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Systematic Review

Big Data Management Algorithms, Deep Learning-Based Object Detection Technologies, and Geospatial Simulation and Sensor Fusion Tools in the Internet of Robotic Things

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Abstract: The objective of this systematic review was to analyze the recently published literature on the Internet of Robotic Things (IoRT) and integrate the insights it articulates on big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools. The research problems were whether computer vision techniques, geospatial data mining, simulation-based digital twins, and real-time monitoring technology optimize remote sensing robots. Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines were leveraged by a Shiny app to obtain the flow diagram comprising evidence-based collected and managed data (the search results and screening procedures). Throughout January and July 2022, a quantitative literature review of ProQuest, Scopus, and the Web of Science databases was performed, with search terms comprising "Internet of Robotic Things" + "big data management algorithms", "deep learning-based object detection technologies", and "geospatial simulation and sensor fusion tools". As the analyzed research was published between 2017 and 2022, only 379 sources fulfilled the eligibility standards. A total of 105, chiefly empirical, sources have been selected after removing full-text papers that were out of scope, did not have sufficient details, or had limited rigor For screening and quality evaluation so as to attain sound outcomes and correlations, we deployed AMSTAR (Assessing the Methodological Quality of Systematic Reviews), AXIS (Appraisal tool for Cross-Sectional Studies), MMAT (Mixed Methods Appraisal Tool), and ROBIS (to assess bias risk in systematic reviews). Dimensions was leveraged as regards initial bibliometric mapping (data visualization) and VOSviewer was harnessed in terms of layout algorithms.

Keywords: Internet of Robotic Things; big data management algorithms; deep learning-based object detection technologies; geospatial simulation; sensor fusion

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1. Introduction

Robot navigation and networked robotic algorithms [1–4], smart sensors, and machine intelligence [5–8] typify the Internet of Robotic Things (IoRT). Artificial intelligence techniques for robot communication can enhance the interactive performance of multi-robot teams in terms of real-world applications, complex operations, cognitive decision-making algorithms, and coordinated action, carrying out their tasks efficiently. Robot control and operation through artificial intelligence and Internet of Things (IoT) configure systems having increased potential to complete elaborate tasks autonomously and collaboratively. IoT assists robot networking and data transfer, optimizing automated and autonomous communication capabilities throughout inherent asynchronous performance of complex multi-device systems by use of streamlined prediction techniques. IoRT empowers smart interconnected devices in supervising the surrounding operations, making swift decisions, and taking expedient actions, while interactively dealing with unplanned events. Individual robots typically make decisions according to the specific observations and insufficient intelligence capability, resulting in tremendous decision-making intermission and imprecise feedback to dynamic environments. Federated machine learning can thoroughly harness the computation performance of distributed robots to attain shared intelligence, improving the capability of carrying out elaborate and demanding interactive tasks. Spatial data analytics, virtual mapping and navigation tools, machine data fusion, and interoperable production systems [9–12] are pivotal in smart factory environments. A massive volume of real-time data can be perpetually shared between robotic technologies and the monitoring hub or cloud services by leveraging open wireless communications and operating systems through swarm coordination and optimized functional and operational capabilities. Cyber-physical production and virtual manufacturing systems [13–16] develop on spatial computing algorithms, sensor data fusion, industrial cloud robotics, and geospatial mapping technologies. IoT robotic platforms integrate dynamic mechanical configurations and digital encoding. Machine learning technologies [17–20] develop on sensor data and IoRT devices. Collaborative unmanned systems typify efficient robot cooperation with smart interconnected devices. Autonomous manufacturing systems integrate spatial computing technology, real-time machine data, intelligent sensor networks [21–24], and augmented reality devices. IoRT develops on cloud computing technologies, machine and deep learning algorithms, and big data analytics. Data mining and acquisition tools [25–28], spatial cognition and swarm intelligence algorithms, predictive smart manufacturing, and digital twin simulations optimize intelligent production systems. Smart factory data, automated simulation modeling, real-time predictive analytics, and enterprise resource planning [29–32] shape virtual manufacturing systems. Networked sensor-based robotic devices [33–36] and fog computing systems develop on swarm intelligence algorithms that assist in data acquisition and sharing.

The objective of this systematic review was to analyze the recently published literature on IoRT and integrate the insights it articulates on big data management algorithms [37–40], deep learning-based object detection technologies [41–44], and geospatial simulation and sensor fusion tools [45–48]. Cooperative unmanned and decentralized tracking systems require mobile clustering algorithms to optimize sensing capabilities. Smart objects can handle contextual data in relation to infrastructure and users through sensors and actuators to infer the environment within semantic IoRT systems and to seamlessly make autonomous decisions. Context-aware IoRT systems develop on sensor data semantic and action modeling tools and on perception and actuation devices. IoT and robotic systems can be optimized with knowledge-based tools and smart connected devices, by integrating semantic layers and context awareness. The actuality and novelty of this paper are configured by addressing how big data processing systems [49–52] develop data mining techniques [53–56], IoRT sensors and devices [57–60], and deep neural networks. Real-time data tracking and monitoring [61–64], machine vision technology, sensor data processing algorithms [65–68], and big geospatial data analytics [69–72] configure smart product innovation and manufacturing system modeling. Our specific contribution is to clarify how mobile connected IoRT devices [73–76], cloud and pattern recognition technologies, networked robotics, and automated machines [77–80] configure autonomous manufacturing units in dynamic simulation environments in terms of robotic behavior control, sensor and actuator interconnections, and real-time data processing and analysis [81–84]. Correlations with previously published literature comprise analyses on how industrial cloud robotics integrates autonomous production systems, smart manufacturing task management [85–88], simulation optimization algorithms, and data visualization tools, while disparities encompass our integration of the sources on how autonomous robotized devices develop on virtual simulation tools, real-time monitoring capabilities [89–92], data fusion techniques, and cloud computing algorithms. The research problems are whether computer vision techniques, geospatial data mining [93–96], simulation-based digital twins, and real-time monitoring technology [97–100] optimize remote sensing robots [101–105].

Research Problem 1: Image recognition technologies, machining process performance, real-time sensor data, and visual recognition tools shape virtual manufacturing systems and autonomous robotized devices.

Research Problem 2: Virtual data modeling, computer vision and process planning algorithms, and intelligent remote operations further autonomous robotized devices.

Research Problem 3: Virtual machine and computational object instantiation tools, digital twin technology, and real-time operational data assist robotized manufacturing systems.

The manuscript is organized as follows: methodology (Section 2), big data management algorithms in IoRT (Section 3), deep learning-based object detection technologies in IoRT (Section 4), geospatial simulation and sensor fusion tools in IoRT (Section 5), deployment of CityGML in IoRT (Section 6), discussion (Section 7), conclusions (Section 8), specific contributions to the literature (Section 9), limitations and further directions of research (Section 10), and practical implications (Section 11).

2. Methodology

Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) guidelines were leveraged by a Shiny app to obtain the flow diagram comprising evidence-based collected and managed data (the search results and screening procedures). Throughout January and July 2022, a quantitative literature review of ProQuest, Scopus, and the Web of Science databases was performed, with search terms comprising "Internet of Robotic Things" + "big data management algorithms", "deep learning-based object detection technologies", and "geospatial simulation and sensor fusion tools". As the analyzed research was published between 2017 and 2022, only 379 sources fulfilled the eligibility standards. A total of 105, chiefly empirical, sources have been selected after removing full-text papers that were out of scope, did not have sufficient details, or had limited rigor (Tables 1 and 2). For screening and quality evaluation so as to attain sound outcomes and correlations, we deployed AMSTAR (Assessing the Methodological Quality of Systematic Reviews), AXIS (Appraisal tool for Cross-Sectional Studies), MMAT (Mixed Methods Appraisal Tool), and ROBIS (to assess bias risk in systematic reviews). Dimensions was leveraged as regards initial bibliometric mapping (data visualization) and VOSviewer was harnessed in terms of layout algorithms (Figures 1–5).

Table 1. Topics and types of identified and selected scientific products.

Topic	Identified	Selected
Internet of Robotic Things + big data management algorithms	124	34
Internet of Robotic Things + deep learning-based object detection technologies	126	35
Internet of Robotic Things + geospatial simulation and sensor fusion tools	129	36
Type of paper		
Original research	272	78
Review	46	27
Conference proceedings	48	0
Book	7	0
Editorial	6	0

Source: Processed by the authors. Some topics overlap.

Table 2. Synopsis of cumulative evidence in relation to inspected topics and descriptive results (research findings).

Cloud computing and wireless communication technologies integrate industrial machines, smart sensors, heterogeneous sensor devices, big data management algorithms, and autonomous robots.	[1–4]
Automated data transmission, sensor data, industrial manufacturing processes, and machine learning techniques configure networked autonomous plants and sensor technologies.	[5–8]
Real-time monitoring industrial sensing and swarm robotic systems, in addition to cloud computing, imaging, and sensing technologies articulate industrial manufacturing processes.	[9–12]

Table 2. *Cont.*

IoRT-based big data mining and analysis, cloud computing and big data technologies, and smart devices shape contextual awareness in uncontrolled environments.	[13–16]
Collaborative interoperable networked unmanned systems deploy intelligent virtual agents, computation technologies and algorithms, and sensor networks.	[17–20]
IoRT-based manipulation and 3D object recognition and tracking tasks can be carried out in unstructured environments by leveraging robotic systems, cloud computing technologies, big data analytics, and machine and deep learning algorithms in terms of robust perceptual capabilities and reliable visual data.	[21–24]
IoT-based robots and robotic systems necessitate environmental location and sound recognition tools, context awareness data, and artificial neural networks to assist in decision making processes.	[25–28]
Tracking mobile IoRT devices is instrumental in robotic operating and fog computing network systems.	[29–32]
IoRT-based operational technologies are pivotal in robot trajectory tracking in dynamic mobile environments and as regards functional interoperability, data integration complexity, and structural connectivity in industrial systems through big data management algorithms.	[33–36]
Spatial clustering of sensing capabilities, deep learning-based object detection technologies, noise algorithms, and networked scheduling mechanisms and communication objects enable robot control and decentralized tracking systems.	[37–40]
Actuation and control methods assist IoRT physical and virtual devices across monitoring and managing context-aware perception and modeling systems by use of multi-agent systems, cloud computing technologies, and failure checking techniques.	[41–44]
Remote robotic cooperation and streaming workflow optimize computer simulation and modeling of data sharing processes through networked cloud robotics, robot clusters, and heuristic algorithms.	[45–48]
Remotely monitoring pervasively embedded connected sensors, automation systems, and smart objects enhance accuracy and robustness of wireless sensor networks and ambient intelligence technologies.	[49–52]
Interoperable connected devices and cyber–physical systems shape autonomous robot coordination by use of visual sensors in terms of data sharing, storage, and analysis.	[53–56]
Fog, edge, and cloud technologies, big data analysis tools, and sensor devices further IoRT networks and assist in processing, sharing, networking, and storing data.	[57–60]
Decision-making and assessment support of data networks, tools, and modeling determine internal states of real-time data processes across IoRT networks.	[61–64]
IoRT sensor and module networking and operating embedded control systems advance scalable data computation and efficient processes across industrial environments.	[65–68]
IoRT networks seamlessly integrate autonomous smart devices, geospatial simulation and sensor fusion tools, intelligent techniques and machines, and deep and machine learning algorithms that are pivotal in industrial data processing and computation.	[69–72]
Fog and edge computing technologies assist the decentralized architecture of IoRT devices in terms of data scalability and interoperability.	[73–76]
Computing task optimization, data processing and replication mechanisms, and sound IoRT techniques and algorithms configure autonomous decentralized robotic systems and functionalities.	[77–80]
Sustainable production and business development can be attained in cyber–physical systems by use of IoRT devices, deep and machine learning-based decision making, and pervasive computing and cloud technologies, increasing data monitoring accuracy.	[81–84]
Routing efficiency and scalability of mobile robots can be achieved through autonomous robot coordination in dynamic decentralized environments and across wireless wearable sensor networks by integrating blockchain technologies, remote sensing environmental data, and sensor-based deep learning techniques.	[85–88]
IoRT devices accurately process and analyze collected data by deploying image recognition technology, geospatial simulation and sensor fusion tools, and intelligent optimization algorithms.	[89–92]
Robot-based assistance of IoT-enabled edge computing technologies requires blockchain-enabled edge computing systems, heterogeneous computational collective intelligence and processes, and distributed edge devices and algorithms.	[93–96]
IoRT-based machine learning techniques and data processing integrate multi-sensor data fusion and deep reinforcement learning algorithms, in addition to cloud, edge, and fog computing technologies.	[97–100]
IoRT devices and machine intelligence develop on swarm robot and machine learning-based perception algorithms to attain optimal routing path and network performance.	[101–105]

Citation correlations have covered how smart interconnected objects and technologies, IoRT devices and wireless networks, and sensors and actuators are necessitated in performance evaluation and analysis of autonomous robotic and motion capture systems. Product lifecycle data, remote sensor networks, machine vision algorithms, and data visualization and processing capabilities optimize immersive 3D and smart manufacturing technologies.

Data monitoring and predictive control algorithms, cognitive computing systems, digital mapping tools, and sensing data fusion shape automated manufacturing and product development processes. Spatial recognition and immersive virtual technologies, data mining tools, neural network and computer vision algorithms, and advanced automation equipment optimize smart production planning and manufacturing environments.

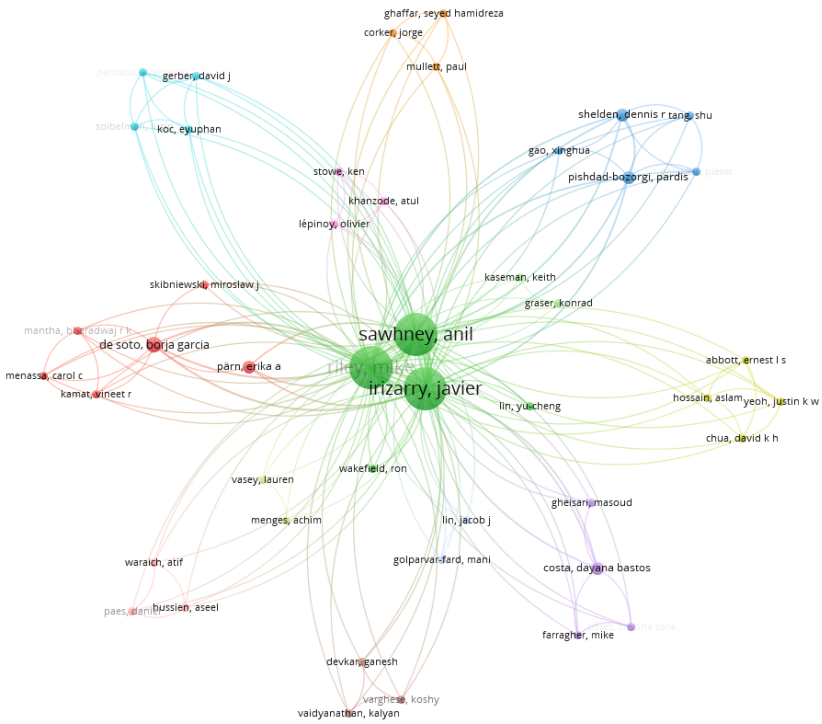

Figure 1. VOSviewer mapping of big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in the Internet of Robotic Things regarding co-authorship.

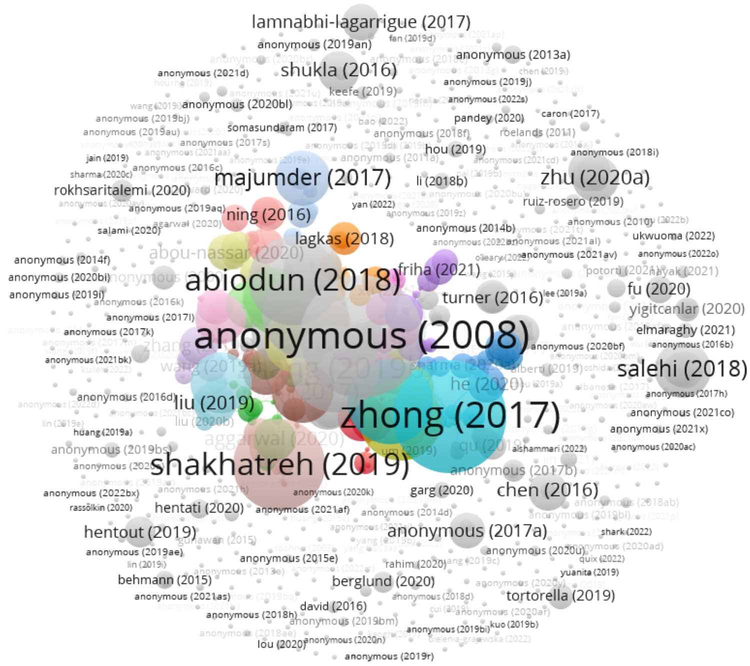

Figure 2. VOSviewer mapping of big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in the Internet of Robotic Things regarding citation.

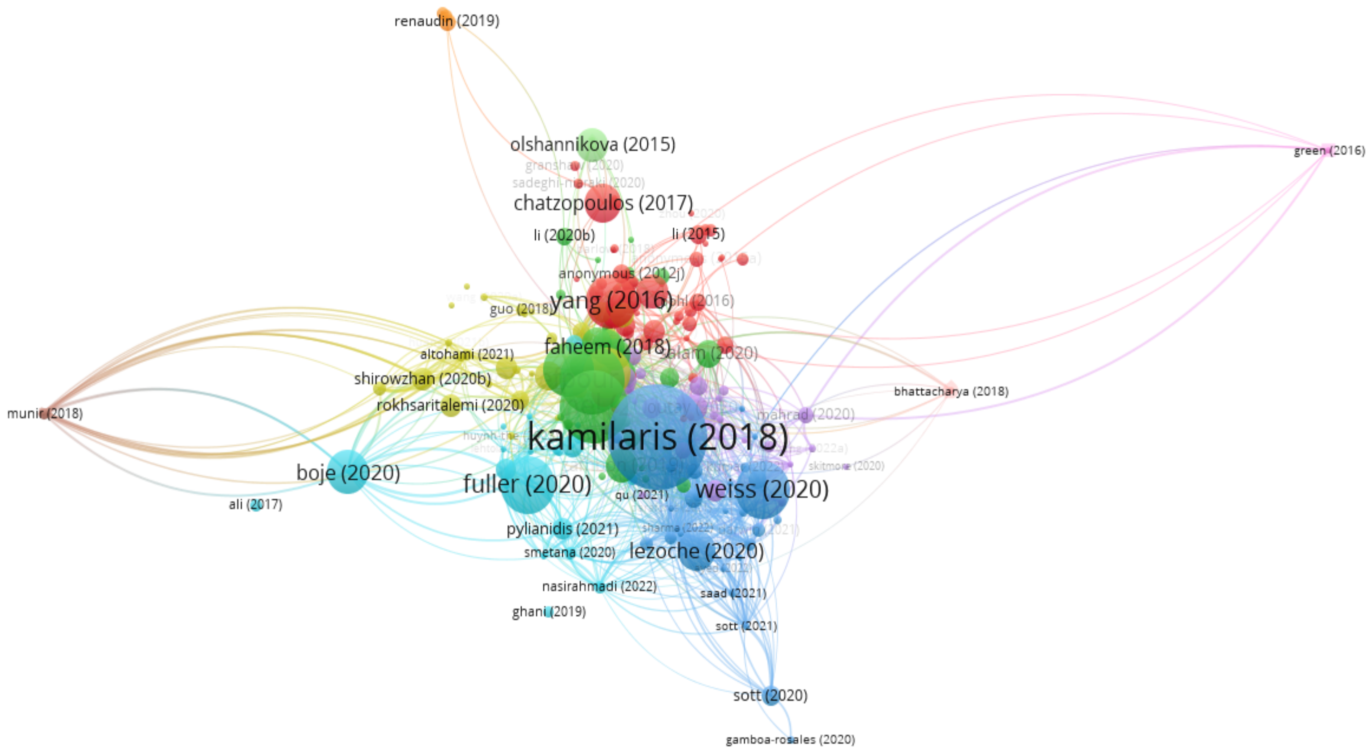

Figure 3. VOSviewer mapping of big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in the Internet of Robotic Things regarding bibliographic coupling.

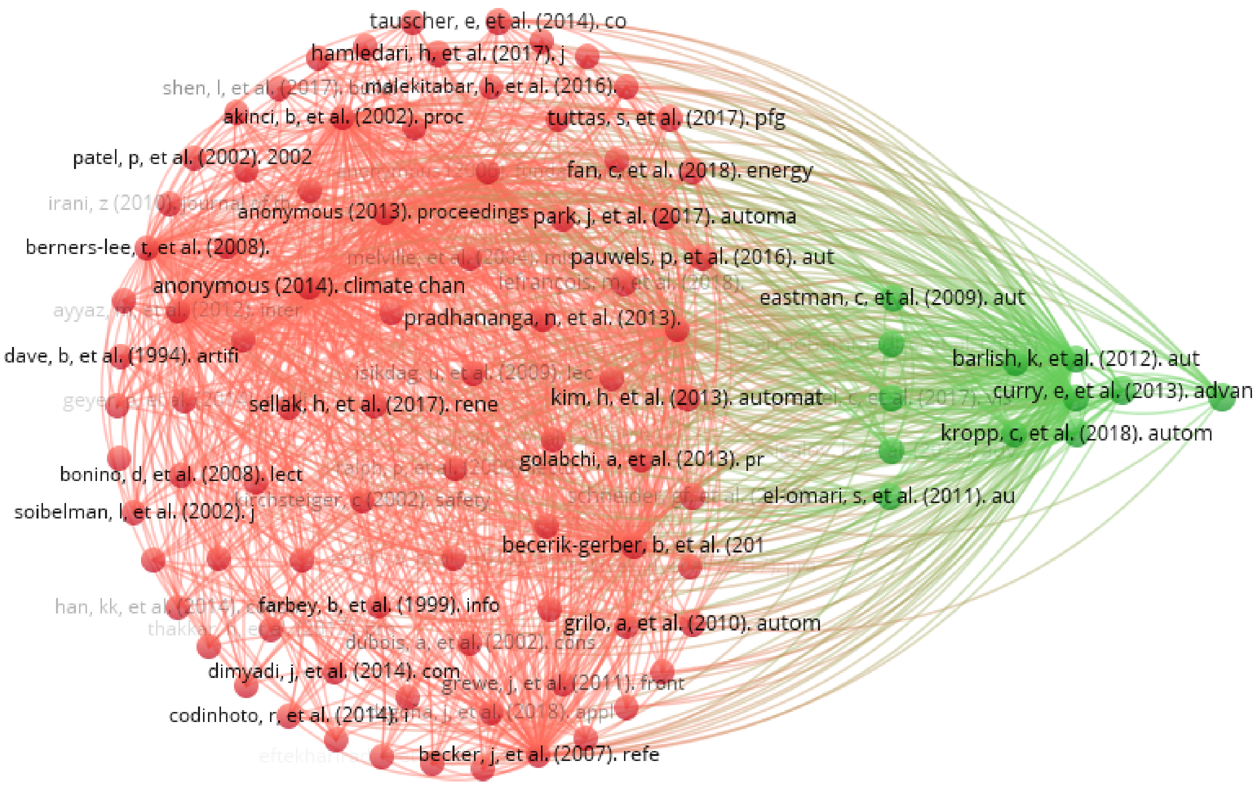

Figure 4. VOSviewer mapping of big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in the Internet of Robotic Things regarding co-citation.

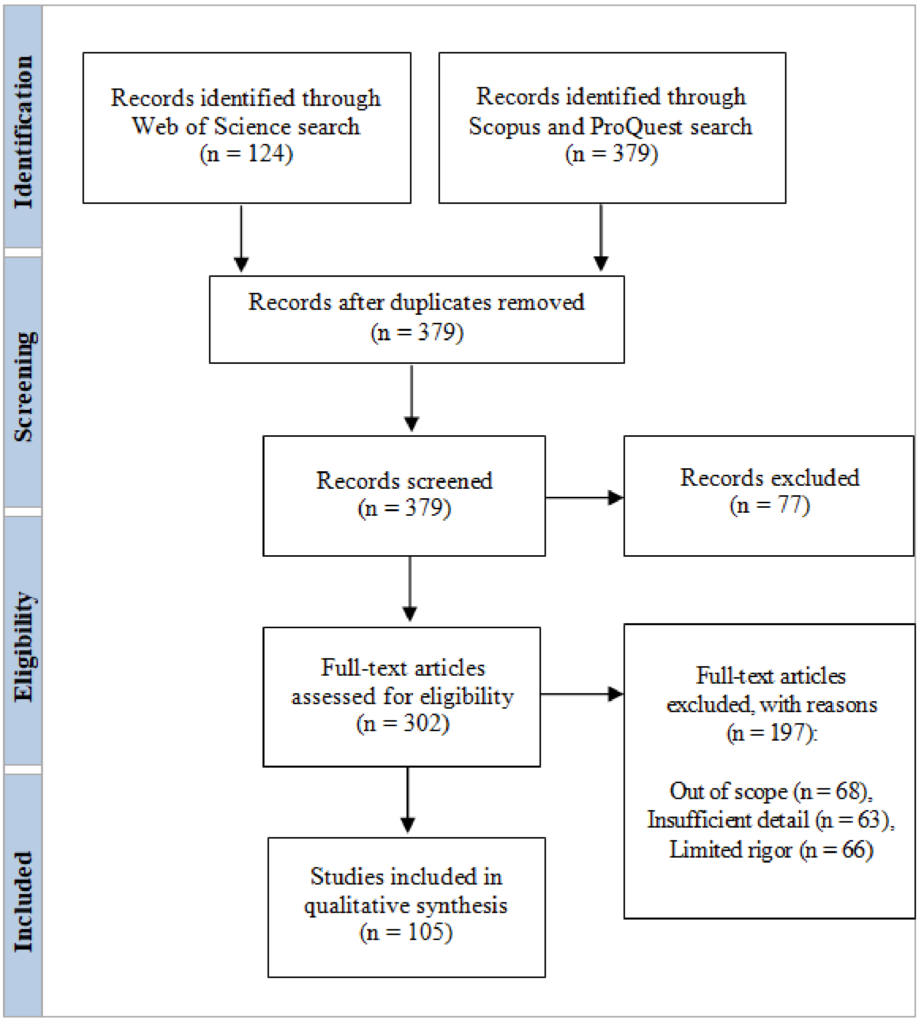

Figure 5. PRISMA flow diagram describing the search results and screening.

3. Big Data Management Algorithms in IoRT

Cloud computing and wireless communication technologies [1–4] integrate industrial machines, smart sensors, heterogeneous sensor devices, big data management algorithms, and autonomous robots. Machine learning technologies develop on sensor data and IoRT devices. Robot navigation and networked robotic algorithms, smart sensors, and machine intelligence typify IoRT. Spatial data analytics, virtual mapping and navigation tools, machine data fusion, and interoperable production systems are pivotal in smart factory environments. Cyber-physical production and virtual manufacturing systems develop on spatial computing algorithms, sensor data fusion, industrial cloud robotics, and geospatial mapping technologies. Automated data transmission, sensor data, industrial manufacturing processes, and machine learning techniques [5–8] configure networked autonomous plants and sensor technologies. Autonomous manufacturing systems integrate spatial computing technology, real-time machine data, intelligent sensor networks, and augmented reality devices. Data mining and acquisition tools, spatial cognition and swarm intelligence algorithms, predictive smart manufacturing, and digital twin simulations optimize intelligent production systems. Real-time monitoring industrial sensing and swarm robotic systems, in addition to cloud computing, imaging, and sensing technologies [9–12] articulate industrial manufacturing processes. Cloud robotics develops on robotic operating systems and devices and on autonomous industrial and remote sensing robots. Unmanned robotic networks and operating systems optimize industrial robot performance and products. Autonomous robotized devices develop on virtual simulation tools, real-time monitoring capabilities, data fusion techniques, and cloud computing algorithms. Automated simulation modeling, digital twin capabilities, remote sensing and edge intelligence technologies, and spatial cognition algorithms shape virtual robotic environments.

IoRT-based big data mining and analysis, cloud computing and big data technologies, and smart devices [13–16] shape contextual awareness in uncontrolled environments. Big data processing systems develop on data mining techniques, IoRT sensors and devices, and deep neural networks. Industrial cloud robotics integrate autonomous production systems, smart manufacturing task management, simulation optimization algorithms, and data visualization tools. Robotized manufacturing systems harness cloud computing technologies, intelligent manufacturing equipment, geospatial mapping and decision support tools, and virtual twinning techniques. Collaborative interoperable networked unmanned systems [17–20] deploy intelligent virtual agents, computation technologies and algorithms, and sensor networks. Cooperative mobile sensing networks require collaborative robots, edge computing technologies, and machine intelligence. Swarm robotic behaviors integrate cognitive robotics, deep and machine learning algorithms, and data communication networks. Real-time data tracking and monitoring, machine vision technology, sensor data processing algorithms, and big geospatial data analytics configure smart product innovation and manufacturing system modeling. Data visualization capabilities and modeling techniques, synthetic data tools, mobility data processing, real-time operational data, and image processing tools articulate autonomous robotic and motion capture systems.

IoRT-based manipulation and 3D object recognition and tracking tasks can be carried out in unstructured environments [21–24] by leveraging robotic systems, cloud computing technologies, big data analytics, and machine and deep learning algorithms in terms of robust perceptual capabilities and reliable visual data. Robotic systems require effective sensor-based perceptual capabilities in terms of 3D object recognition and visual depth data to carry out manipulation tasks coherently across unstructured environments. Robotic operating systems deploy computer vision and simulation modeling algorithms, cognitive data analytics, and spatial data visualization tools. Computer vision techniques, geospatial data mining, simulation-based digital twins, and real-time monitoring technology optimize remote sensing robots. Machine data mining, dynamic mapping processes, cognitive data visualization, predictive modeling techniques, and real-time data processing optimize autonomous manufacturing control. IoT-based robots and robotic systems [25–28] necessitate environmental location and sound recognition tools, context awareness data, and artificial neural networks to assist in decision making processes. Context awareness data, environmental location, and inference mechanisms enhance autonomous robot decision-making processes in dynamic environments through sensor-based motion control. Sensor technologies and actuators integrated in IoT-based robots can articulate multi-robot system collective behavior, coordination, and control. Cloud computing tools and sensing and semantic technologies can assess real-time performance of mobile robot swarms. Real-time monitoring of IoT-enabled robotic swarms is enabled by deep learning techniques, cognitive algorithmic processes and automation technologies, and cloud networked robotics. Cognitive manufacturing systems, plant equipment diagnosis, and factory floor data articulate industrial robotic networks. Smart factory data, automated simulation modeling, real-time predictive analytics, and enterprise resource planning shape virtual manufacturing systems. Tracking mobile IoRT devices [29–32] is instrumental in robotic operating and fog computing network systems. Computer vision-based systems, intelligent sensing devices, industrial product lifecycle management, and digital twin modeling configure networked cloud robotics. Cyber-physical production and robotized manufacturing systems integrate cloud computing technologies, data mining and predictive modeling algorithms, and virtual mapping tools. Multiple robots can interconnect efficiently to complete tasks and have collective operation performance optimized by IoRT and fog computing network systems. Mobile robot devices connected to a fog computing network can transfer several difficult computing operations to the connected fog node and thus having growing processing performance, decreasing computing time intermission and energy use cost, as their communication capabilities are significantly adjustable to carry out complex tasks while organizing and taking measures in unexpected situations. IoRT-based operational technologies [33–36] are pivotal in robot trajectory tracking in dynamic mobile environments and as regards functional interoperability, data integration complexity, and structural connectivity in industrial systems through big data management algorithms. Image recognition technologies, machining process performance, real-time sensor data, and visual recognition tools shape virtual manufacturing systems and autonomous robotized devices. Cloud computing and spatial data analytics, data-driven decision support, machine learning algorithms, and smart process planning assist virtual equipment systems and robotic environments. Trajectory tracking of mobile robots can be optimized through spatial simulation algorithms. Operational and data technologies assist industrial systems in terms of structural connectivity (Table 3).

Table 3. Synopsis of evidence in relation to inspected topics and descriptive results (research findings).

Cloud computing and wireless communication technologies integrate industrial machines, smart sensors, heterogeneous sensor devices, big data management algorithms, and autonomous robots.	[1–4]
Automated data transmission, sensor data, industrial manufacturing processes, and machine learning techniques configure networked autonomous plants and sensor technologies.	[5–8]
Real-time monitoring industrial sensing and swarm robotic systems, in addition to cloud computing, imaging, and sensing technologies articulate industrial manufacturing processes.	[9–12]
IoRT-based big data mining and analysis, cloud computing and big data technologies, and smart devices shape contextual awareness in uncontrolled environments.	[13–16]
Collaborative interoperable networked unmanned systems deploy intelligent virtual agents, computation technologies and algorithms, and sensor networks.	[17–20]
IoRT-based manipulation and 3D object recognition and tracking tasks can be carried out in unstructured environments by leveraging robotic systems, cloud computing technologies, big data analytics, and machine and deep learning algorithms in terms of robust perceptual capabilities and reliable visual data.	[21–24]
IoT-based robots and robotic systems necessitate environmental location and sound recognition tools, context awareness data, and artificial neural networks to assist in decision making processes.	[25–28]
Tracking mobile IoRT devices is instrumental in robotic operating and fog computing network systems.	[29–32]
IoRT-based operational technologies are pivotal in robot trajectory tracking in dynamic mobile environments and as regards functional interoperability, data integration complexity, and structural connectivity in industrial systems through big data management algorithms.	[33–36]

4. Deep Learning-Based Object Detection Technologies in IoRT

Spatial clustering of sensing capabilities, deep learning-based object detection technologies, noise algorithms, and networked scheduling mechanisms and communication objects [37–40] enable robot control and decentralized tracking systems. Virtual data modeling, computer vision and process planning algorithms, and intelligent remote operations further autonomous robotized devices. Predictive modeling and computational prediction tools, sensor data fusion, and digital twin-based monitoring optimize virtual robotic environments. Network scheduling mechanisms assist robotic systems in performing tasks by transferring communication data. Actuation and control methods assist IoRT physical and virtual devices across monitoring and managing context-aware perception and modeling systems [41–44] by use of multi-agent systems, cloud computing technologies, and failure checking techniques. Robot learning and cloud computing algorithms, cyber-physical cognitive systems, real-time data simulation, and virtual twin modeling configure smart manufacturing plants. Smart production management, remote sensing and immersive visualization systems, virtual simulation algorithms, and data-driven planning technologies articulate autonomous manufacturing processes. Product development processes and intelligent manufacturing equipment require remote sensing and cognitive computing systems, virtual data modeling, synthetic data tools, and smart connected devices. IoRT integrates cloud tools, algorithmic machines, and multi-agent agents.

Remote robotic cooperation and streaming workflow optimize computer simulation and modeling of data sharing processes [45–48] through networked cloud robotics, robot clusters, and heuristic algorithms. Predictive maintenance tools, simulation modeling processes, smart production systems, and automated assembly machines are pivotal in industrial cloud robotics. Virtual machine and computational object instantiation tools, digital twin technology, and real-time operational data assist robotized manufacturing systems. Computation offloading necessitates networked cloud robotics, task semantics, big data clusters, and heuristic algorithms for energy efficiency, decreased execution times, and low operating costs, leading to relevant performance gains. Remotely monitoring pervasively embedded connected sensors, automation systems, and smart objects [49–52] enhance accuracy and robustness of wireless sensor networks and ambient intelligence technologies. Mobile connected IoRT devices, cloud and pattern recognition technologies, networked robotics, and automated machines configure autonomous manufacturing units in dynamic simulation environments in terms of robotic behavior control, sensor and actuator interconnections, and real-time data processing and analysis. Deep reinforcement learning algorithms and visual navigation tools assist autonomous robotic systems in real-time intelligent sensor data sharing. Object recognition algorithms in wireless sensor networks require accuracy and robustness of ambient intelligence technologies in terms of computation time and localization techniques by use of virtual simulation modeling tools. Reinforcement learning algorithms and IoRT can improve behavior control and real-time remote monitoring of autonomous robotic systems in smart environments by use of big data technologies, computer vision tools, and connected sensors. Environment mapping algorithms and spatial simulation tools can manage deep learning-based robotic behavior control in uncertain environments through visual perception and navigation technologies, handling real-world task complexities.

Interoperable connected devices and cyber–physical systems shape autonomous robot coordination [53–56] by use of visual sensors in terms of data sharing, storage, and analysis. Virtual simulation modeling, data mining and reinforcement learning algorithms, product lifecycle monitoring, and smart process planning configure robotic operating systems. Process mining techniques, predictive simulation tools, computer vision algorithms, and digital twin technologies further remote sensing robots. Internet-connected devices and environment mapping algorithms can monitor autonomous robotic systems and processes through networked robot-based data fusion and visual data sensing and processing for improved performance of mobile operation guidance and control. Cyber–physical systems can enhance the interoperability of coordinated devices and of autonomous robots. Robot sensing systems integrate semantic technology for device coordination. Fog, edge, and cloud technologies, big data analysis tools, and sensor devices [57–60] further IoRT networks and assist in processing, sharing, networking, and storing data. As regards business process interconnection, IoRT require real-time accurate data analysis and deep learning-based object detection technologies while taking into account the computational complexity of sensing data. Intelligent manufacturing environments and cyber-physical production systems develop on decision-making process automation, digital twin and cloud computing technologies, and smart infrastructure sensors. Remote sensing and computing technologies can determine swarm robotic behaviors through spatial data collection and handling across interconnected networks of smart sensors for IoT-based business process efficiency. The computational complexity of edge and cloud intelligence, real-time sensing data analysis, decentralized architecture of smart interconnected devices, and scalable analytic tools typify blockchain-based Industrial IoT networks.

Decision-making and assessment support of data networks, tools, and modeling [61–64] determine internal states of real-time data processes across IoRT networks. Performance evaluation of perception inference assessment tools in autonomous robotic and motion capture systems requires data-driven techniques, environmental parameters, decision tree algorithms, and simulation data mining. Modeling and simulation tools, real-time data collection, deep learning-based object detection technologies, and sensor measurement shape autonomous robotic and motion capture systems. Virtual simulation modeling and motion capture tools require real-time data collection through artificial intelligence planning software for robotic autonomous systems. IoRT sensor and module networking and operating embedded control systems [65–68] advance scalable data computation and efficient processes across industrial environments. Digital twin-based product development, virtual data analytics, machining process monitoring, and performance prediction tools articulate industrial robotic networks. Cognitive data visualization, condition monitoring data, virtual modeling technology, and assembly process planning optimize networked cloud robotics. Real-time massive data computation develops on IoT-based measurement unit devices and flexibility and scalability of robotic autonomous systems in industrial environments. (Table 4).

Table 4. Synopsis of evidence in relation to inspected topics and descriptive results (research findings).

Spatial clustering of sensing capabilities, deep learning-based object detection technologies, noise algorithms, and networked scheduling mechanisms and communication objects enable robot control and decentralized tracking systems.	[37–40]
Actuation and control methods assist IoRT physical and virtual devices across monitoring and managing context-aware perception and modeling systems by use of multi-agent systems, cloud computing technologies, and failure checking techniques.	[41–44]
Remote robotic cooperation and streaming workflow optimize computer simulation and modeling of data sharing processes through networked cloud robotics, robot clusters, and heuristic algorithms.	[45–48]
Remotely monitoring pervasively embedded connected sensors, automation systems, and smart objects enhance accuracy and robustness of wireless sensor networks and ambient intelligence technologies.	[49–52]
Interoperable connected devices and cyber–physical systems shape autonomous robot coordination by use of visual sensors in terms of data sharing, storage, and analysis.	[53–56]
Fog, edge, and cloud technologies, big data analysis tools, and sensor devices further IoRT networks and assist in processing, sharing, networking, and storing data.	[57–60]
Decision-making and assessment support of data networks, tools, and modeling determine internal states of real-time data processes across IoRT networks.	[61–64]
IoRT sensor and module networking and operating embedded control systems advance scalable data computation and efficient processes across industrial environments.	[65–68]

5. Geospatial Simulation and Sensor Fusion Tools in the IoRT

IoRT networks seamlessly integrate autonomous smart devices, geospatial simulation and sensor fusion tools, intelligent techniques and machines, and deep and machine learning algorithms [69–72] that are pivotal in industrial data processing and computation. Smart interconnected objects and technologies, IoRT devices and wireless networks, and sensors and actuators are necessitated in performance evaluation and analysis of autonomous robotic and motion capture systems. Data visualization and virtual simulation tools, remote sensing technologies, and smart product development are pivotal in manufacturing process performance and execution systems. Product lifecycle data, virtual simulation tools, intelligent sensing devices, and augmented reality capabilities articulate process manufacturing and cognitive computing systems. Seamless integration of smart devices in IoT-based embedded systems necessitates object recognition algorithms, multi-sensor fusion technology, and geospatial data mining tools across intelligent industrial infrastructure. Industry 4.0 wireless networks and robotic autonomous systems develop on IoT-based interconnected smart devices and deep and machine learning algorithms. Fog and edge computing technologies assist the decentralized architecture of IoRT devices [73–76] in terms of data scalability and interoperability. Autonomous robotized devices require immersive visualization systems, real-time operational data, cognitive automation and extended reality technologies, and virtual simulation modeling. Data visualization tools, sensing and computing technologies, predictive maintenance tools, and virtual reality mapping configure virtual robotic environments. Virtual process simulation, edge computing algorithms, interoperable automation systems, and production process modeling articulate remote sensing robots. Predictive simulation and virtual reality modeling tools, remote sensing data, image processing techniques, and fault diagnosis systems shape networked cloud robotics.

Computing task optimization, data processing and replication mechanisms, and sound IoRT techniques and algorithms [77–80] configure autonomous decentralized robotic systems and functionalities. Blockchain-based robotic and cloud computing technologies optimize data analysis tools in terms of efficiency and accuracy, visual navigation efficiency, situation awareness and control systems, and task allocations across decentralized multi-agent robotic systems. Data accuracy, reliability, and accessibility are instrumental in complex task achievement by swarm robotics systems in unstructured dynamic environments. IoRT data management requires smart autonomous robot systems and networks in complex task distributions. Ground mobile robots integrate distributed situation awareness and control systems in making rapid decisions and performing complex tasks in dynamic unstructured environments by use of mapping and navigation tools in terms of virtual simulation modeling and geospatial data mining. Multi-agent decentralized autonomous robotic systems developed on blockchain and cloud computing technologies require dynamic analysis tools as regards task allocations. Sustainable production and business development can be attained in cyber–physical systems by use of IoRT devices, deep and machine learning-based decision making, and pervasive computing and cloud technologies [81–84], increasing data monitoring accuracy. Autonomous robotic and motion capture systems integrate computer vision algorithms, context-aware event processing, and data mining techniques. Autonomous monitoring of data governance, collection, and analysis across IoRT networks is pivotal in network connectivity, geospatial simulation and sensor fusion tools, remote business process management, and cloud and edge computing systems. Product lifecycle data, remote sensor networks, machine vision algorithms, and data visualization and processing capabilities optimize immersive 3D and smart manufacturing technologies. Data monitoring and predictive control algorithms, cognitive computing systems, digital mapping tools, and sensing data fusion shape automated manufacturing and product development processes. Industrial IoT-based business process management of complex unstructured events integrates object localization algorithms, geospatial mapping tools, and multi-sensor fusion technology.

Routing efficiency and scalability of mobile robots can be achieved through autonomous robot coordination in dynamic decentralized environments and across wireless wearable sensor networks [85–88] by integrating blockchain technologies, remote sensing environmental data, and sensor-based deep learning techniques. Industrial cloud robotics develops on preventive maintenance scheduling, product condition monitoring, data-driven planning technologies, and augmented reality algorithms. Product simulation models, data mining and spatio-temporal fusion algorithms, remote sensing technologies, and decision support tools optimize robotized manufacturing systems. IoRT devices accurately process and analyze collected data [89–92] by deploying image recognition technology, geospatial simulation and sensor fusion tools, and intelligent optimization algorithms. By collecting and processing heterogeneous networked industrial data, IoRT devices and cyber–physical systems assist in knowledge representation and transfer and in collaborative optimization of production performance throughout pervasive computing environments. Machine learning techniques, real-time data monitoring, interconnected sensor networks, and blockchain technologies configure smart process manufacturing and automation systems. Edge computing and digital manufacturing technologies integrate product lifecycle management, real-time process monitoring, interactive data visualization, and virtual simulation modeling.

Robot-based assistance of IoT-enabled edge computing technologies [93–96] requires blockchain-enabled edge computing systems, heterogeneous computational collective intelligence and processes, and distributed edge devices and algorithms. Networked sensor-based robotic devices and fog computing systems develop on swarm intelligence algorithms that assist in data acquisition and sharing. Virtual simulation tools, spatial computing technologies, digital twin modeling, and remote sensing data are pivotal in robotic operating systems. Industrial robotic networks integrate virtual machining systems, spatial data visualization tools, data-driven planning technologies, and process mining tools. Edge computing technologies and networking capabilities enable self-organization of computational collective intelligence as regards robotic behavior and multi-agent systems through simulation operations in realistic settings. IoRT integrates fog computing networks for real-time data gathering and sharing. IoRT-enabled edge computing technologies harness swarm intelligence algorithms in intelligent decision-making processes. Data acquisition through collaborative tasks optimize robot network clusters and wireless sensor networks. IoRT-based machine learning techniques and data processing [97–100] integrate multi-sensor data fusion and deep reinforcement learning algorithms, in addition to cloud, edge, and fog computing technologies. Autonomous robotic and motion capture systems develop on machine and deep learning algorithms and geospatial simulation and sensor fusion tools as regards big data heterogeneity and complexity. Visual surveillance and data mining tools, virtual modeling technology, production process optimization, and digital twin modeling further smart manufacturing systems. Data mining techniques and processing capabilities, industrial process monitoring, smart spatial planning, and real-time sensor data typify virtual manufacturing systems. Machine learning techniques further IoT data processing and smart device interconnection. Robot visual control systems enhance learning efficiency and decision processes throughout heterogeneous time-varying motion phases. IoRT devices and machine intelligence develop on swarm robot and machine learning-based perception algorithms [101–105] to attain optimal routing path and network performance. Autonomous robotic and motion capture systems harness task scheduling and cloud computing algorithms across wireless sensor networks. Sensor control and visual perception algorithms further industrial data sharing, storage, mining, and analysis. Machine and reinforcement learning algorithms and distributed wireless sensor networks articulate autonomous routing decisions and enhance big data scalability. Spatial recognition and immersive virtual technologies, data mining tools, neural network and computer vision algorithms, and advanced automation equipment optimize smart production planning and manufacturing environments. IoRT requires coherent data transmission, mining, and analysis across task scheduling and operation mechanisms. IoRT integrates wireless sensor networks and machine learning algorithms to complete tasks and connectivity maintenance for data gathering and collaborative movements. (Table 5).

Table 5. Synopsis of evidence in relation to inspected topics and descriptive results (research findings).

IoRT networks seamlessly integrate autonomous smart devices, geospatial simulation and sensor fusion tools, intelligent techniques and machines, and deep and machine learning algorithms that are pivotal in industrial data processing and computation.	[69–72]
Fog and edge computing technologies assist the decentralized architecture of IoRT devices in terms of data scalability and interoperability.	[73–76]
Computing task optimization, data processing and replication mechanisms, and sound IoRT techniques and algorithms configure autonomous decentralized robotic systems and functionalities.	[77–80]
Sustainable production and business development can be attained in cyber–physical systems by use of IoRT devices, deep and machine learning-based decision making, and pervasive computing and cloud technologies, increasing data monitoring accuracy.	[81–84]
Routing efficiency and scalability of mobile robots can be achieved through autonomous robot coordination in dynamic decentralized environments and across wireless wearable sensor networks by integrating blockchain technologies, remote sensing environmental data, and sensor-based deep learning techniques.	[85–88]
IoRT devices accurately process and analyze collected data by deploying image recognition technology, geospatial simulation and sensor fusion tools, and intelligent optimization algorithms.	[89–92]
Robot-based assistance of IoT-enabled edge computing technologies requires blockchain-enabled edge computing systems, heterogeneous computational collective intelligence and processes, and distributed edge devices and algorithms.	[93–96]
IoRT-based machine learning techniques and data processing integrate multi-sensor data fusion and deep reinforcement learning algorithms, in addition to cloud, edge, and fog computing technologies.	[97–100]
IoRT devices and machine intelligence develop on swarm robot and machine learning-based perception algorithms to attain optimal routing path and network performance.	[101–105]

6. Deployment of CityGML in IoRT

CityGML was adjusted to the purposes of our systematic review in relation to IoRT in terms of landscape planning, modelled data objects, and 3D geospatial data configured through sensors and simulations (Figure 6). Artificial intelligence-based decision-making algorithms, biometric sensor and immersive 3D technologies, and event modeling and forecasting tools articulate big-data-driven cognitive manufacturing. Decision intelligence and modeling tools, visual imagery technologies, and spatial computing algorithms assist interconnected virtual services in cyber-physical management systems [106–108]. Predictive modeling tools and visual perception algorithms enable ambient sound recognition software across IoT sensing networks. Spatial cognition algorithms, deep learning-based ambient sound processing, and behavioral predictive analytics configure IoRT-based geospatial simulation systems [109–112]. Sensing and computing technologies, cognitive artificial intelligence algorithms, and visual imagery tools further immersive digital simulations. Ambient sound recognition and processing tools, visual perception algorithms, and remote sensing technologies articulate predictive geospatial modeling. Remote big data management tools, deep learning-based sensing technologies, and environment mapping algorithms shape visual and spatial analytics in IoRT. Virtual simulation algorithms, visual perception technologies, and geospatial mapping tools optimize behavioral analytics in immersive work environments [113–116]. Spatial analytics harnesses virtual navigation tools and cognitive artificial intelligence and object tracking algorithms. Object recognition algorithms, machine perception technologies, and data visualization tools enable simulation modeling processes. Spatial cognition and visual perception algorithms and deep neural network and remote sensing technologies are pivotal in IoRT-based geospatial simulation systems. Geospatial mapping technologies, decision and control algorithms, and deep learning artificial intelligence tools assist digital twin modeling in IoRT. Immersive, virtual, and cognitive technologies develop on movement and behavior tracking tools and image processing computational algorithms [117–120]. Virtual navigation tools, multisensor fusion technologies, and deep learning computer vision and image processing computational algorithms are pivotal in immersive shared spaces. Object perception and motion planning algorithms and spatial data acquisition and ambient scene detection tools further spatial computing and immersive technologies in the virtual economy. Motion control and context awareness algorithms and virtual navigation and data mining tools shape immersive technologies in geospatial simulation systems. IoRT integrates visual cognitive algorithms, dynamic routing technologies, and simulation modeling tools in the virtual economy [121–124]. Behavioral predictive analytics deploys simulation modeling tools, machine and deep learning algorithms, and spatial computing and immersive technologies. Acoustic environment recognition algorithms and visual imagery and remote sensing tools optimize spatial computing and immersive technologies. Perception and cognition algorithms, vision sensing and image recognition technologies, and spatial awareness tools develop on virtual modeling processes. Movement and behavior tracking tools, computer and machine vision algorithms, and deep learning-based image classification systems are instrumental in haptic and biometric sensor technologies [125–128].

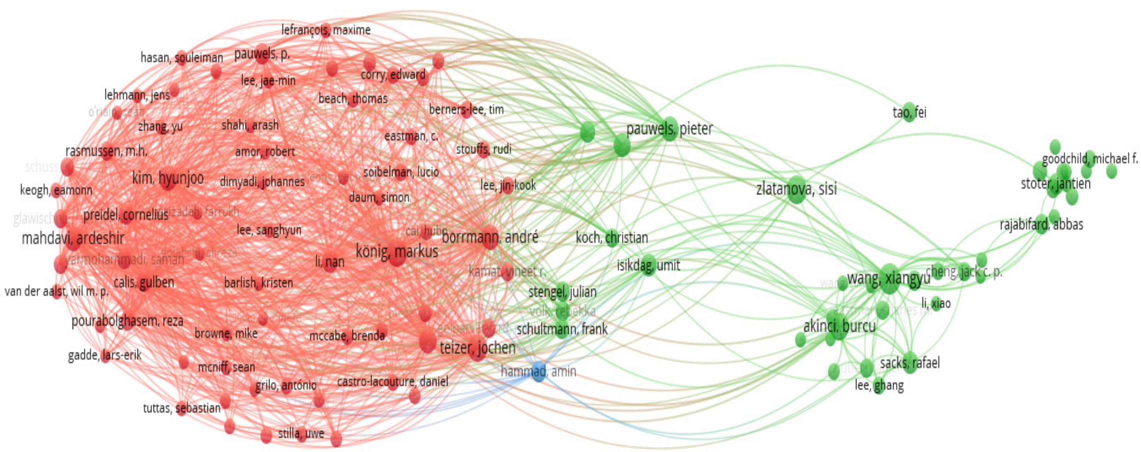

Figure 6. VOSviewer mapping of CityGML deployment in the Internet of Robotic Things regarding co-citation.

7. Discussion

Autonomous monitoring of data governance, collection, and analysis across IoRT networks [1–4] is pivotal in network connectivity [5–8], geospatial simulation and sensor fusion tools [9–12], remote business process management [13–16], and cloud and edge computing systems. Modeling and simulation tools [17–20], real-time data collection, deep learning-based object detection technologies, and sensor measurement [21–24] shape autonomous robotic and motion capture systems. Machine learning techniques, real-time data monitoring, interconnected sensor networks [25–28], and blockchain technologies configure smart process manufacturing and automation systems. Virtual process simulation, edge computing algorithms, interoperable automation systems [29–32], and production process modeling [33–36] articulate remote sensing robots. Predictive maintenance tools, simulation modeling processes, smart production systems [37–40], and automated assembly machines [41–44] are pivotal in industrial cloud robotics. Data visualization capabilities and modeling techniques [45–48], synthetic data tools, mobility data processing, real-time operational data [49–52], and image processing tools articulate autonomous robotic and motion capture systems. Data visualization tools, sensing and computing technologies [53–56], predictive maintenance tools, and virtual reality mapping configure virtual robotic environments. Visual surveillance and data mining tools [57–60], virtual modeling technology, production process optimization [61–64], and digital twin modeling further smart manufacturing systems. Cognitive data visualization, condition monitoring data [65–68], virtual modeling technology, and assembly process planning [69–72] optimize networked cloud robotics. Cooperative mobile sensing networks [73–76] require collaborative robots, edge computing technologies, and machine intelligence. Digital twin-based product development, virtual data analytics, machining process monitoring [77–80], and performance prediction tools articulate industrial robotic networks. Intelligent manufacturing environments and cyber-physical production systems [81–84] develop on decision-making process automation [85–88], digital twin and cloud computing technologies, and smart infrastructure sensors. Machine and reinforcement learning algorithms and distributed wireless sensor networks [89–92] articulate autonomous routing decisions and enhance big data scalability. Swarm robotic behaviors integrate cognitive robotics, deep and machine learning algorithms, and data communication networks. Industrial robotic networks integrate virtual machining systems, spatial data visualization tools, data-driven planning technologies [93–96], and process mining tools. Smart production management, remote sensing and immersive visualization systems, virtual simulation algorithms, and data-driven planning technologies [97–100] articulate autonomous manufacturing processes. Cyber-physical production and robotized manufacturing systems [101–105] integrate cloud computing technologies, data mining and predictive modeling algorithms [106–108], and virtual mapping tools.

Artificial intelligence techniques for robot communication can enhance the interactive performance of the multi-robot team in terms of real-world applications, complex operations, cognitive decision-making algorithms, and coordinated action, carrying out their tasks efficiently. A massive volume of real-time data can be perpetually shared between robotic technologies and the monitoring hub or cloud services by leveraging open wireless communications and operating systems through swarm coordination and optimized functional and operational capabilities. Context-aware IoRT systems develop on sensor data semantic and action modeling tools and on perception and actuation devices. Real-time monitoring of IoT-enabled robotic swarms is enabled by deep learning techniques, cognitive algorithmic processes and automation technologies, and cloud networked robotics. Computation offloading necessitates networked cloud robotics, task semantics, big data clusters, and heuristic algorithms for energy efficiency, decreased execution times, and low operating costs, leading to relevant performance gains. Remote sensing and computing technologies can determine swarm robotic behaviors through spatial data collection and handling across interconnected networks of smart sensors for IoT-based business process efficiency. Ground mobile robots integrate distributed situation awareness and control systems in making rapid decisions and performing complex tasks in dynamic unstructured environments by use of mapping and navigation tools in terms of virtual simulation modeling and geospatial data mining. Data acquisition through collaborative tasks optimize robot network clusters and wireless sensor networks.

Robot control and operation through artificial intelligence and IoT configure systems having increased potential to complete elaborate tasks autonomously and collaboratively. IoT robotic platforms integrate dynamic mechanical configurations and digital encoding. IoT and robotic systems can be optimized with knowledge-based tools and smart connected devices, by integrating semantic layers and context awareness. Multiple robots can interconnect efficiently to complete tasks and have collective operation performance optimized by IoRT and fog computing network systems. Object recognition algorithms in wireless sensor networks require accuracy and robustness of ambient intelligence technologies in terms of computation time and localization techniques by use of virtual simulation modeling tools. Computational complexity of edge and cloud intelligence, real-time sensing data analysis, decentralized architecture of smart interconnected devices, and scalable analytic tools typify blockchain-based Industrial IoT networks. Multi-agent decentralized autonomous robotic systems developed on blockchain and cloud computing technologies require dynamic analysis tools as regards task allocations. Machine learning techniques further IoT data processing and smart device interconnection.

IoT assists robot networking and data transfer, optimizing automated and autonomous communication capabilities throughout inherent asynchronous performance of complex multi-device systems by use of streamlined prediction techniques. Collaborative unmanned systems typify efficient robot cooperation with smart interconnected devices. Robotic systems require effective sensor-based perceptual capabilities in terms of 3D object recognition and visual depth data to carry out manipulation tasks coherently across unstructured environments. Mobile robot devices connected to a fog computing network can transfer several difficult computing operations to the connected fog node and thus have growing processing performance, decreasing computing time intermission and energy use cost, as their communication capabilities are significantly adjustable to carry out complex tasks while organizing and taking measures in unexpected situations. Reinforcement learning algorithms and IoRT can improve behavior control and real-time remote monitoring of autonomous robotic systems in smart environments by use of big data technologies, computer vision tools, and connected sensors. Virtual simulation modeling and motion capture tools require real-time data collection through artificial intelligence planning software for robotic autonomous systems. Industrial IoT-based business process management of complex unstructured events integrates object localization algorithms, geospatial mapping tools, and multi-sensor fusion technology. Robot visual control systems enhance learning efficiency and decision processes throughout heterogeneous time-varying motion phases.

IoRT empowers smart interconnected devices in supervising the surrounding operations, making swift decisions, and taking expedient actions, while interactively dealing with unplanned events. IoRT develops on cloud computing technologies, machine and deep learning algorithms, and big data analytics. Context awareness data, environmental location, and inference mechanisms enhance autonomous robot decision-making processes in dynamic environments through sensor-based motion control. Trajectory tracking of mobile robots can be optimized through spatial simulation algorithms. Operational and data technologies assist industrial systems in terms of structural connectivity. Environment mapping algorithms and spatial simulation tools can manage deep learning-based robotic behavior control in uncertain environments through visual perception and navigation technologies, handling real-world task complexities. Real-time massive data computation develops on IoT-based measurement unit devices and flexibility and scalability of robotic autonomous systems in industrial environments. Edge computing technologies and networking capabilities enable self-organization of computational collective intelligence as regards robotic behavior and multi-agent systems through simulation operations in realistic settings. IoRT requires coherent data transmission, mining, and analysis across task scheduling and operation mechanisms.

Individual robots typically make decisions according to the specific observations and insufficient intelligence capability, resulting in tremendous decision-making intermission and imprecise feedback to dynamic environments. Cooperative unmanned and decentralized tracking systems require mobile clustering algorithms to optimize sensing capabilities. Sensor technologies and actuators integrated in IoT-based robots can articulate multi-robot system collective behavior, coordination and control. Network scheduling mechanisms assist robotic systems in performing tasks by transferring communication data. Internet-connected devices and environment mapping algorithms can monitor autonomous robotic systems and processes through networked robot-based data fusion and visual data sensing and processing for improved performance of mobile operation guidance and control. Seamless integration of smart devices in IoT-based embedded systems necessitates object recognition algorithms, multi-sensor fusion technology, and geospatial data mining tools across intelligent industrial infrastructure. IoRT integrates fog computing networks for real-time data gathering and sharing. IoRT integrates wireless sensor networks and machine learning algorithms to complete tasks and connectivity maintenance for data gathering and collaborative movements.

Federated machine learning can thoroughly harness the computation performance of distributed robots to attain shared intelligence, improving the capability of carrying out elaborate and demanding interactive tasks. Smart objects can handle contextual data in relation to infrastructure and users through sensors and actuators to infer the environment within semantic IoRT systems and to seamlessly make autonomous decisions. Cloud computing tools and sensing and semantic technologies can assess real-time performance of mobile robot swarms. IoRT integrates cloud tools, algorithmic machines, and multi-agent agents. Cyber–physical systems can enhance the interoperability of coordinated devices and of autonomous robots. Industry 4.0 wireless networks and robotic autonomous systems develop on IoT-based interconnected smart devices and deep and machine learning algorithms. IoRT-enabled edge computing technologies harness swarm intelligence algorithms in intelligent decision-making processes.

8. Conclusions

Significant research has analyzed how IoRT data management requires smart autonomous robot systems and networks in complex task distributions. Autonomous robotic and motion capture systems develop on machine and deep learning algorithms and geospatial simulation and sensor fusion tools as regards big data heterogeneity and complexity. This systematic literature review inspects outstanding published peer-reviewed sources as regards big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in IoRT. We show how robotic operating systems deploy computer vision and simulation modeling algorithms, cognitive data analytics, and spatial data visualization tools. Predictive simulation and virtual reality modeling tools, remote sensing data, image processing techniques, and fault diagnosis systems shape networked cloud robotics. Industrial cloud robotics develops on preventive maintenance scheduling, product condition monitoring, data-driven planning technologies, and augmented reality algorithms. We clarify that autonomous robotic and motion capture systems harness task scheduling and cloud computing algorithms across wireless sensor networks. Data visualization and virtual simulation tools, remote sensing technologies, and smart product development are pivotal in manufacturing process performance and execution systems. Product development processes and intelligent manufacturing equipment require remote sensing and cognitive computing systems, virtual data modeling, synthetic data tools, and smart connected devices. The findings gathered from the above analyses indicate that robotized manufacturing systems harness cloud computing technologies, intelligent manufacturing equipment, geospatial mapping and decision support tools, and virtual twinning techniques. Data accuracy, reliability, and accessibility are instrumental in complex task achievement by swarm robotics systems in unstructured dynamic environments. Robot learning and cloud computing algorithms, cyber-physical cognitive systems, real-time data simulation, and virtual twin modeling configure smart manufacturing plants.

9. Specific Contributions to the Literature

This systematic review addresses a hot emerging topic (that is, big data management algorithms, deep learning-based object detection technologies, and geospatial simulation and sensor fusion tools in the IoRT) that has not been covered up to the present time in the literature as regards how blockchain-based robotic and cloud computing technologies optimize data analysis tools in terms of efficiency and accuracy, visual navigation efficiency, situation awareness and control systems, and task allocations across decentralized multi-agent robotic systems. Computer vision-based systems, intelligent sensing devices, industrial product lifecycle management, and digital twin modeling configure networked cloud robotics. Edge computing and digital manufacturing technologies integrate product lifecycle management, real-time process monitoring, interactive data visualization, and virtual simulation modeling. No previous research has analyzed how cloud robotics develops on robotic operating systems and devices and on autonomous industrial and remote sensing robots. Autonomous robotic and motion capture systems integrate computer vision algorithms, context-aware event processing, and data mining techniques. Sensor control and visual perception algorithms further industrial data sharing, storage, mining, and analysis. As regards business process interconnection, IoRT require real-time accurate data analysis and deep learning-based object detection technologies while taking into account computational complexity of sensing data.

10. Limitations and Further Directions of Research

As limitations, by analyzing only original research and review articles published in scholarly outlets indexed in ProQuest, Scopus, and the Web of Science between 2017 and 2022, outstanding sources on IoRT sensor and module networking and operating embedded control systems may have been omitted. Subsequent interest should be directed towards how virtual simulation modeling, data mining and reinforcement learning algorithms, product lifecycle monitoring, and smart process planning configure robotic operating systems. The scope of our systematic review does not move forward IoRT-based big data mining and analysis, cloud computing and big data technologies, and smart devices. Practical consequences would be how virtual simulation tools, spatial computing technologies, digital twin modeling, and remote sensing data are pivotal in robotic operating systems. Thus, cognitive manufacturing systems, plant equipment diagnosis, and factory floor data articulate industrial robotic networks. Academic implications of this systematic review chiefly integrate the need of continuing research on mobile connected IoRT devices, cloud and pattern recognition technologies, networked robotics, and automated machines. Future research should investigate computing task optimization, data processing and replication mechanisms, and sound IoRT techniques and algorithms. Subsequent analyses should develop on how deep reinforcement learning algorithms and visual navigation tools assist autonomous robotic systems in real-time intelligent sensor data sharing. Automated simulation modeling, digital twin capabilities, remote sensing and edge intelligence technologies, and spatial cognition algorithms shape virtual robotic environments. Attention should be directed to how autonomous robotized devices require immersive visualization systems, real-time operational data, cognitive automation and extended reality technologies, and virtual simulation modeling.

11. Practical Implications

By collecting and processing heterogeneous networked industrial data, IoRT devices and cyber–physical systems assist in knowledge representation and transfer and in collaborative optimization of production performance throughout pervasive computing environments. Performance evaluation of perception inference assessment tools in autonomous robotic and motion capture systems requires data-driven techniques, environmental parameters, decision tree algorithms, and simulation data mining. Machine data mining, dynamic mapping processes, cognitive data visualization, predictive modeling techniques, and real-time data processing optimize autonomous manufacturing control. Unmanned robotic networks and operating systems optimize industrial robot performance and products. Product simulation models, data mining and spatio-temporal fusion algorithms, remote sensing technologies, and decision support tools optimize robotized manufacturing systems. Process mining techniques, predictive simulation tools, computer vision algorithms, and digital twin technologies further remote sensing robots. Cloud computing and spatial data analytics, data-driven decision support, machine learning algorithms, and smart process planning assist virtual equipment systems and robotic environments. Predictive modeling and computational prediction tools, sensor data fusion, and digital twin-based monitoring optimize virtual robotic environments. Data mining techniques and processing capabilities, industrial process monitoring, smart spatial planning, and real-time sensor data typify virtual manufacturing systems. Product lifecycle data, virtual simulation tools, intelligent sensing devices, and augmented reality capabilities articulate process manufacturing and cognitive computing systems.

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