and respond to more competitive, demand-driven markets.

IMPACTS ON MANUFACTURING AUTOMATION

Efficacy has always been prioritized above adaptability in automated manufacturing systems and processes. Rigid, completely automated solutions are no longer effective in the setting of mass personalization. In order to mass-produce affordable personalized items, manufacturing automation must be both productive and versatile.

Smart Manufacturing Standard Dimensions

Integrating many systems and procedures requires standardization. When it comes to large-scale smart manufacturing implementation, standardization is the biggest obstacle. To maximize business outputs across various smart manufacturing technologies and solutions, it is vital to standardize architectures, data interchange formats, semantics, and interfaces; this is essential to smart manufacturing's collaborative and interconnected nature (Figure 4).

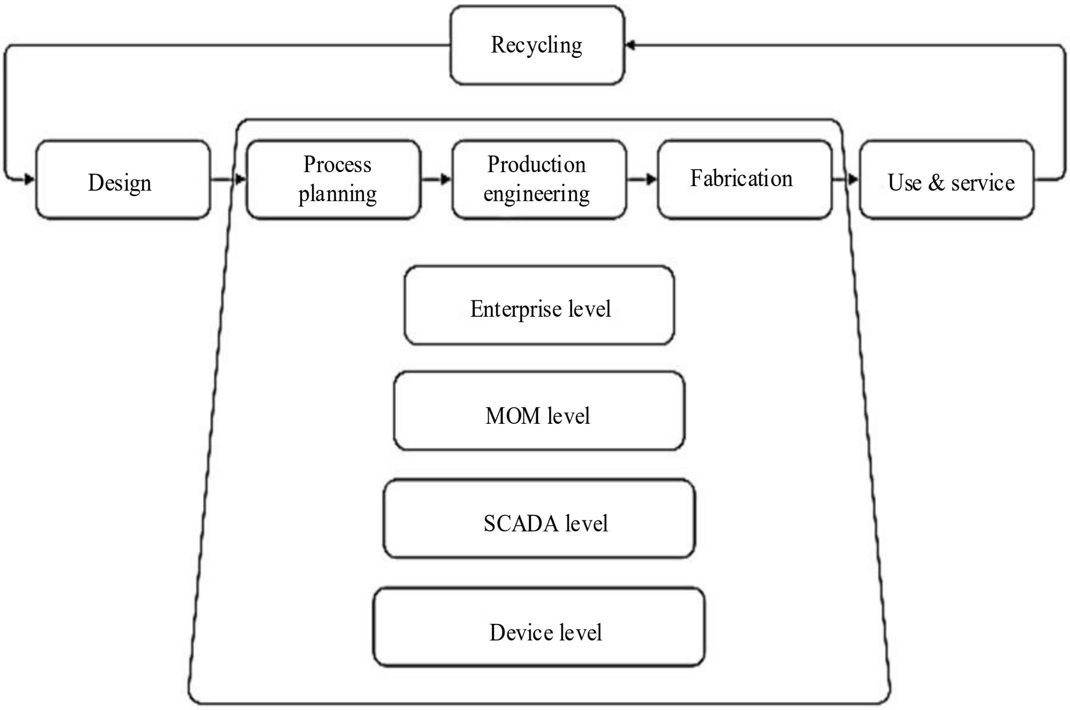

Figure 4. Smart manufacturing automation dimensions [18].

The product lifecycle stages supported by automation levels, from design to recycling, are integrated through device, SCADA, MOM (Figure 4), and enterprise levels for efficient manufacturing and service.

Quality Control In Smart Manufacturing

Robots, AI, and other cutting-edge tech are used for quality control in smart manufacturing, machine vision, and automation systems to ensure precision, consistency, and efficiency. These intelligent systems enable real-time monitoring, defect detection, and adaptive control, significantly improving product quality, reducing waste, and supporting the shift toward Industry 4.0 manufacturing practices.

ROBOTIC SYSTEMS FOR QUALITY CONTROL

Robotic systems have transformed quality control in manufacturing by enhancing precision, consistency, and efficiency through the use of industrial robotic arms, collaborative robots (cobots), and AMRs. Industrial arms are commonly used for high-precision tasks like inspection and testing, while cobots work safely alongside humans in semi-automated environments, and mobile robots assist with dynamic inspection and material handling. These robots are widely applied in inspection, functional testing, sorting, and packaging, often equipped with advanced robotic vision systems and specialized end-effectors such as grippers, suction devices, and sensor probes. For example, robotic arms with integrated vision inspect welds in the automotive industry, cobots examine PCBs in electronics, and mobile robots sort produce in food processing using hyperspectral imaging. Such systems significantly improve quality assurance, reduce operational costs, and enhance safety, making them integral to modern smart manufacturing.

Types of Robots in Manufacturing

Robotic systems in manufacturing environments are broadly classified into industrial robots, collaborative robots, and mobile robots, each serving distinct operational roles and functional capabilities.

Industrial Robots (Robotic Arms)

Industrial robots, typically in the form of robotic arms, are developed for use in controlled settings requiring accuracy throughout repeated operations. Articulated robots, SCARA robots, delta robots, and gantry robots are all part of this category. Articulated robots, which have rotary joints, are widely used for applications such as welding, painting, and assembly.

Collaborative Robots (Cobots)

Cobots do away with the necessity for safety cages by operating safely near human workers. These mechatronic devices include force-limiting sensors and user-friendly control panels, allowing for quick deployment and reconfiguration. Cobots are predominantly used in light-duty operations such as machine tending, inspection, and packaging, making them ideal for, because of their scalability and inexpensive rollout, small and medium-sized businesses.

Mobile Robots

Mobile robots are autonomous or semi-autonomous systems capable of navigating dynamic environments. They are primarily categorized into Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs). AGVs follow predefined paths using magnetic tapes, wires, or markers, and are suitable for repetitive material transport.

Robotic Vision Systems in Various Manufacturing Sectors

Robotic vision systems and end-effectors are critical components in automating quality control tasks in manufacturing. Vision systems, equipped with high-resolution cameras and AI-based image processing, enable robots to perform complex inspections such as surface defect detection, alignment verification, and dimensional analysis with high accuracy. Tools with specialized ends, such as grippers and suction cups, allow robots to interact effectively with various objects, adapting to product size, shape, and material. Case studies across sectors like automotive, electronics, pharmaceuticals, and food processing demonstrate the successful deployment of these technologies. For instance, in the automotive industry, robots inspect weld seams and paint finishes; in electronics, they handle delicate components with precision; while in food processing, vision-guided robots sort products by quality and size, showcasing improved efficiency, consistency, and safety.

TECHNOLOGIES ENABLING AUTOMATED QUALITY CONTROL

This section presents the key technologies including cloud robotics, machine vision, AI, ML, digital twins, collaborative robots, PLCs, and CPS, all driving smarter, flexible, and efficient industrial automation.

Cloud Robotics

There are several competing definitions of CR, and different laboratories use them in very different ways. The advantages of the limitless computing power, memory, and programming ability are highlighted by Ken Goldberg of UC Berkeley, resulting in a novel kind of collaborative robot intelligence based on knowledge sharing and acquisition [19].

Figure 5 shows the distributed computing resources and datasets that robots linked to cloud computing infrastructure may use. Additionally, robots can share training and labelling data for learning. This approach is proposed by Cloud Robotics. Robotics in the cloud include a network design, Elastic computing and the M2M/M2C communication framework [20].

Machine Vision

Industry professionals often use the phrase "machine vision" to refer to the tools and techniques that allow for autonomous inspection and analysis of various applications via the use of imaging [21]. The following industrial applications of MV are shown in Figure 6: material inspection, object identification, pattern recognition, analysis of electronic components, recognition of signatures, optical character recognition, money recognition, and more.

Artificial Intelligence

AI is a subfield of computer science that aims to build computers with cognitive abilities comparable to those of humans. ML, computer vision, NLP, and planning and decision making are all subfields that fall under its umbrella [22]. Robots equipped with AI can take in data from their surroundings, process it, apply what they have learnt, and ultimately make judgements.

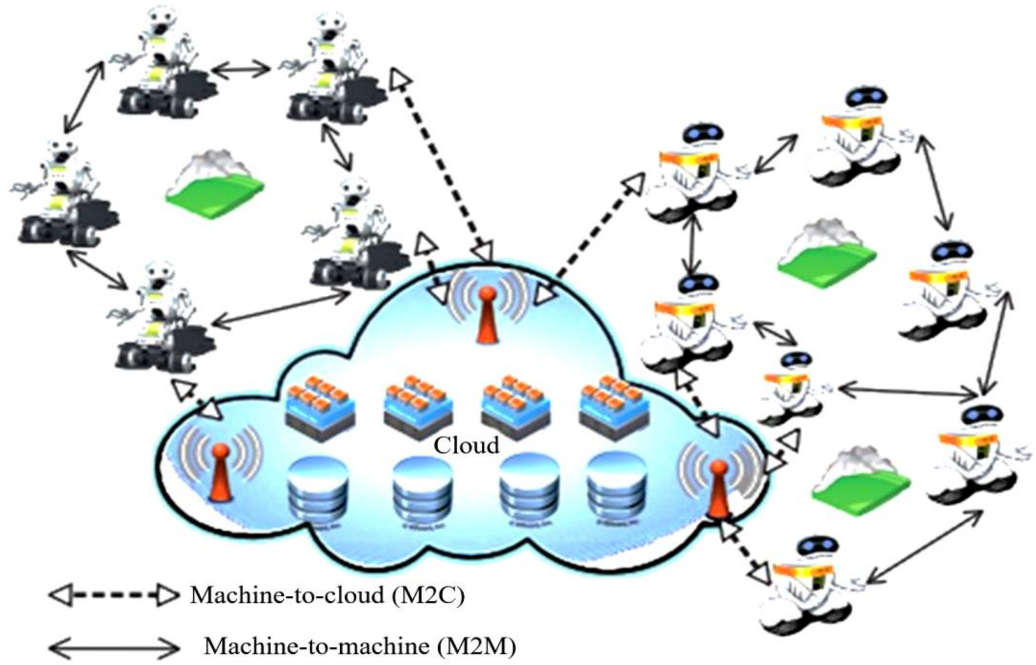

Figure 5. Cloud robots [20].

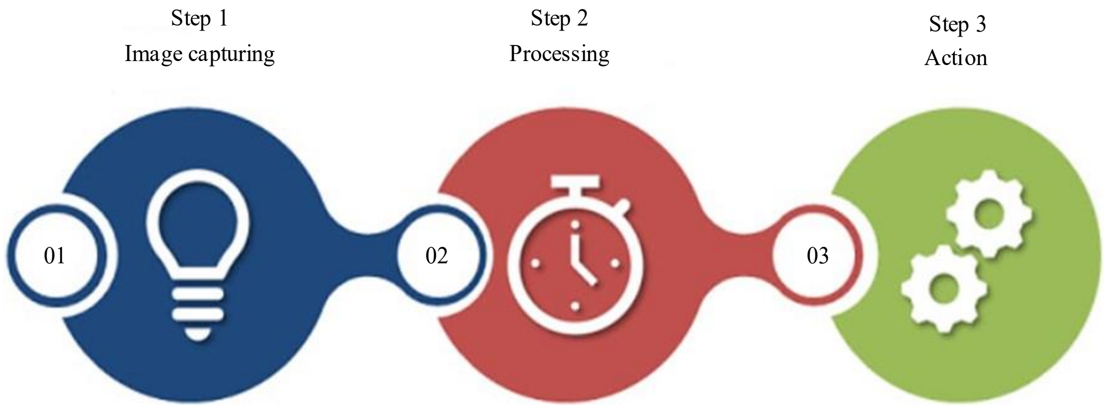

Figure 6. Steps of machine vision [21].

A thorough evaluation of the project and its requirements is the first step in the MV process.

Machine Learning

ML is a method by which computers can automatically sift through massive amounts of data, find patterns, and use what they have learnt to make predictions and decisions [23]. The “reinforcement ML” that AlphaGo Zero makes advantage of begins starting from the ground up using just the Go rules [24]. The current limitation of ML is that it is difficult to comprehend and explain the reasoning process or provide a rationale for the suggestions made by these self-learning computers since their inner workings are a mystery.

Digital Twin

The “SIMCON” project, which aimed to define production control logics via the real-time connection of virtual simulations with actual production, is where the idea of digital twins in manufacturing first originated. Digital twins originated as described by Grieves and Vickers as a way of creating a digital construct that describes a physical system.

Robotics (Industrial and Collaborative)

The word “cobot” refers to a kind of robot that can either work with people to complete a job or that may coexist in a single workplace with humans, hence has some design elements that make it more suitable for cobots (Figure 7) [25].

Several technical advancements have made collaborative robots safe.

Programmable Logic Controllers (PLCs)

International Electrotechnical Commission (IEC) 61131 is a standard for PLCs and specifies their construction standards and recommendations [26]. It can even program in C/C++ with certain high-end PLCs. Similar to Pascal and Function Block Diagram (FBD), ST is a text-based, high-level sequential programming language. FBD is a block-based architectural language that allows users to visually express functionalities.

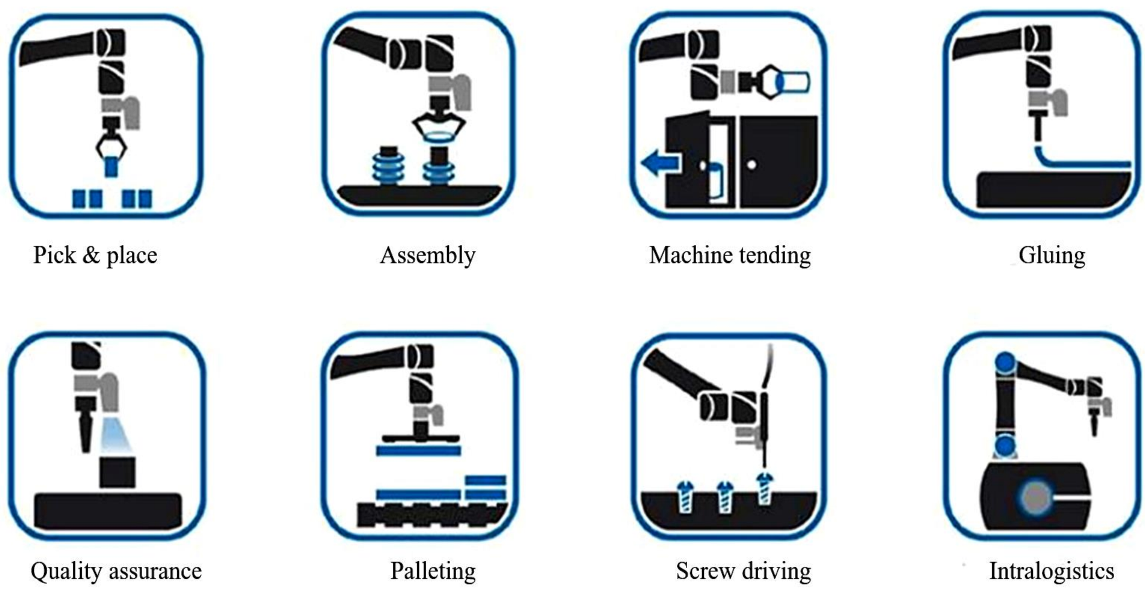

Figure 7. Human-robot collaboration (cobots) [25].

Cyber-Physical System (CPS)

CPS combines computational resources with those of mechanical or electrical systems. Physical systems, information systems, the result of integration and heterogeneous systems, and the need for predictability, real-time capability, and security are the four defining features of CPS. In a processing or manufacturing line, the physical system is a mechanical component, such as an electromechanical system or actuator. The information system places a greater emphasis on memory management, data storage, and the network.

CHALLENGES OF AUTOMATION AND ROBOTICS IN MANUFACTURING

This section highlights key challenges in automation and robotics for manufacturing. Challenges include deployment complexities, simulation-to-reality gaps, learning inefficiencies, and balancing automation with human roles.

Smart Industrial Robot Deployment and Control

The difficulties include, but are not limited to, a wide range of environmental factors, a shortage of trained workers, and issues with functional correctness and dependability [27]. Smart manufacturing has made it so that specialized systems tuned to different environments cannot be maintained. Lighting, field of view distance, and object type are just a few of the many variables that may significantly impact the accuracy of a CV-based system. Industrial robots do low-skill jobs that once needed human brains and dexterity; they also replace mundane, meaningless work, and they are quite dangerous.

Reinforced, Imitated or Combined Learning Strategies

Robots that rely on computer vision do well in unpredictable settings, but their lack of adaptability is due to their reliance on explicit programming. Robots can learn new tasks on their own with the help of deep reinforcement learning (DRL), although this method has limitations due to the reality gap and inefficient samples. In industrial applications, combining DRL with imitation learning, which uses expert demonstrations can increase training efficiency, performance, and decrease the need for exploration.

Use of Simulations and Synthetic Data

There are several methods and phases in which simulations and synthetic data might aid in the development of intelligent industrial robotic systems. Opportunities abound, including the generation of cheap and massive volumes of data, the acceleration of the design cycle while cutting costs, and the provision of a safe and completely regulated testing environment [28]. Issues arise because real-life conditions vary significantly from those in simulations, leading to a decline in the system's accuracy when used in such settings. The problem of translating learnt models from simulation to reality is exacerbated by a myriad of real-world factors, including physical simulations, virtual representations of objects, recreations of sensor data, artificial lightning, and many other parts of the actual environment.

The Road to Future Factories

In the future of smart factories, mastering a new skill will not need much effort or time. No company benefits from a halt when smart manufacturing supply networks must be reorganized [29]. The pandemic crisis highlighted the advantages of digitization for several factories, while also revealing numerous difficulties and a lack of automation, which had an effect on the economy overall. Industrial robots need to advance towards cognitive robotics and mimic human performance if they are to reach a highly automated and flexible state.

LITERATURE REVIEW

This literature review explores advancements in cloud robotics, machine vision, Industry 4.0 robotics, BIM-CNC integration, joystick-controlled automation, and intelligent manufacturing systems, highlighting their applications, benefits, challenges, and future directions in enhancing industrial productivity, quality, and automation.

Manonmani *et al.* (2025) [30]

The study discusses the advancements in cloud robotics and their industrial applications, highlighting the synergy between cloud infrastructure and robotic platforms. Key technologies like AI, ML, and the IOT are explored for their roles in enhancing scalability, computational efficiency, and real-time data processing. The findings suggest that cloud robotics can significantly improve productivity, cost-efficiency, and flexibility in manufacturing and other sectors, with future research directions aimed at promoting its broader adoption [30].

Deng *et al.* (2024) [31]

The study introduces the types of vision technologies, overviews the typical applications of machine vision for quality inspection in aerospace manufacturing (including component surface inspection, drilling quality inspection, assembly quality inspection, and gluing quality inspection), analyzes the advantages, challenges, and development trends of machine vision for quality inspection in aerospace manufacturing, and looks forward to future research directions to support further research and application. Machine vision is widely used in aerospace manufacturing for automated production, quality inspection, and robot guidance [31].

Adetunla *et al*. (2024) [32]

The study is an attempt to present the role of robotics in manufacturing in the framework of Industry 4.0 thoroughly. It attempts to look deeper into the basic premises that robotics follows, its integration with the other technologies that constitute the 4th industrial revolution, applications in various fields of manufacturing, obstacles to implementations, and the way robotics might evolve as it continues to change the future of manufacturing. The age of Industry 4.0 has opened a new trend in manufacturing, with the implementation of the latest technologies, traditional manufacturing techniques are being altered. Robotics science is the science and art of applying robots to enhance the process of manufacture in terms of automation, adaptability and productivity [32].

Qiao (2023) [33]

The study looks at how building information modelling (BIM) and CNC work together in practice. Next, BIM has become more integrated with the mechanical and electrical industries, which has altered the traditional use of mechanical and electrical engineering. Now, BIM can determine the project's green index, economic index, budget, and other values right from the start of architectural design, all based on the data creation mode. The reverse calculation is one way that BIM may enhance the electromechanical calculation technique, which in turn can improve the conventional numerical control design approach. As a result, several branches of electrical and mechanical engineering have adopted BIM [33].

Hussain *et al*. (2022) [34]

The manufacturing and control industries are facilitated to be automated to achieve a productive level. Therefore, the automation within the industrial sectors fulfils the demands of the consumers to a great extent. This is through the automation of the joystick and robotic technology. The industrial joystick serves as a control device in operating the machines of different size with the right direction. The robotic arm gets operated by the manipulation of the joystick. The joystick is used to control the overall movement of the robot. This automation on the industry contributes to improving the newer innovations with real time execution [34].

Li and Huo (2021) [35]

It is based on the PLC to establish the digitally networked and intelligent system architecture operation model of intelligent manufacturing system; and the operation model of intelligent manufacturing system realizes the functions of perception of state, real-time analysis, independent decision-making, and precise operation of intelligent manufacturing system. In the intelligent manufacturing process, it will be an entirely automated and man-free manufacturing process. The model of finite state machine usually being applied to modeling and simulation of manufacturing systems is not able to handle complexity and distributed problems, and the functional hierarchy model is not able to model data flow [35].

Table 1 summarizes key literature on advanced manufacturing technologies, highlighting diverse approaches like cloud robotics, machine vision, BIM-CNC integration, and intelligent systems. It outlines their benefits, challenges, and limitations in improving automation, efficiency, and precision across industrial application.

CONCLUSION AND FUTURE WORK

The integration of advanced technologies such as cloud robotics, machine vision, artificial intelligence AI, ML, digital twins, collaborative robots, PLCs, and CPS has significantly transformed modern manufacturing. These technologies collectively enhance production efficiency, flexibility, and quality control while reducing downtime and operational costs. Despite their potential, the successful deployment of automation and robotics faces persistent challenges, including technical limitations, the need for skilled personnel, system interoperability, and safety concerns. The reviewed literature highlights ongoing research efforts to overcome these obstacles and demonstrates the practical value of automation across various industrial sectors. The synergy between digital technologies and robotics paves the way for smart, adaptive, and responsive manufacturing systems in the Industry 4.0 era.

Table 1. Research on automation and robotics in manufacturing.

Reference	Focus on	Approach	Key findings	Challenges	Limitations/gaps
Manonmani *et al*. (2025) [30]	Cloud robotics in industry	Review of cloud-robotics technologies	Enhances scalability, cost-efficiency, and flexibility	Latency, data security	Broader adoption and integration needed
Deng *et al*. (2024) [31]	Machine vision in aerospace quality inspection	Application-focused analysis	Improves inspection efficiency and automation	Complexity in adapting to various tasks	Further research for broader implementation
Adetunla *et al*. (2024) [32]	Robotics in Industry 4.0	Conceptual exploration and analysis	Robotics improves automation and flexibility in manufacturing	Implementation challenges	Need for standardization and integration strategies
Qiao *et al*. (2023) [33]	BIM-CNC in mechatronics	Analytical review	Enhances green/economic index and CNC design efficiency	Complex data management	Limited control flow modeling with current techniques
Hussain *et al*. (2022) [34]	Joystick-controlled industrial robotics	Application case study	Improves control precision and reduces errors	Sensor-based control complexity	Focused on specific hardware (joystick)
Li *et al*. (2021) [35]	Intelligent manufacturing systems	System modeling with PLC and big data	Enables real-time analysis, autonomous decisions, full automation	Modeling accuracy, safety risks	Existing models can't handle complex control flows

To create standardized frameworks and interoperable platforms as a top priority for future research is important to enable the smooth integration of diverse robotic and automation technologies. Emphasis must also be placed on enhancing cobots through safe, intuitive, and intelligent interfaces. Bridging the simulation-to-reality gap, improving data transparency, and ensuring cybersecurity will be critical for deploying autonomous systems at scale. Moreover, continued efforts are needed to advance explainable AI and interpretable ML to build trust and accountability in decision-making processes. Expanding these technologies into SMEs and incorporating sustainability metrics into automation strategies will be vital for inclusive and responsible industrial growth.

REFERENCES

1. Ani O. Advanced manufacturing with machine learning: enhancing predictive maintenance, quality control, and process optimization. Al-Rafidain J Eng Sci. 2024; 2(2): 280–300.
2. Garg S. AI-Driven Innovations in Storage Quality Assurance and Manufacturing Optimization. Int J Multidiscip Res Growth Eval. 2020; 1(1): 143–7.
3. Papulová Z, Gažová A, Šufliarský Ľ. Implementation of automation technologies of industry 4.0 in automotive manufacturing companies. Procedia Comput Sci. 2022; 200: 1488–97.
4. Kohnová L, Salajová N. Industrial Revolutions and their impact on managerial practice: Learning from the past. Probl Perspect Manag. 2019; 17(2): 462–478.
5. Goyal A. Enhancing Engineering Project Efficiency through Cross-Functional Collaboration and IoT Integration. Int J Res Anal Rev. 2021; 8(4): 396–402.
6. Garg S. Next-Gen Smart City Operations with AIOps & IoT : A Comprehensive look at Optimizing Urban Infrastructure. J Adv Dev Res. 2021; 12(1): 1–9.
7. Liu Y, Zhao W, Liu H, Wang Y, Yue X. Coverage path planning for robotic quality inspection with control on measurement uncertainty. IEEE/ASME Trans Mechatronics. 2022; 27(5): 3482–93.
8. Mineo C, Vasilev M, Cowan B, MacLeod CN, Pierce SG, Wong C, et al. Enabling robotic adaptive behaviour capabilities for new industry 4.0 automated quality inspection paradigms. Insight-Non-Destructive Test Cond Monit. 2020; 62(6): 338–44.
9. Goyal A. Integrating IoT and Agile Methodologies for Smarter Engineering Solutions. Int J Sci Res Arch. 2023 Apr 30; 8(2): 754–66. Available from: https://ijsra.net/node/6924
10. Çiçekler M, Tutuş A. Overview of Quality Control in the Paper Industry. In: 1st International Conference on Recent Academic Studies. 2023; 100–10.
11. Kaushik R, Rawat A, Tiwari A. An Overview on Robotics and Control Systems. Int J Tech Res Sci. 2021; 6(10): 13–7.
12. Liu Z, Liu Q, Xu W, Wang L, Zhou Z. Robot learning towards smart robotic manufacturing: A review. Robot Comput Integr Manuf. 2022; 77: 102360.
13. Moru DK, Borro D. A machine vision algorithm for quality control inspection of gears. Int J Adv Manuf Technol. 2020; 106(1): 105–23.
14. Melo AF, Corneal LM. Case study: evaluation of the automation of material handling with mobile robots. Int J Qual Innov. 2020; 6(1): 3.
15. Jadhav A, Jadhav VS. A review on 3D printing: An additive manufacturing technology. Mater Today Proc. 2022; 62: 2094–9.
16. Galindo-Salcedo M, Pertúz-Moreno A, Guzmán-Castillo S, Gómez-Charris Y, Romero-Conrado AR. Smart manufacturing applications for inspection and quality assurance processes. Procedia Comput Sci. 2022; 198(2020): 536–41.
17. Chandu HS. Enhancing Manufacturing Efficiency: Predictive Maintenance Models Utilizing IoT Sensor Data. International Journal for Science and Advance Research in Technology (IJSART). 2024; 10(9): 58–66.
18. Lu Y, Xu X, Wang L. Smart manufacturing process and system automation – A critical review of the standards and envisioned scenarios. J Manuf Syst. 2020 Jul; 56(Jul): 312–25. Available from: https://linkinghub.elsevier.com/retrieve/pii/S027861252030100X
19. Jordan S, Haidegger T, Kovács L, Felde I, Rudas I. The rising prospects of cloud robotic applications. In: 2013 IEEE 9th International Conference on Computational Cybernetics (ICCC). 2013; 327–32.
20. Patel R. Advancements in Renewable Energy Utilization for Sustainable Cloud Data Centers : A Survey of Emerging Approaches. Int J Curr Eng Technol. 2023; 13(5): 447–54.
21. Javaid M, Haleem A, Singh RP, Rab S, Suman R. Exploring impact and features of machine vision for progressive industry 4.0 culture. Sensors Int. 2022; 3: 100132.
22. Maddali G. Enhancing Database Architectures with Artificial Intelligence (AI). Int J Sci Res Sci Technol. 2025; 12(3): 296–308.
23. Majumder RQ. Machine Learning for Predictive Analytics: Trends and Future Directions. Int J Innov Sci Res Technol. 2025; 10(4): 3557–64.
24. Wang W, Siau K. Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity. J Database Manag. 2019 Jan; 30(1): 61–79.

25. Franklin CS, Dominguez EG, Fryman JD, Lewandowski ML. Collaborative Robotics: New Era of Human–Robot Cooperation in the Workplace. J Safety Res. 2020 Sep; 74: 153–60.
26. Krupa P, Limon D, Alamo T. Implementation of model predictive control in programmable logic controllers. IEEE Trans Control Syst Technol. 2020; 29(3): 1117–30.
27. Smids J, Nyholm S, Berkers H. Robots in the workplace: a threat to—or opportunity for—meaningful work? Philos Technol. 2020; 33(3): 503–22.
28. Choi H, Crump C, Duriez C, Elmquist A, Hager G, Han D, *et al.* On the use of simulation in robotics: Opportunities, challenges, and suggestions for moving forward. Proc Natl Acad Sci. 2021; 118(1): e1907856118.
29. Murugandi K, Seetharaman R. Analysing the Role of Inventory and Warehouse Management in Supply Chain Agility : Insights from Retail and Manufacturing Industries. Int J Curr Eng Technol. 2022; 12(6): 583–90.
30. Manonmani A, Akash S, Aswinraj A, Manikandan A. Literature Review on Advanced Cloud Robotics for Enhanced Industrial Automation. In: 2025 IEEE International Conference on Electronics and Renewable Systems (ICEARS). 2025; 46–51.
31. Deng L, Liu G, Zhang Y. A Review of Machine Vision Applications in Aerospace Manufacturing Quality Inspection. In: 2024 4th International Conference on Computer, Control and Robotics (ICCCR). 2024; 31–9.
32. Adetunla A, Akinlabi E, Jen TC, Ajibade SS. Analysing the Roles of Robotics in Manufacturing Organizations in the Era of Industry 4.0. In: 2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG). 2024; 1–5.
33. Qiao D. Research on BIM and Numerical Control Technology Based on Mechatronics. In: 2023 7th International Conference on Robotics, Control and Automation (ICRCA). 2023; 6–10.
34. Hussain S, George RP, Ahmad N, Jahan R. Machine Learning Methods of Industrial Automation System in Manufacturing and Control Sector using Joystick with and Robotic Technology. In: 2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART). 2022; 1134–40.
35. Li T, Huo C. Research on Intelligent Manufacturing System Model Based on Programmable Logic Controller. In: 2021 IEEE 4th International Conference on Information Systems and Computer Aided Education (ICISCAE). 2021; 353–7.

