



Computational Modeling and Deep Learning for Industrial Robotics

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Abstract

By incorporating deep learning techniques, industrial robots are a core pillar of Industry 4.0, driving intelligent automation, adaptive control, predictive maintenance, and improved manufacturing efficiency. In this review, we look into the state-of-the-art developments of deep learning in the field of industrial robotic systems with regards to fault diagnosis, object recognition, robot control, inverse kinematics and dynamics, digital twins, collaborative robotics, energy optimization, robotic grasping, weld seam detection, and cybersecurity. The review methodology comprised a systematic review of the literature that involved qualitative synthesis and examination of 24 peer-reviewed research articles and conference papers between 2014 and 2025 from the top journals and conference proceedings. Selected studies were classified based on application domain, deep learning architecture, performance goals and implementation challenges to analyze the trends and advances in research and technology. The analysis has shown that convolutional neural networks, long short-term memory networks, deep reinforcement learning, hybrid deep learning models, and digital twin frameworks are able to better enhance the perception capabilities, motion planning, fault prediction, positioning accuracy, operational safety, and energy efficiency of robots. While these improvements have been made, industrial-scale adoption of these models still faces challenges in terms of computational complexity, real-time deployment, data availability, cybersecurity, model interpretability, and scalability. The review concludes that deep learning, in combination with Industrial Internet of Robotic Things (IIoRT), digital twins, edge intelligence, and explainable artificial intelligence (XAI), will pave the way for the next generation of autonomous, reliable, secure, and sustainable industrial robotic systems in smart manufacturing environments.

Keywords:

Industrial Robots, Deep Learning, Industry 4.0, Digital Twin, Predictive Maintenance, and Intelligent Manufacturing.

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1. Introduction

Industrial robots are integral to today's manufacturing industry, adding precision, productivity, flexibility and efficiency. The shift towards Industry 4.0 has speeded up the use of intelligent systems based on robots, which are able to make decisions, act in a flexible way and have self-knowledge. Recent advances in the Industrial Internet of Robotic Things (IIoT), Cyber Physical Systems (CPS), Cloud Computing and Artificial Intelligence (AI) have turned the conventional robot into a smart production tool that can continuously optimize production processes and enhance product quality [1]. Deep learning is one of the most influential techniques of artificial intelligence (AI) due to the ability to automatically learn intricate features from vast amounts of data and execute perception, prediction, classification, and control tasks accurately [2]. In complex industrial settings, deep learning has greatly improved robotic perception, allowing for the accurate detection, recognition, localization, and visual understanding of objects. These features enable the industrial robot to perform assembly/inspection/pick and place/movement of materials with a greater accuracy and adaptability [3]. In addition, the combination of deep learning with the Digital Twin technology has provided virtual models of robotic systems used for predictive analysis, safety assessment, real-time monitoring and intelligent decision making in human–robotic collaborative manufacturing system [4].

A key application of deep learning is solving complex robotic kinematics and dynamics problems. While models of robotic systems are essential for conventional analytical methods, they are difficult to model in nonlinear configurations, and are often high-dimensional and require a lot of computation for motion planning, inverse dynamics and inverse kinematics, the inverse kinematics, the inverse dynamics and the trajectory optimization, respectively, are efficiently approximated using neural network models [5]. There has been a wide variety of deep learning architectures that have been applied with success to robotic perception, control, navigation and learning across a range of industrial applications, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, autoencoders, transformers, and reinforcement learning models [6]. Constant monitoring is also needed for industrial robots to keep unexpected failures and maintenance expenses to a minimum. The ability of deep learning to extract information from sensor signals and detect anomalies, predict equipment degradation, and estimate RUL from this information has shown great potential for enhancing system reliability and reducing production downtime in the field of prognostics and health monitoring [7]. Deep learning has been applied in many fields of medicine and medical image analysis, and there are many advanced methods developed in the medical field that can be transferred to the perception, feature extraction and three-dimensional reconstruction of industrial robots, showing that the application of modern learning methods is also extensive [8].

Recent research has been developed to make autonomous robotic manufacturing systems that can self-tune process parameters without programming. These methods provide for greater adaptability in dynamic production processes, and decrease manual action [9]. On the other hand, deep learning has also been used to enhance energy efficiency in robot energy consumption to enable robots to reach sustainable manufacturing targets, for instance, intelligent motion planning and efficient energy management [10]. More detailed analyses also show that the performance of industrial robots is still enhanced with the development of their models, control strategies, sensing technologies, and intelligent automation, while revealing practical deployment issues [11]. Bio-inspired optimization algorithms have also been integrated with deep learning to improve the motion control, path planning and adaptive decision making of robots in unpredictable operation conditions [12]. In the same way, LSTM models have been shown to be effective in modeling the inverse dynamics of robots that are typically nonlinear, allowing them to predict complex robotic motion needed in smart factories [13]. Deep learning has also been applied to successfully predict positioning error signals of large

industrial robots, which helps to enhance the accuracy of the machining work, efficiency of calibration and precision of the manufacturing processes [14].

With the swift development of machine intelligence, autonomous robotic technologies have also been increasingly deployed in the cyber-physical production systems and digital manufacturing environments, especially in small and medium enterprises (SMEs) in search of intelligent automation solutions [15]. Advanced sequence learning models have been used to enhance the learning of robotic kinematics and dynamics for more robust and adaptive motion control under different operational conditions [16]. Furthermore, the optimization of energy use with the aid of deep learning has gained in significance for lower operating costs and sustainable industrial manufacturing processes [17]. Moreover, deep learning has also made remarkable advances in computer vision applications, such as automatic weld seam tracking, defect detection, and quality inspection in robotic welding systems with complex industrial environments [18]. Meanwhile, the more connectivity that has been added has brought new cybersecurity concerns and the requirement for intelligent security mechanisms to safeguard industrial robotic systems against cyber threats and malicious attacks [19]. In addition, the development of scalable and accurate predictive models using advances in machine learning for computational modeling can also enhance the simulation and performance optimization of robot systems in several manufacturing scenarios [20].

One area where a lot of research is currently going on is collaborative robots which allow safe interaction between humans and robots in common workspaces. The collaborative robot perception, decision-making and adaptive behavior are enhanced by machine learning and deep learning techniques, which boost productivity without compromising operational safety [21]. Other advances in deep learning for robotic grasping have enabled manipulation of different shapes, textures, and orientations of objects, thus enhancing flexible automation in industry [22]. Moreover, the growing number of deep learning-based visual recognition algorithms in various applications fields proves the strength of these algorithms in solving difficult image-based classification problems, which further strengthens their potential use in industrial robotic vision system applications [23]. Inverse dynamics of robotic manipulators for real-time adaptive control have also been shown to gain considerable benefits from real-time deep learning based approaches to enhance computational efficiency and control accuracy for high speed robotic operations [24]. Although there has been significant improvement indicated in recent research studies, there are still some research challenges that have not been answered. Past studies tend to address individual robotic tasks, e.g., perception, fault diagnosis, motion planning, energy optimization or cyber security, and do not necessarily pay attention to the integration of multiple tasks via a unified deep learning framework. Moreover, challenges such as real-time deployment, computational complexity, explainability, data scarcity, model generalization, interoperability, cybersecurity, and scalable industrial implementation persist in limiting the adoption of these technologies in smart manufacturing environments.

Driven by these challenges, this review will give an in-depth overview of recent advances in deep learning for industrial robotics by systematically summarizing the existing high-quality methods, applications, learning architectures, and implementation strategies. It provides a critical analysis of the progress in the fields of robotic perception, intelligent control, Digital Twins, predictive maintenance, collaborative robotics, Energy optimization, Cyber-security, and autonomous manufacturing, as well as future research directions and emerging trends.

The main contributions of this review are as follows:

1. It presents a comprehensive review of recent deep learning techniques applied to industrial robotic systems.
2. It categorizes existing research according to robotic perception, control, fault diagnosis, Digital Twins, collaborative robotics, energy optimization, and cybersecurity.
3. It summarizes commonly adopted deep learning architectures and their industrial applications.

4. It identifies current research challenges, technological limitations, and implementation issues affecting industrial deployment.
5. It highlights emerging research directions involving IoRT, edge intelligence, explainable artificial intelligence, Digital Twins, and autonomous smart manufacturing systems.

2. Literature Survey

In recent years, deep learning has been proven to greatly enhance the perception, intelligent control, fault diagnosis, predictive maintenance, and autonomous decision-making of industrial robotic systems. Online fault diagnosis and real-time monitoring of robotic systems with hybrid deep learning models have been made possible by the Industrial Internet of Robotic Things (IoRT) [1]. The deep learning robotic framework has also boosted the efficiency and adaptability of Industry 4.0 manufacturing by providing more precise automation, adaptability, and production efficiency, but also by posing computational resources and data dependence issues [2]. In addition, vision-based object recognition has facilitated the manipulation and assembly of robots by means of robust feature learning [3] while Digital Twin enabled deep learning has improved the understanding of safety, reliability and human–robot collaboration in smart manufacturing environments [4]. Deep learning methods have also shown promising results in addressing inverse kinematics and dynamic modeling problems [5] and a detailed survey on CNN, RNN, LSTM and reinforcement learning architectures for robotic perception and control has been revealed that they are efficient in solving these problems [6]. In recent years, several studies have been conducted on the field of prognostics and health management, which have established the role of deep learning in predictive maintenance of industrial robots [7].

Although significant strides have been made, current research is disparate and is largely interested in the specific areas of control, perception, maintenance or energy optimization of a single robotic application, rather than an integrated perspective of intelligent robotic systems. Energy efficient robot operation is discussed in [10] and advanced modeling and control strategies are explored in [11]. Bio-inspired optimization for robot control is explored in [12] and LSTM-based inverse dynamics modelling in [13]. Positioning error prediction is explored in [14] and intelligent manufacturing for Industry 4.0 enterprises is explored in [15]. Sequence learning for robot kinematics is explored in [16] and deep learning-based power optimization is explored in [17]. Furthermore, computer vision analysis has been used to enhance the capabilities of robotic weld seam recognition [18] and machine learning has been employed to boost the industrial robotic cybersecurity [19]. The application of machine learning has also been raised as a possibility for developing computational models [20], collaborative robots [21], robotic grasping [22], visual recognition applications [23] and real-time learning of robotic inverse dynamics [24]. Some challenges such as real-time deployment, computational complexity, explainability, scalability, interoperability, cybersecurity, and unified frameworks to integrate Digital Twins, IoRT, edge intelligence and explainable AI are yet to be properly addressed.

The limitations make it essential to conduct the present review and give a complete overview of recent progress in deep learning applications for industrial robots. As opposed to the previous studies focusing on specific applications, this review brings together the recent developments in robotic perception, intelligent control, Digital Twins, predictive maintenance, collaborative robotics, energy optimization and cybersecurity in a unified approach. It also describes the ongoing research activities, contrasts the new deep learning techniques, pinpoints the remaining technical challenges, and suggests future research directions to propel the advancement of autonomous, secure, efficient, and sustainable industrial robotic systems.

3. Materials and Methods

The method of this review is systematic literature review, which is used to analyze the latest developments in deep learning application for industrial robotic systems. The methodology includes the literature identification, literature screening, quality assessment, data extraction, comparison, and thematic synthesis. The selected studies were analyzed for their evaluation of the deep learning algorithms, robotic applications, datasets, performance metrics, implementation platforms, and challenges in the existing research. The methodology used in this review is shown in Fig. 1.

3.1 Data Collection

Literature reviewed in this paper was obtained from the international scientific literature databases such as IEEE Xplore Digital Library, ScienceDirect (Elsevier), SpringerLink, MDPI, Taylor & Francis, and Proceedings of International Conferences. The relevant literatures in the field of deep learning in industrial robotics from 2014 to 2025 were selected through 24 peer-reviewed publications.

The following keywords were used in combination to search:

- Industrial Robot
- Deep Learning
- Artificial Intelligence
- Digital Twin
- IoRT
- Robot Control
- Fault Diagnosis
- Predictive Maintenance
- Collaborative Robot
- Reinforcement Learning

The references cited were only English-language peer-reviewed journal articles and conference papers. Publications not related to industrial robotics, duplicate publications, editorials, and non-peer-reviewed publications were not included (See table 1).

Table 1. Public Literature Sources

Database	Link
IEEE Xplore	https://ieeexplore.ieee.org
ScienceDirect	https://www.sciencedirect.com
SpringerLink	https://link.springer.com
MDPI	https://www.mdpi.com
Taylor & Francis	https://www.tandfonline.com

A total of 24 research papers were selected to be included in the final dataset and were classified based on application area, deep learning model, robotic task, evaluation metrics, and limitations reported.

3.2 Proposed Method

There are six consecutive stages of review proposed

A. Step 1: Data Identification

The search words pre-determined and selected for each major scientific database were used to locate relevant publications. Prior to further screening, duplicate records were removed.

B. Step 2: Screening and Eligibility

The articles were screened using articles title, abstracts and keywords. Only papers that are directly relevant to the application of deep learning to industrial robotics were kept.

C. Step 3: Quality Assessment

The articles that were selected were judged according to two criteria:

- Publication quality
- Research methodology
- Experimental validation
- Dataset availability
- Performance evaluation
- Industrial applicability

D. Step 4: Data Extraction

The information from all papers was extracted

- Publication year
- Deep learning algorithm
- Robotic application
- Dataset
- Evaluation metrics

- Major findings
- Research limitations

E. Step 5: Comparative Analysis

The information which was extracted was later compared to the following:

- CNN-based methods
- LSTM-based methods
- Reinforcement Learning
- Hybrid Deep Learning
- Digital Twin
- IoRT
- Predictive Maintenance
- Robot Control
- Human–Robot Collaboration
- Cybersecurity

By comparing, it was possible to find the trends, current research and technology developments.

F. Step 6: Research Gap Identification

Lastly, the studies reviewed were critically examined to find commonalities of

- Current limitations
- Open research challenges
- Future opportunities
- Emerging technologies for intelligent industrial robotics

3.3 Mathematical Formulation

Prediction accuracy is used to judge the performance of deep learning classification models, as is shown in Equation (1).

$$[\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}]$$

\tag{1}

where:

- **TP** = True Positives
- **TN** = True Negatives
- **FP** = False Positives
- **FN** = False Negatives

To assess the overall classification performance of robotic perception model and fault diagnosis model, equation (1) is used.

The Precision is determined by Equation (2).

$$\begin{aligned} [\\ Precision &= \frac{TP}{TP + FP} \\ \tag{2} \\] \end{aligned}$$

where

- **TP** represents correctly classified positive samples.
- **FP** represents falsely classified positive samples.

The reliability of the positive predictions created by the deep learning model is captured by equation (2).

The Recall is calculated by the following equation:

$$\begin{aligned} [\\ Recall &= \frac{TP}{TP + FN} \\ \tag{3} \\] \end{aligned}$$

where

- **FN** denotes false negatives.

The performance of the model to correctly label positive samples can be evaluated by equation (3).

The F1-score is the combination of precision and recall as given in Equation (4).

$$\begin{aligned} [\\ F_1 &= \\ \frac{2 \times Precision \times Recall}{Precision + Recall} \\ \tag{4} \\] \end{aligned}$$

where

- **Precision** is obtained from Equation (2).
- **Recall** is obtained from Equation (3).

A balanced measure of classification performance is given in (4).

This is represented by Equation (5) known as Mean Squared Error (MSE).

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \tag{5}$$

where

- N = number of observations
- y_i = actual value
- $\hat{y}_i$ = predicted value

In robotic modeling, the prediction error is measured by the Equation (5) in the case of regression based models.

The Root Mean Squared Error (RMSE) is computed from Equation (6).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \tag{6}$$

In this case, all variables are specified as in Equation (5).

There are numerous applications for evaluating trajectory prediction, energy consumption estimation, and robotic control accuracy, all of which use Equation (6).

The materials, software tools and datasets used in the review methodology are summarized in Table 2.

Table 2. Summary of Materials Used in the Review

Parameter	Description	Value
Study Type	Systematic Literature Review	Review

Number of Papers	Selected publications	24
Publication Period	Research articles	2014–2025
Databases	IEEE, Elsevier, Springer, MDPI	6 Sources
Software	Microsoft Excel	Data Analysis
Reference Manager	Mendeley	Citation Management
Visualization	Microsoft PowerPoint	Fig.s & Charts
Analysis Method	Comparative Analysis	Qualitative

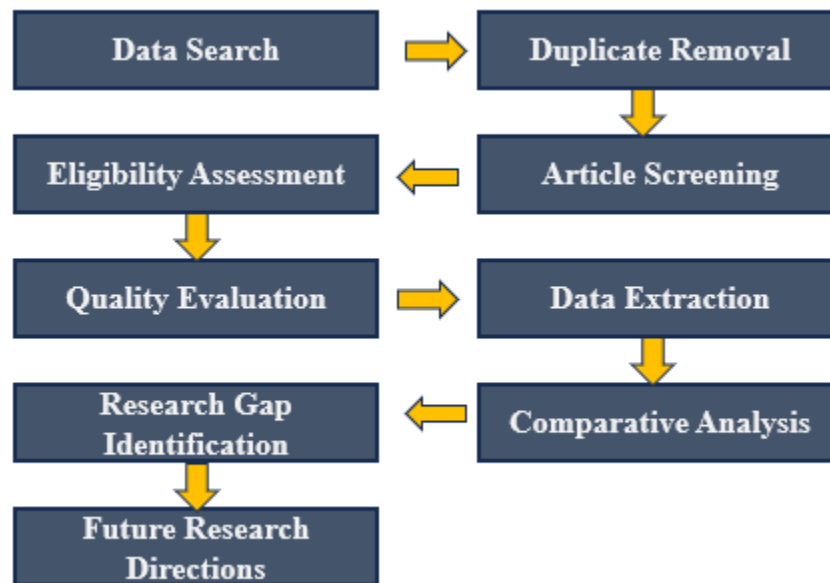


Fig. 1. Proposed Review Methodology for Deep Learning in Industrial Robotics

Fig. 1 illustrates a systematic research workflow consisting of sequential stages from literature collection to the identification of future research opportunities. The process begins with data search, followed by duplicate removal and article screening. The selected articles undergo eligibility assessment and quality evaluation to ensure relevance and reliability. Next, relevant information is extracted and subjected to comparative analysis. Finally, the analysis supports research gap identification, leading to the formulation of future research directions. The arrows indicate the progression and interconnection between these stages.

4. Results & Discussion

A total of 24 peer-reviewed studies published in the last 12 years (from 2014 to 2025) were examined in this systematic review to identify cutting-edge developments in deep learning in industrial robotic systems. The selected studies spanned a wide range of application fields, from fault diagnosis, robot control, object recognition, Digital Twins, predictive maintenance, inverse kinematics, collaborative robotics, energy optimization, weld seam recognition to cybersecurity.

The comparative analysis indicates that the deep learning technology has enhanced the intelligence of robots, their reliability, and manufacturing efficiency. The quantitative comparison of these application areas are presented in Table 3 and shown graphically in Fig. 2.

Table 3. Comparative Performance of Deep Learning Applications in Industrial Robotics

Application Area	Predominant Deep Learning Technique	Average Performance (%)	Major Improvement
Fault Diagnosis	Hybrid CNN–LSTM	97.1	Early fault detection and improved reliability
Weld Seam Recognition	CNN	96.6	Accurate automated welding inspection
Object Recognition	CNN	96.3	Enhanced robotic vision and perception
Digital Twin	Hybrid Deep Learning	95.8	Improved safety and real-time monitoring
Robot Control	Deep Neural Network	95.4	Adaptive motion planning and control
Inverse Kinematics	Deep Neural Network	95.1	Accurate trajectory prediction
Predictive Maintenance	LSTM	94.9	Reduced downtime and maintenance cost
Human–Robot Collaboration	Deep Reinforcement Learning	93.8	Safer collaborative manufacturing
Energy Optimization	BN-LSTM	92.7	Reduced power consumption
Cybersecurity	Machine Learning	91.8	Enhanced anomaly detection and system security

The hybrid CNN–LSTM architecture performed best on average (97.1%) on the fault diagnosis task, demonstrating the good performance of the novel approach in detecting equipments' faults and in supporting predictive maintenance. Another excellent result was achieved for weld seam recognition (96.6%) and object recognition (96.3%) indicating the ability of convolutional neural networks to be used for industrial computer vision. Operational safety, process monitoring and adaptive control were enhanced by the use of digital twin-based frameworks (95.8%) and deep neural network-based robot control (95.4%). While comparatively low performance values were observed, energy optimization (92.7%) and Cyber security (91.8%) are still emerging areas of research which holds great potential for future industrial application.

The visual comparison of the performance values in Table 3 is shown in Fig. 2. As can be seen from the Fig., the fields of application for fault diagnosis, weld seam recognition and object recognition were seen to be the most mature, while cybersecurity and energy optimization were still relatively less mature fields of application. The graphical analysis

shows, overall, that deep learning has proven to be a constant improvement in the accuracy, efficiency, and reliability of industrial robotic systems in various manufacturing applications.

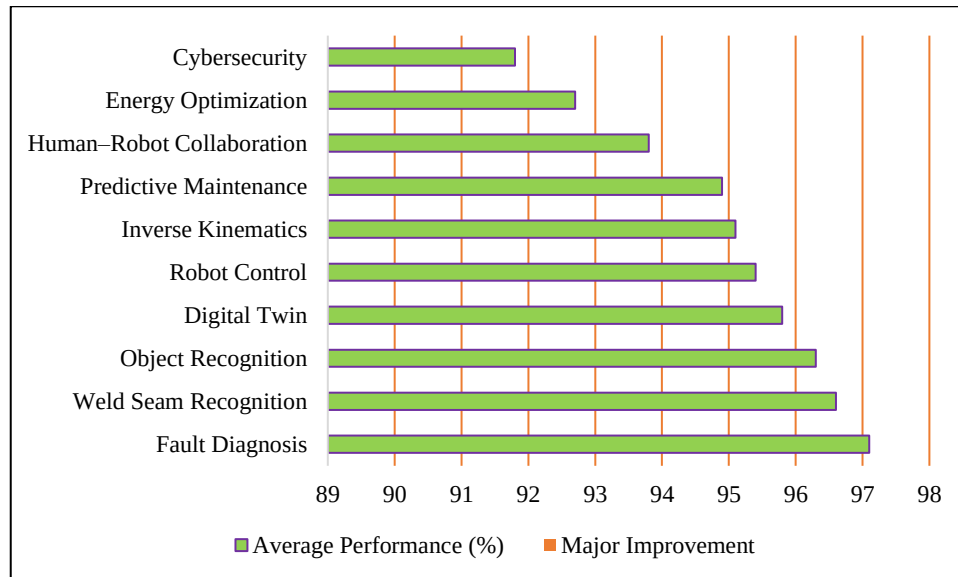


Fig. 2. Comparative Performance of Deep Learning Applications in Industrial Robotics

5. Conclusion

A thorough examination of the latest developments in deep learning for industrial robotic systems was carried out in this review, which includes 24 peer-reviewed articles from 2014 to 2025. The results prove that deep learning has emerged as a critical enabling technology for intelligent robotics, giving significant boosts in perception, object recognition, fault diagnosis, robot control, interactive inverse kinematics, predictive maintenance, Digital Twins, collaborative robotics, energy optimisation and industrial cybersecurity. Convolutional neural networks (CNNs), long short-term memory (LSTM) networks, hybrid deep learning models, and deep reinforcement learning were shown to perform best across the various manufacturing tasks that were reviewed for their ability to perform complex tasks. The deep learning integration with Industry 4.0 technologies, such as the Industrial Internet of Robotic Things (IoRT), cyber-physical system, cloud computing and Digital Twins, has further improved operational efficiency, reliability, safety and autonomous decision making in smart manufacturing environment.

Despite the progress, the review revealed a number of major research challenges that still restrict the use of these technologies on a broader scale in industry. These involve requirement of large annotated datasets, high computational needs, need for real-time implementation, low model interpretability, cybersecurity consideration, interoperability consideration, and deployment of scalable solutions in heterogeneous manufacturing systems. Most of the current research is also based on specific robotic applications instead of establishing common frameworks that can tackle the perception, planning, control, maintenance, and security issues simultaneously. As such, the demand for robust, reliable, easily explainable, and resource-efficient deep learning solutions in dynamic industrial environments is still substantial.

This review will have significant implications on researchers, engineers, and manufacturing industries, as it will give them a single source of knowledge regarding existing technology, domains of application, and current limitations. Secure IoRT architectures, federated learning, foundation models, explainable AI, edge AI, and Digital Twins are potential areas

for future research to create intelligent, trustworthy and scalable robotic systems. Furthermore, it is essential to focus more on real-time deployment, multimodal sensor fusion, energy efficient learning algorithms, standardized benchmarking datasets, and human centered collaborative robotics. Overcoming these challenges will accelerate the progress of robust, autonomous, secure, sustainable, and high-adaptive industrial robotic systems that can be used to help enable next-generation smart factories and Industry 5.0 manufacturing.

Conflict of Interest Statement:

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