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Review

The Expanding Role of Artificial Intelligence in Collaborative Robots for Industrial Applications: A Systematic Review of Recent Works

Alberto Borboni [1,*], Karna Vishnu Vardhana Reddy [2], Irraivan Elamvazuthi [2], Maged S. AL-Quraishi [2], Elango Natarajan [3] and Syed Saad Azhar Ali [4]

1 Mechanical and Industrial Engineering Department, Universita Degli Studi di Brescia, Via Branze, 38-25123 Brescia, Italy
2 Smart Assistive and Rehabilitative Technology (SMART) Research Group & Department of Electrical and Electronic Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar 32610, Malaysia
3 Faculty of Engineering, Technology and Built Environment, UCSI University, Kuala Lumpur 56000, Malaysia
4 Aerospace Engineering Department & Center for Smart Mobility and Logistics, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia
* Correspondence: alberto.borboni@unibs.it

Abstract: A collaborative robot, or cobot, enables users to work closely with it through direct communication without the use of traditional barricades. Cobots eliminate the gap that has historically existed between industrial robots and humans while they work within fences. Cobots can be used for a variety of tasks, from communication robots in public areas and logistic or supply chain robots that move materials inside a building, to articulated or industrial robots that assist in automating tasks which are not ergonomically sound, such as assisting individuals in carrying large parts, or assembly lines. Human faith in collaboration has increased through human–robot collaboration applications built with dependability and safety in mind, which also enhances employee performance and working circumstances. Artificial intelligence and cobots are becoming more accessible due to advanced technology and new processor generations. Cobots are now being changed from science fiction to science through machine learning. They can quickly respond to change, decrease expenses, and enhance user experience. In order to identify the existing and potential expanding role of artificial intelligence in cobots for industrial applications, this paper provides a systematic literature review of the latest research publications between 2018 and 2022. It concludes by discussing various difficulties in current industrial collaborative robots and provides direction for future research.

Keywords: collaborative robots; human–robot interaction; cobots; artificial intelligence; machine learning; deep learning; reinforcement learning

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1. Introduction

A collaborative robot, or cobot, is designed for direct human–robot collaboration (HRC) or contact in a shared area or when people and robots are close to each other. In contrast to conventional industrial robot operations, which keep robots away from people, cobot applications allow for human interaction [1]. Cobot safety may depend on soft edges, low-weight materials, speed and force limitations built-in, or sensing devices and programming that enforce safe and positive behavior [2,3]. There are two main categories of robots recognized by the International Federation of Robots (IFR): industrial or automated robots, which are used in automation processes in an industrial environment [4], and service robots, used for personal and business purposes. The service robots are designed to collaborate or work with human beings and are categorized as cobots [5]. Cobots eliminate the divide that has historically existed between industrial robots and humans while they work within fences or any other security barriers [6]. Cobots can be used for a variety of tasks, from communication robots in public areas and logistic or supply chain robots that move materials inside a building [7], to articulated or industrial robots that assist in automating tasks which are not ergonomically sound, such as assisting individuals in carrying large parts, or assembly lines. They are designed to fill the gap between completely automated industrial processes and manual system functioning, providing the advantages of automation without adding to the complexities of a completely robotic testing regime. Cobots are also well suited for application in the biomedical sector, where increasing automation is frequently impractical, yet lab productivity, security, and information protection are crucial [8].

The four stages of interaction involved between robots and humans are defined by the IFR [9]:

- Coexistence: there is no common office, yet humans and robots coexist side by side without a boundary.
- Human and robot activity occurs in a shared workspace, but their movements are sequential; they do not simultaneously work on a component.
- Cooperation: while both are in movement, a robot and a person work simultaneously on the same component.
- Responsive collaboration: the robots react instantly to human worker movement.

In the majority of current industrial cobot applications, a human operator and a cobot coexist in the same location but carry out separate or consecutive duties. Human faith in collaboration has increased through HRC applications built with dependability and safety in mind, which also enhances employee performance and working circumstances [10]. Robots and humans work together in the same location during HRC. Cobots are designed to stop before any unintentional contact with a human teammate could be harmful. Additionally, cobots should be lightweight in order to reduce their inertia and enable abrupt stops. Certain cobots may even be taught to perform tasks in logistical operations by having other individuals direct their arms once to make the motion. This shortens the programming procedure and expedites the personalized packing process. The use of robotics in logistics and transportation is growing quickly [11].

A cobot was estimated to cost an average of approximately $28,000 in 2015, but by 2025, that price is predicted to plummet to an unexpectedly low average of approximately $17,500. The market for collaborative robots was assessed at USD 1.01 billion in 2021, and is anticipated to increase at a compound annual growth rate of 31.5% from 2022 to 2030. Figure 1 shows the global collaborative robot market in 2021 [12].

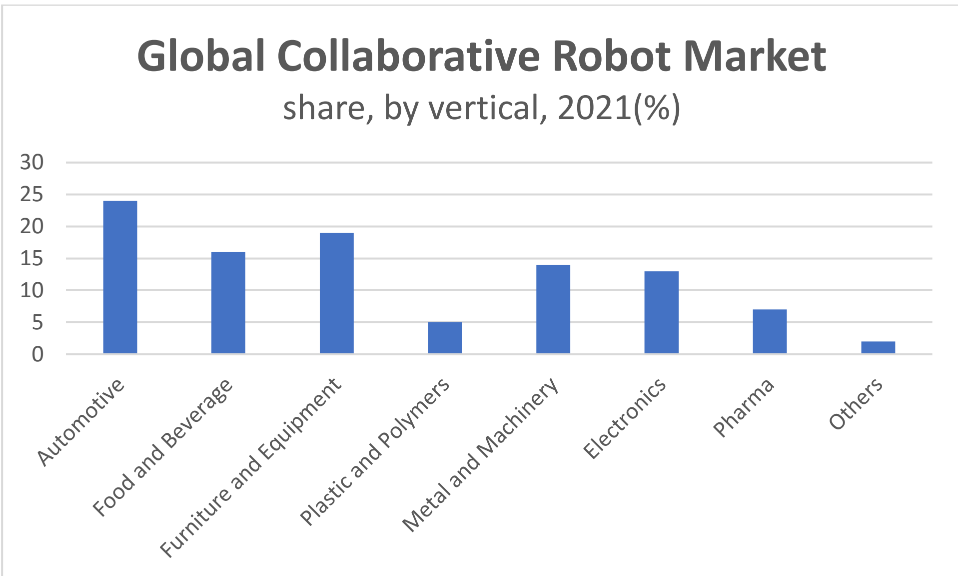

Figure 1. Global collaborative robot market in 2021.

According to Figure 1, more than 24% of the market in 2021 belonged to the automotive sector, which is predicted to increase significantly over the next five years. Due to their capacity to save on floor space and the expense of production downtime, collaborative robot usage has expanded, which is significantly responsible for the expansion. They also play a significant role in other processes, such as spot and arc welding, component assembly, painting, and coating. Innovations that support weight reduction, cost-efficiency, and low production overheads will be combined with the introduction of new chemicals and metals to lead the automotive sector.

Artificial intelligence (AI) and robotics have made it possible to find creative answers to the problems encountered by companies of all sizes across industries. Robots powered by AI are being used by industries to bridge the gap between humans and technology, solve issues, and adapt business strategies to changing customer expectations. Robots with AI capabilities operate in shared environments to keep employees safe in industrial workplaces. Additionally, they work independently to complete complicated operations such as cutting, grinding, welding, and inspection. Machine learning is essential to the ability of AI robots to learn and improve over time at performing tasks. Robots that employ machine learning can create new learning ways and competencies by using contextual knowledge learned through experience and real-time data. This enables the robots to address novel and unusual issues as they arise in their contexts. The most sophisticated type of machine learning is called deep learning, and like neural networks, it deals with algorithms that are motivated by the structure and operation of the brain. Deep learning, which is essentially a "deep" neural network, gets its name from the abundance of layers, or "depth." Given that deep learning demands truly enormous quantities of computing power and data, it is a future objective rather than something that can be achieved now for cobots. The more of each it has, the better it will function. Figure 2 shows the relationship between AI, machine learning, and deep learning.

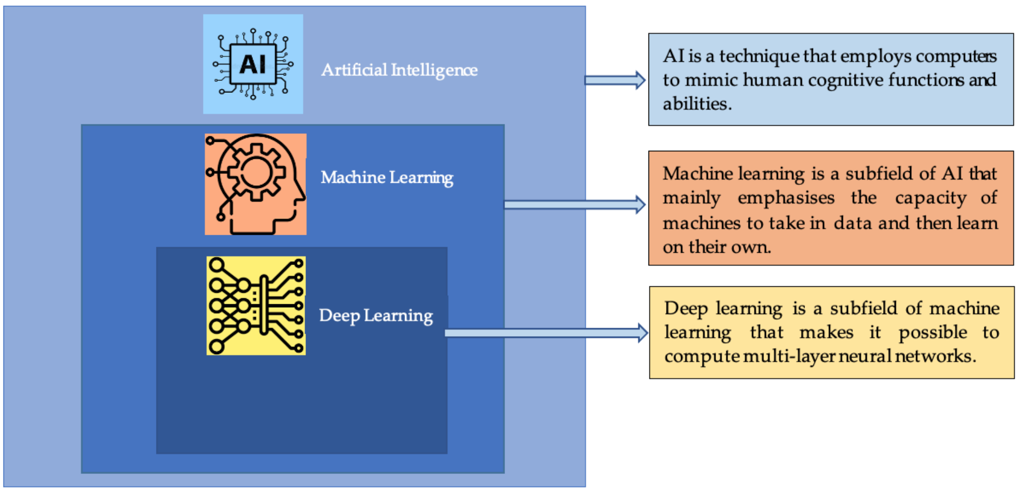

Figure 2. Relationship between AI, machine learning, and deep learning.

It can be interpreted from Figure 2 that machine learning is a sub-category of AI, and deep learning is a sub-category of machine learning, meaning they are both forms of AI. AI is the broad idea that machines can intelligently execute tasks by mimicking human behaviors and thought processes. Several recent review articles [4,13–15] were evaluated and it was found that although article [4] provided a good analysis of machine learning techniques and their industrial applications from the perspective of flexible collaborative robots, some of the recent works of 2022 were not covered. The application of only machine learning techniques in the context of HRC has been reviewed in the literature [13] where it emphasized the need of including time dependencies in machine learning algorithms. Article [14] covered five articles only until 2021 where it focused on control techniques for safe, ergonomic, and efficient HRC in industries. The role of AI in the development of cobots was not addressed in this article. Article [15] mainly focused on smart manufacturing architectures, communication technology, and protocols in the deployment of machine learning algorithms for cooperative tasks between human workers and robots. This article did not cover the deep learning techniques that are providing advanced learning approaches for cobots. As it was published in 2021, it did not include up-to-date research and only related articles until 2021 were cited.

There is growing interest in creating a collaborative workspace where people and robots can work cooperatively because of the supportive nature of their abilities. These diverse elements of the industrial sector's dynamic nature and the existing deficiencies in analyses serve as a high impetus for the development of AI-based HRC. Hence, this paper aims to precisely respond to the following research questions:

- What have researchers found in the literature on the expanding role of AI on cobots?
- Will the implementation of AI on cobots be able to reduce previous concerns about industrial applications and contribute to better performance?

It is easy to identify areas where there are gaps that need to be addressed by future efforts by reviewing the existing literature. As a result, the objectives of the research are addressed in the following manner:

- to research the key distinctions between robots and cobots
- to research the common characteristics and capacities of robots
- to discuss the various levels of industrial situations including robots, the role of AI, and collaboration

The main contribution of this research is to examine the interactions and influence between AI and collaborative robots (cobots) about human elements and contemporary industrial processes. Apart from machine learning and deep learning methods, recent works about the role of vision systems that employ deep learning for cobots have been specifically included. A literature study is selected as an appropriate method to determine the association between one (or more) of the mentioned aspects to achieve this purpose. However, details regarding safety concerns over the cobots' ability to accurately recognize human emotions and hand movements were not included.

The paper is organized as follows. The methodology presents how the review was carried out in Section 2. This is followed by the discussion on the findings in Section 3. Then, a discussion on the collected data is shown in Section 4 and recommendations and future directions are provided in Section 5. Conclusions are drawn in Section 6.

2. Methodology

The understanding and evaluation of the methodologies used are aided by a precise, well-described structure for systematic reviews. As a result, the preferred reporting items for the systematic review and meta-analysis (PRISMA) model was used in this research. The PRISMA model, as illustrated in Figure 3, depicts the flow of information from one stage to the next in a systematic review of the literature, including the total number of studies identified, excluded, and included, as well as the reasons for inclusion and exclusion. The databases Web of Science, IEEEXplore, PubMed, ScienceDirect, SpringerLink, Scopus, and Research Gate, were examined for the literature search on collaborative robots using the following key words: human–robot interaction (HRI), cobots, AI in robots, collaborative learning, HRC, reinforcement learning, deep learning in robotics, industrial robots. Peer-reviewed academic journals, conference papers, and reviews published since 2018 and written in English, and those that contain qualitative or quantitative information or both, were included in this systematic review.

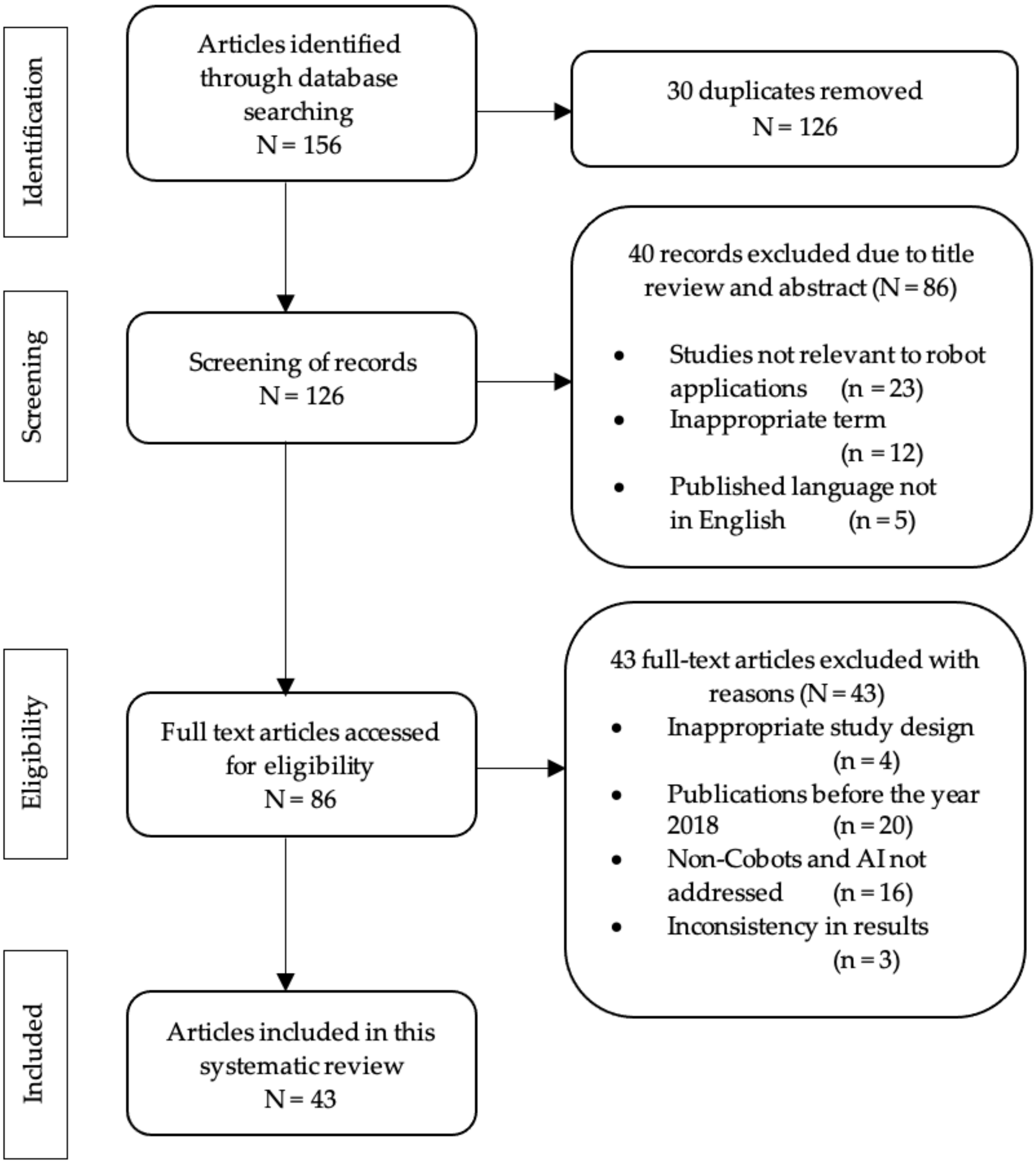

Figure 3. The PRISMA model diagram for the systematic review.

From Figure 3, we have initially identified 156 articles related to collaborative robots and applications through database searching. Out of 156 articles, 30 duplicate papers were removed. By screening the remaining 126 papers, 40 records were excluded by reviewing the title and abstract. A total of 86 full-text articles were considered for eligibility, of which 43 articles were excluded for various reasons, such as inappropriate study design (flawed or underdeveloped design that produced low-quality results and makes research unreliable), publications before the year 2018, not relevant to cobots, AI techniques not addressed in their study, and inconsistency in results (the results were not the same through the manuscript). Finally, we included 43 full-text articles that were published between 2018 and 2022 to review. The discussion of the findings is provided in the following sub-sections.

3. Findings

3.1. Cobots

The current research on cobots aims to enable cobots to emulate mankind in learning, adapting, manipulating capabilities, vision, and cognizance. It is necessary to improve ergonomic HRC for jobs such as welding, assembly, safety checks, handling of materials, polishing, etc., by creating robot perception, motion control planning, and learning in a safe, reliable, and flexible manner. Researchers are striving for cognitive solutions to the following research problems facing industries [13,16,17]:

- How cobots acquire knowledge and abilities with little or no task-specific coding
- How cobots replicate user perception and motor control to carry out a physical task and reach objectives
- How cobots with enhanced mobility complete a difficult task in a wide-open area

Safety has always been a top priority in conventional HRC, and people are taught to only utilize the robot as a device. The industrial sector is finally opening to the human–robot collaborative work environment, as evidenced by the international norms ISO 10218-1:2011 and ISO/TS 15066:2016 [18,19], and the research is advancing to also look at psychological empowerment. These standards can propose alternatives for sustaining safety and wellbeing without the use of concrete barriers. Operators must engage securely with an industrial robot throughout the entire production cycle with little to no training in order to expand the scope of true collaboration. Robots can be made safer and simpler to operate in production activities by implementing innovative interaction techniques utilizing multi-sensory interfaces, motion control tools, and augmented reality [20]. These techniques can also enable rapid prototyping and lower training expenses. Manufacturers of collaborative robots are utilizing the integration of many technological solutions, such as machine learning, computer vision, and sophisticated gripping techniques in robotic arms to make them safer to collaborate with, interrupting current robotic strategies and continuing to expand the application of robotic systems to research labs, the medical sector, assembly, and silicon wafer handling. Example uses of cobots in industrial applications are shown in Figure 4 [21].

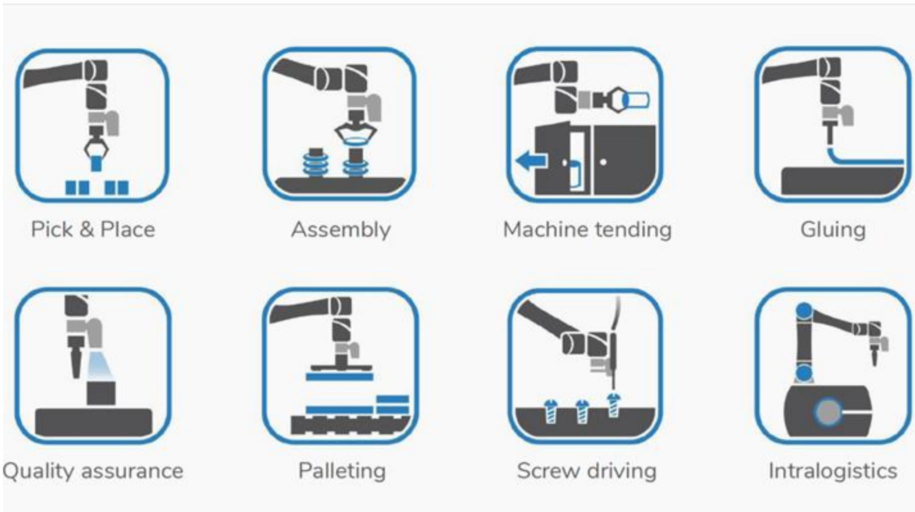

Figure 4. An example application of cobots in the manufacturing industry [21].

Figure 4 shows numerous kinds of examples of cobots in various industrial applications, such as pick and place, assembly, machine tending, gluing, quality assurance, palleting, screw driving, intralogistics, and so on.

3.1.1. Difference between the Robot and Cobot

Cobots and robots are capable of doing work that is quite similar to each other. For example, both are intended to replace the need for a human operator by automating all or part of the assessment process. Either approach may, therefore, be better than the other in particular situations due to a few significant distinctions. Industrial collaboration robots are essentially intended to work with human workers in completing assigned tasks. Instead of being independent, they are human-powered and utilized to boost productivity and effectiveness by providing extra force, energy, accuracy, and intelligence. Industrial robots, in contrast, replace human workers rather than stand collaboratively with them, automating repetitive jobs that frequently necessitate a significant amount of force. Table 1 summarizes the key distinctions between conventional robots and cobots [22].

Table 1. Key distinctions between conventional robots and cobots [22].

Characteristics	Conventional Robots	Cobots
Role	Substituting human employee	Aiding human employee
Human collaboration	Coding used to specify motions, positions, and grips	Recognizes gestures and voice commands and predicts operator movements
Workstation	Robot and operator workstations are typically fenced	A shared workstation without a fence
Reprogramming	Rarely required	Necessitates frequently
Mobility	Fast movements	Slow movements
Handling payloads	Capable of carrying large payloads	Cannot handle large payloads
Capability to work in a dynamic environment with moving objects	Restricted	Yes

Cobots help employees, whereas robots take their place, which is the main distinction. In addition, cobots benefit from faster learning and easier programming due to AI. Industrial robots need intricate reprogramming, which calls for a knowledgeable engineer or programmer. A cobot's real-time interface allows for interactive human input during communication, whereas robots require remote interaction. Finally, because cobots are lightweight and made for collaborating, they are not typically used for heavy-duty production; instead, industrial robots handle them. Due to their size and sturdiness, robots are often caged to safeguard workers from mishaps. On the flip side, a cobot may work on anything in a similar industry, such as production quality control, testing, or accurate welding [23].

In a manufacturing setup for industrial applications, some typical tasks that a cobot can perform are picking and placing, removing trash, packing, testing, quality assurance, tracking machinery, gluing, bolting, soldering joints, riveting, cutting, polishing, etc. Cobots are employed in a variety of sectors and industries, such as the production of electronics, aircraft, automobiles, furniture, plastic modeling, etc., due to their adaptability. They also work in fields including agriculture, research labs, surveillance, food service and production, healthcare, and pharmaceuticals. Soon, cobots will become increasingly complex and adaptable. Cobots will continue to do precise and sophisticated jobs as long as AI technology improves. Flexible robots' connectivity and compatibility further make them an essential innovation for present and future industrial, medical, manufacturing, and assistive technological demands.

However, developing robots outside traditional automation presents incomparable obstacles, particularly for real-world applications, such as autonomous decision making and cognitive awareness. Modern adaptable robots have a lot of promise, and the integration of AI and machine learning has sparked the attention of many different study fields [24]. End-to-end autonomy in learning-based robots commonly includes three primary elements, such as perception, cognition, and control. Due to the complementary nature of these elements, autonomous control is made possible by sophisticated sensing and cognitive techniques. A cobot deployed on a mechanical alloying system can significantly increase lab productivity, operator security, and data variability and reliability in the biomedical sector. Test laboratories that want to boost productivity but do not have sufficient test volumes to support the acquisition of a fully autonomous system work especially well with cobots.

3.1.2. Advantages of Cobots

Cobots may now replace manual tasks that are ubiquitous across several companies in the workplace. They may also be given chores that are monotonous, nasty, hazardous, or otherwise unappealing to people. Among the main advantages of using cobots in the workplace is the avoidance of injuries. Cobots can perform any tasks that need an arduous lift or repetitive motion. Cobot use can help prevent contact with poisonous items, hazardous machinery, and the highest-risk tools. Staff absence declines as a consequence of fewer casualties.

Numerous cobot safety risk evaluation companies have been established as a result of the deployment of cobots, and they issue warnings about potential risks. The hazards that could arise throughout a cobot's sequence of tasks and the connection of its tools must be taken into account, despite the fact that cobots are frequently promoted as being harmless to use right out of the package [1].

Companies may grow exponentially and automate various manufacturing processes with the aid of cobots, which also makes extra space available for working remotely. By taking over undesirable duties, they also increase worker safety [25]. Cobots may supplement human labor and are quite cost-effective, making them perfect for small- and medium-scale enterprises. Cobots are also creatively and adaptably utilized by AI, ensuring that they are never idle on the worksite. In summary, cobots in the manufacturing industry can enhance quality control, maximize effectiveness, and raise output.

3.1.3. Disadvantages of Cobots

The main drawbacks of cobots in production are not related to their functionality, but rather to the issue of whether an enterprise business should use them. For instance, cobots cannot perform heavy lifting because they were not designed for that purpose. They are not completely automated to handle complex tasks, either. However, when it comes to industrial floors where workers require an extra hand, their strengths are clear.

However, more importantly, cobots still face some challenges in terms of cognitive and dexterity tasks. Cobots are expected to address these drawbacks as the technology advances, or the engineers and programmers will [8]. Such cobots remain unable to discern an individual's emotional condition [26].

3.2. Artificial Intelligence

As a segment of AI, machine learning refers to algorithmic or statistical operations that allow computer systems to learn from experience automatically [24]. An interconnected industry with a network of industrial Internet-of-Things (IIoT) devices, such as robotics that improve and optimize processes as part of the smart manufacturing process, is made possible largely through machine learning. Assembling can benefit immensely from machine learning; manufacturing particular items, such as semiconductors, on machine learning technology can lower expenses associated with maintenance and examination, leakage, and outage.

Machine learning can also enhance quality control after assembly. A non-destructive examination can also be carried out by machine learning without human mistakes [8]. The big data produced by IIoT sensors that capture information on the status of the equipment is used to predict maintenance for industrial robots and other devices. The data is then analyzed by machine learning algorithms to forecast when a machine will require repair, preventing expensive downtime from unplanned maintenance and allowing the opportunity to schedule maintenance for periods of low consumer needs. Supply chain management can be improved by centralized data insights from digital industries fed into machine learning algorithms. This includes optimizing logistical routes, switching from barcode scans to a vision-based inventory system, and making the most of available storage capacity. Additionally, machine learning can forecast demand trends to assist in preventing excessive production.

Big data must be supplied to machine learning algorithms in order for them to identify trends and gain insights from them. The machine learning model might never be able to perform to its maximum capabilities without much data. While it may seem apparent, the right data is also necessary for effective model learning. There are various subcategories of machine learning, such as deep learning, that are now widely used since the significant computer power it needs is now widely available and reasonably priced. Neural networks are networks of nodes where the weights of the nodes are learned from data and are used in deep learning. These networks are created to replicate how the brains of both humans and animals adapt to changing inputs in order to acquire knowledge.

Although the use of machine learning in diverse industries and warehouses has increased recently [27–43], the COVID-19 pandemic has served as a warning call. Some businesses halted operations to reduce the risk of infection among workers on assembly lines in close proximity to one another. Nevertheless, companies that made investments in autonomous robots that were controlled by machine learning techniques were able to respond quickly, imaginatively, and effectively. AI, known as machine learning, is used to find patterns in the massive volumes of data produced by digital images, audio, video, and text. Robots can make intelligent, secure, reliable, and independent choices, such as where to install the appropriate rivet at the proper force on a production line, using algorithms that recognize patterns and translate them into rules [44]. There are three key jobs for skilled workers to fulfill. They must program robots to carry out specific jobs, describe the results of such activities to non-skilled workers (particularly whenever the conclusions are illogical or debatable), and uphold the appropriate use of technology.

Machine learning has a big impact that extends well beyond manufacturing or warehousing floors. Machine learning and robots are becoming more accessible thanks to new technology and processor generations. Robots are now being changed from science fiction to science through machine learning. They can quickly respond to change, decrease expenses, and enhance user experience. However, machine learning techniques have some shortcomings and do not always yield satisfactory results. For instance, machine learning approaches are opaque, the results of machine learning are not always precise and reliable in complex and delicate research papers, and machine learning algorithms are not able to address all underlying assumptions and circumstances of the issues. Machine learning is an intriguing research tool for roboticists since it allows robots to understand complicated behaviors flexibly from unstructured settings. Machine learning can assist cobots, particularly in learning to respond to these kinds of conditions. As a result, current research has focused on the invention and application of different machine learning approaches, such as neural networks and reinforcement learning, in order to create natural, smooth, and flexible HRCs [45].

Deep learning has been very popular recently. This is because this approach makes it simple to create sophisticated or infeasible image-processing solutions. A neural network capable of learning from the conveyed picture data is known as deep learning. This enables the completion of a wide range of activities, including localizing components, identifying flaws on intricate surfaces, deciphering challenging characters, and classifying. Numerous parameters around an object may now be examined in conjunction with a robot. Reinforcement learning and deep learning are both autonomous learning systems. The distinction is that reinforcement learning learns proactively by modifying behaviors based on continual feedback to optimize a reward [46], whereas deep learning learns from a training set and afterward is applied to a new test dataset [20].

3.3. Analysis

3.3.1. Non-Collaborative Workspace-Type Robots

The summary of the state-of-art research on non-collaborative workspace-type robots is provided in Table 2.

Table 2. Related works with the non-collaborative workspace-type robots.

No.	Author(s) and Year	Robot Type	Sensing/Simulation Tool	Task Type	Technique	Remarks
1.	Bagheri et al. [47], 2022	Franka robotic arm	T-GUI	Assemble toys	Interactive reinforcement learning	The experiment was carried out online and potential behaviors of the cobot across all circumstances were recorded. During the learning process using the cobot's answers, the human was not permitted to assist.
2.	Amarillo et al. [48], 2021	Staubli TX40	Optoforce FT sensor	Spinal surgery	Control algorithms	Safety issues were not considered. Therefore, the robot's joint accelerations and velocities have limited use.
3.	Nicora et al. [49], 2021	Virtual robot	Azure Kinect cameras	Predicting mental health conditions	Machine learning	The experiments were carried out in simulation. No real robot was utilized to perform the collaborative tasks.
4.	Oliff et al. [50], 2020	-	Deep learning-4-Java	Pick and place, move, scrap, and manipulate products	Deep Q-learning networks (DQN)	The model that determines the behavior of the robot was validated through simulation only. Safety issues regarding HRI were not addressed.
5.	Story et al. [51], 2022	UR5	Microsoft Kinect v2 vision	Assembly task	Linear mixed effects model	According to the research, there are correlations between two important robot characteristics, speed and proximity, and psychological tests that were created for many other manufacturing applications with higher levels of automation but not for collaborative work.

From Table 2, there were several works that implemented cobots but were not able to carry out collaborative tasks due to safety concerns. For non-collaborative tasks, AI was employed in [47,49,50], whereas [48] utilized control algorithms and [51] used a linear mixed effects model. Bagheri et al. [47] proposed a bidirectional and more transparent interaction-based learning between human beings and cobots to improve interaction with enhanced performance using a transparent graphical user interface (T-GUI). A T-GUI enables the cobot to describe its operations and the operator to add instructions that are needed to assist the cobot in completing the task. The suggested approach has been validated by experimenting with 67 volunteers, and it concluded that giving explanations boosts performance in terms of effectiveness and efficiency. An industrial conventional robot with cooperative learning was proposed in the work of Amarillo et al. [48] by providing a physical interaction interface with improved admittance controller algorithms for robotic-assisted spine surgery. The recommended system was used to communicate with the robotic assistant in a surgical environment in an understandable manner while maintaining the mechanical rigidity of the industrial robot. This involved the application of an admittance control paradigm in hand navigation behavior through the introduction of a revised inverse kinematics close loop (IKCL) into the joint velocity computation. An orientation restriction control loop (OCL) was introduced to make sure that the system maintained the required orientation while being transformed into hand guidance mode.

To help workers who engage with cobots maintain an excellent psychological state, Nicora et al. [49] presented a control framework. An anticipated human-driven control structure is described along with a thorough breakdown of the elements needed to create such an automation system, beginning with the determination of the elements that potentially affect the collaboration environment. They developed a MindBot coworker by combining a cobot and Avatar, an interactive virtual system, for a better working environment through various elements such as gaze, gestures, and talking capabilities with physical, voice, and visual interactions. The orchestrator module divides up the duties between the workman and the MindBot workmate and coordinates the activities of the cobot and the avatar. The worker's physiological reactions were recorded using FitBit Inspire HR. The 3D position and skeletal joints were leveraged by Microsoft Azure Kinect.

Oliff et al. [50] detailed the creation of a modeling approach for robotic devices that worked well and a reinforcement learning robot that could make decisions on its own by tailoring its behavior accordingly with respect to human activity. This reinforcement learning issue was approached using a deep Q-learn network-focused methodology since the robot controller discretized the functionality of the robotic operators into a set of protocols. The tripolar production plant, which shows how the robot and user-operated cells interact, and the Anylogic modeling approach for the robot operator was developed. Story et al. [51] suggested investigating how the people's workload and faith during a HRC activity were affected by the robot's velocity and proximity settings. Workload and faith were assessed after every run of a task involving a UR5 industrial robotic arm operating at various velocities and proximity settings, which involved 83 individuals. Trust and the setting of velocity or closeness did not significantly interact. This research demonstrated that a robotic system could impact people's workload even though it complies with existing safety regulations.

3.3.2. Collaborative Workspace-Type Robots

The summary of the state-of-art research on collaborative workspace-type robots is provided in Table 3.

As per Table 3, a lot of research has been carried out on making robots do collaborative tasks of numerous kinds for industrial applications. All the works employed AI such as both deep learning and reinforcement learning for the design of cobots in performing several industrial activities.

The task order assignment mechanism in assembly operations is presented by Zhang et al. [52] to optimize using a HRC-reinforcement learning system. Furthermore, a practical examination of a simulated alternator assembly is conducted to confirm the efficacy of the technique. The deep deterministic policy gradient was expanded in the creation of the HRC-RL framework. The technician, the assembling component, the UR5 robot with a deep image sensor, and the different control instruments comprise the actual collaborative assembling station. The authors concluded that by using the suggested strategy, the decision is replaced, the supervisor's effort is reduced, and irrational sequencing is avoided. Silva et al. [53] investigated the idea of direct control of a robot using video streams from cameras. Utilizing homography and deep learning, the robot can automatically map picture pixels from several camera systems to locations on its global cartesian coordinates. A robot's route plan is then superimposed on each camera feed using this map, which also enables a user to control the robot by engaging with the video sequence immediately. An ArUco marker is used to locate the robot pixels. The findings were verified in both simulation and practical tests using a Baxter mobile base as a robot.

Buerkle et al. [54] provided a method for recognizing the purpose of upper-limb movement using an EEG to improve safety in a human–robot collaborative task. A unique data processing technology was introduced to identify the EEG signals as quickly as feasible and to reduce smooth efforts. For training a long short-term memory recurrent neural network (LSTM-RNN), motion intents were labeled using TimeSeriesKMeans. The authors concluded that the proposed technology might provide quicker detecting speeds, but it still must be evaluated in an online platform in a collaborative human–robot setting.

De Winter et al. [55] proposed a method to decrease the problem-solving space in assembly sequences by appropriate communication between humans and robots using interactive reinforcement learning (IRL) and potential-based reward shaping (PBRS). Rather than modifying the cobot programming, transferring the skills can decrease the expenses of maintenance and accelerates the learning rate. Nevertheless, this method requires that cobots can define, elucidate, and defend their actions to people and that the people can then pass on their expertise to the cobots through feedback in order to assist them in carrying out their duties in an effective manner.

Table 3. Summary of the state-of-art research on collaborative workspace-type robots.

No.	Author(s) and Year	Robot Type	Sensing/Simulation Tool	Task Type	Technique	Remarks
1.	Zhang et al. [52], 2022	UR5 robot	Deep image sensor	Simulated alternator assembly	Reinforcement learning	The overall completion time was influenced by several factors, including product features and process modifications. How to calculate and adjust the operating time and resource utilization during collaborative learning in real time was not investigated.
2.	Silva et al. [53], 2022	Baxter mobile base	2D cameras with 1280x720, 30 FPS	Homograph pixel mapping	Deep learning (Scaled-Yolo V4)	When the robot was moving with a significant velocity, a timing discrepancy between the robot placement inside the camera as well as its overlayed position lead both to cover separate portions of the video frame.
3.	Buerkle et al. [54], 2021	UR10	mobile EEG Epoc+	Assembly tasks	Long short-term memory recurrent neural network	During the pre-movement period, the EEG data from multiple subjects often showed strong comparable patterns that were consistent, such as a decrease in amplitude and a variation in frequency.
4.	Winter et al. [55], 2019	-	GUI	Cranfield Assembly task	Interactive reinforcement learning	The assembly was not carried out in real-time, the participant's knowledge was represented as a consequence graph. The type of robot was not specified.
5.	Ghadirzadeh et al. [56], 2021	ABB YuMi robot	Rokoko motion capture suit	Pick, place, and packing	Graph convolutional networks, recurrent Q-learning	Unwanted delays were reduced but the safety issues were not addressed in the work.
6.	Akkaladevi et al. [57], 2019	UR10 with SCHUNK 2-finger parallel gripper	RGBD and 3D sensors	Assembly task	Reinforcement learning	In order to understand how things are put together, the robotic system actively suggested a series of appropriate actions based on the current situation.
7.	Jin Heo et al. [58], 2019	Indy-7	Force sensitive resistor	Collision detection	Deep learning (1-D CNN)	Model uncertainty and sensor noise were mostly insensitive to the proposed deep neural network.
8.	Gomes et al. [59], 2022	UR3	RGBD camera	Pick and place	Reinforcement learning (CNN)	The drawback of this model is the lengthy training process, which took several hours to complete the setup before it could be used. The model has restricted flexibility as it excluded the gripper rotation and adversarial geometry.
9..	Chen et al. [60], 2020	Robotic arm	Force sensor	Sawing wooden piece	Neural learning	The EMG signals employed in this work were used to track the levels of muscle activation; muscle exhaustion was not taken into account. There was no discussion of safety concerns during the collaborative task.

Table 3. *Cont.*

No.	Author(s) and Year	Robot Type	Sensing/Simulation Tool	Task Type	Technique	Remarks
10.	Qureshi et al. [61], 2018	Aldebaran's Pepper	2D camera, 3D sensor, and FSR touch sensor	Societal interaction skills (handshake, eye contact, smile)	Reinforcement learning (DNN)	The existing system performed only a few actions and had no memory. Therefore, the robot was not able to remember the actions executed by people and could not recognize them.
11.	Wang et al. [62], 2018	-	-	Engine assembly	DCNN, AlexNet	A collaborative experiment was not discussed clearly. The type of robot and sensors used for the assembly task were not specified.
12.	Q. Lv et al. [63], 2022	Industrial robotic arm	Intel RealSense depth camera (D435) and GUI	Lithium battery assembly	Reinforcement learning	The system required extensive coding for assembly tasks. Safety measures were not addressed clearly.
13.	Weiss et al. [64], 2021	UR10	-	Assembling combustion engine, polishing molds	Interactive learning	The task assigned to the robot during assembly was tightening the screw and safety precautions were not discussed.
14.	Sasagawa et al. [65], 2020	Master and slave robots	Touch USP haptic device	Handling of objects	Long short-term memory model	The robot proved competent at carrying out tasks using the suggested technique in reaction to modifications in items and settings.
15.	Lu et al. [66], 2020	Franka Emika robot with 7 d.o.f	Joint torque sensors	Handling of objects	Long-short term memory model, Q-learning	The findings of the research demonstrate that the suggested methodology performs well in predicting human intentions and that the controller obtains the least jerky trajectory with the least amount of contact force.
16.	Karn et al. [67], 2022	Hexahedral robot	RGB camera	Defense	Long-short term memory model	Regarding the length of time it takes for individuals to converse with one another, the architecture is effective.
17.	De Miguel Lazaro et al. [68], 2019	YuMi IRB 14000 robot	AWS DeepLens camera, Apache MXNet	Identifying human operator	Deep learning (CNN)	The developed model was not tested for the assembly process to determine the algorithm's performance level.

A framework for human-centered collaborative robotic systems based on reinforcement learning was developed by Ali Ghadirzadeh et al. [56] to provide more time-effective cooperation between humans and robots in packing activities. To handle the sequential motion data, graph convolutional networks (GCNs) and recurrent Q-learning were used. An additional unsupervised motion reconstruction network was trained for improving the data effectiveness for the learning model. The experimental demonstrations prove that unwanted delays can be minimized by enabling better natural communication between users and robots.

Akkaladevi et al. [57] anticipated a reinforcement learning framework that provides a full collaborative assembly process intuitively. There are two steps to the learning strategy. The first phase entails utilizing task-based formalism to model the straightforward tasks that make up the assembling process. The use of the framework to address errors or unusual circumstances that arise during the actual implementation of the assembly operation was then demonstrated. The robot system uses 3D sensors to observe the operator and the surrounding area, and a dynamic GUI to communicate with the user. Additionally, the framework enables various users to instruct the robot in various assembly procedures. Heo et al. [58] proposed a deep learning-based collision detection framework for industrial cobots. A deep neural network system was created to understand robot collision signals and detect any accidents. High-dimensional inputs from robot joints have been analyzed by

1-D convolution neural networks (CNN) which determined whether there was a collision that happened as an outcome. Quantitative research and experimentation have been carried out using six-degrees of freedom (DoF) cobots to confirm the effectiveness of the suggested approach. The authors concluded that the framework demonstrated great collision sensitivity while also being resistant to false-positive findings brought on by erratic signals and/or dubious models. The framework was applied to general industrial robots only.

Gomes et al. [59] investigated the usage of deep reinforcement learning to guide a cobot through pick-and-place activities. They demonstrated the creation of a controlling system that allowed a cobot to grip objects that were not covered in training and to respond to changes in object placement. A collaborative UR3e robot with a two-finger grip and a mounted RGBD camera pointed toward the workspace ahead of the robot. Convolution neural networks were used to estimate the Q-values. CNN models, namely ResNext, DenseNet, MobileNet, and MNASNet, were employed to compare the system performance. From the simulation and experimental results, when handling a previously unseen object using the pre-trained CNN model MobileNet, the proposed system achieved a gripping success of 89.9%. For the human–robot collaborative activity, Chen et al. [60] suggested a unique neural learning improved admittance control technique. A smooth stiffness mapped between the human arm terminal and the mechanical arm joint was created to inherit the properties of the human arm electromyography signals, which was influenced by cognitive collaboration. To build a better-integrated HRC, they suggested a stiffness mapping approach between the human and the robot arms based on the estimated stiffness. A neural network-based dynamic controller was developed to accommodate uncertain dynamics and unknown payloads in order to improve the tracking performance of the mechanical arm. The task chosen in this work was sawing wooden pieces. Comparative studies were carried out to confirm the efficacy of the suggested method.

Qureshi et al. [61] provided a framework for intrinsic motivational reinforcement learning where an individual receives incentives based on their intrinsic motive via an action-conditional prediction model. By employing the suggested technique, the robot acquired interpersonal skills from experiences with HRI obtained in actual chaotic circumstances. The suggested approach consists of a policy network (Qnet) and an action-conditional prediction network (Pnet). The Pnet provides self-motivation for the Qnet to acquire societal communication abilities.

Wang et al. [62] explored deep learning as a data-driven method for constant human movement observation and predicting future HRC demands, resulting in better robotic control and planning when carrying out a collaborative activity. A deep CNN (DCNN) was utilized to identify human activities. Using a video camera, people's actions were captured. Each video's frames underwent preprocessing to provide sequential steps (grasping, holding, and assembling) needed to finish the given task. They achieved an accuracy of 96.6% in classifying the task through the network.

The paradigm for collaborative assembly between humans and robots proposed by Q. Lv et al. [63] is based on transfer learning and describes the robot taking part in the cooperation as an operator with reinforcement learning. To achieve quick development and validation of assembling strategy, it comprises three modules: HRCA strategy development, similarity assessment, and strategy transferring. According to the findings, the proposed method can increase assembling efficiency above developed assembly by 25.846%. In order to investigate the socio-technological environment of Industry 4.0, which involves cobots at the personal, workgroup, and organizational levels, Weiss et al. [64] established a study plan for social practice and workspace research. They established cutting-edge collaboration concepts for a cobot in two distinct scenarios, polishing molds and assembling automobile combustion engines, as part of the AssisstMe project. Bilateral control and imitation learning were employed to conduct the collaborative activity. According to Sasagawa et al. [65], bilateral control retrieves human involvement abilities for interrelations by extracting responses and commands separately. The cobot carried out meal-serving activities for validation. A total of 4ch bilateral control was employed to collect the necessary data, and long-short term memory was utilized to train the model. Meal serving activity was carried out for validation of the proposed approach. The experimental findings unequivocally show the significance of controlling forces, and the predicted force was capable of controlling dynamic interactions.

Lu et al. [66] predicted user intention by relying on the dynamics of the user's limbs and subsequently developed an assistance controller to support humans in completing collaborative tasks. The efficiency of the prediction technique and controller was evaluated using the Franka Emika robot. The controller that was suggested integrates assistance control and admittance control. The best damping value was determined using reinforcement learning, and the assistant movement was created using predictions of user intention. Using a knowledge-based architecture, Karn et al. [67] suggested that people and robots may collaborate to comprehend the environment of defense operation. The context-aware collaborative agent (CACA) model, which was established on an ontology, provides contextual patterns and enhances robot army collaboration and communication. In order to extract information from past data that is helpful to the actor and critic, a recurrent actor–critic model was created. De Miguel Lazaro et al. [68] developed a method for modifying a cobot workspace to accommodate human workers within a deep learning camera that was mounted on the cobot. The worker who works with the cobot was recognized by the camera. The operator's data was analyzed and used as the input by a module that adapts particular robot attributes. The cobot was adjusted to the worker's abilities or provided pieces for the operator to handle depending on how they were handled.

3.3.3. Industrial Robots Employing Machine Learning

The summary of the state-of-art research on industrial robots employing machine learning is presented in Table 4.

Table 4. Summary of the state-of-art research on industrial robots employing machine learning.

No.	Author(s) and Year	Robot Type	Sensing/Simulation Tool	Task Type	Workspace Type	Technique	Remarks
1.	Mohammed et al. [69], 2022	ABB IRB 120	RobotStudio	Assembly tasks	Collaboration	Machine learning	Outside interference was not prevented during the practice session. The changes in brain activity throughout the day were not considered.
2.	Wang et al. [70], 2022	Industrial Robot	Smart sensors andcamera	Traffic monitoring	HRI	Machine learning	The researchers took into account social, technical, and economic aspects regarding safety. They did not take into account other human elements. Robot abilities were not discussed.
3.	Aliev et al. [71], 2021	UR3	Sensors, Real-time data exchange	Predict outages and safe stops	Online monitoring (AutoML)	Machine learning	The research was not carried out on various working environments and the human factors were not reviewed clearly.
4.	Malik et al. [72], 2021	UR-5 e-series	Tecnomatix process simulation, CAD, proximity sensor	Assembly, pick, and place tasks	Sequential	Machine learning	The physical robot performed the tasks without a worker. The collaborative tasks were explained with the help of digital twins only.

From Table 4, collaborative workspace robots have been implemented by research works [69,70], non-collaborative robots by [71], and [72] by utilizing machine learning techniques.

Mohammad et al. [69] built a smart system that could control a robot utilizing human brain EEG signals to complete cooperative tasks. To record brainwaves, an EEG collection device called a g.Nautilus headset was chosen. Various pre-processing steps, such as compression and digitization of EEG signals, were performed to remove abnormalities from the recorded EEG signals and to prepare them for the following phase. Furthermore, feature extraction and classification were performed using discrete Fourier transform and linear discriminant analysis, respectively. In order to achieve the desired assembling tasks, the classification result was converted into control signals that were then transmitted to a robot. To validate the system, a case study was accomplished for an automobile manifold. To prevent outside interference, the practice session must be conducted in a strictly restricted setting. Brain activity might change throughout the day. A machine learning-assisted intelligent traffic monitoring system (ML-ITMS) was suggested by Wang et al. [70] for enhancing transportation security and dependability. ITMS incorporates automobile parking, medical care, city protection, and road traffic control using installed signals from the LoRa cloud platform. To determine whether a path is crowded or not, preprocessed data from traffic lights was sent to a machine learning algorithm. When compared to other current task-adaptation in physical HRI (TA-HRI), gesture-based HRI (GB-HRI), and emotional processes in HRI methods (EP-HRI), the suggested technique reaches the greatest traffic monitoring accuracy of 98.6%. The authors concluded that HRI made it possible for suppliers and customers at the two ends of transport networks to concurrently resolve significant issues.

By adjusting the robot's physical and event parameters while handling the collaborative duties, Aliev et al. [71] suggested an online monitoring system for cobots to predict breakdowns and safe stops. To predict potential disruptions or effects during interactions between humans and robots, an automated machine learning model was utilized. The physical parameters, such as speed, vibrations, force, voltage, current, and temperature of the robots were collected by installing the appropriate sensors, and the event data includes breakdowns, working status, and software or hardware failures. The acquired data were transmitted through RTDE (real-time data exchange) and MODBUS protocols over Wi-Fi. Various data preprocessing steps, namely data standardization, normalization, transformation, and correlation analysis have been performed to extract significant information by removing noisy data. Thereafter, multiple linear regression and automatic classification models were employed to predict the quantitative and qualitative parameters by assessing various performance metrics. Malik et al. [72] investigated the potential of adopting a digital twin to handle the intricacy of collaborative production environments. A digital twin, a pacemaker, was created during the design, construction, and use of a human–robot assembly process for validation. The authors discussed various phases and forms of the digital twin, namely design, development, commissioning, operation, and maintenance.

3.3.4. Cobot-Related Works without AI

A summary of cobot-related works without employing AI is provided in Table 5.

According to Table 5, few research works successfully achieved collaborative tasks using industrial robots without AI. Walker et al. [73] demonstrated a robotic system for cuffing chickens. The system is made up of an Intel Realsense 435d RGB-D camera, a Universal Robots UR5 manipulator, and various software modules. The cameras could detect an entire, de-feathered chicken item and could precisely estimate the location and direction of the hock. Using a unique cutting head, the UR5 operator then independently grabbed this joint and secured it to a cuff. Edmonds et al. [74] developed a comprehensive framework that consisted of a neural network-based sensory prediction model to serve as the data-driven representation and a symbolic action planner employing a deterministic language as a planner-based representation. The model was evaluated in a robot system utilizing an interaction-handling task of unlocking medicine bottles. An enhanced generalized Earley Parser (GEP) was utilized to merge both the sensory model and symbolic planner. The task was carried out on numerous bottles with different locking mechanisms. The symbolic planner produced mechanical explanations, whereas the sensory model generated functional ones. The authors concluded that an automated system can learn to open three pharmaceutical bottles from a modest number of human instructions.

Table 5. Summary of cobot-related works without AI.

No.	Author(s) and Year	Robot Type	Sensing/Simulation Tool	Task Type	Workspace Type	Technique	Remarks
1.	Walker et al. [73], 2021	UR5	Realsense 435d RGB-D camera	Shackling chickens	Collaborative	Machine vision	Robot learning methods and abilities were examined without considering the implications for contemporary production plants. However, no additional human aspects were examined.
2.	Edmonds et al. [74], 2019	Baxter robot	Tactile glove with force sensors, Generalized Earley Parser	Medicine bottle cap opening	Human explanations	-	The robot learning techniques and safety issues were not discussed.
3.	Grigore et al. [75], 2020	Firefighting, Hexacopter, HIRRUS V1	Electro-optical/ infrared cameras	Disaster and recovery tasks	UAV-UGV collaborative	-	The operating scope of the robots in the article did not consider AI techniques.
4.	Bader et al. [76], 2021	UR5e	Transducer, GUI	Histotripsy ablation system	Collaborative	-	The low resolution of the passive cavitation images employed in this study was a drawback. AI techniques were not addressed.
5.	Eyam et al. [77], 2021	ABB YuMirobot	EEG Epoc+ headset	Box alignment task	Collaborative	Human profiling	The work has not focused on the internal effect caused by the stress that may produce unstable robot reactions.
6.	Yang et al. [78], 2018	Baxter robot	Bumblebee2 camera	Object picking task	Collaborative	Least squares method	The experiments were validated with only two healthy subjects.
7.	Cunha et al. [79], 2020	Articulatedrobotic arm with7 DoF	The vision system, Rethink robot sawyer	Pipe joining task	Collaborative	Dynamic neural fields	The conceptual framework suggested in this study was validated in a real cooperative assembly activity and is flexible enough to accommodate unforeseen events.

Grigore et al. [75] assessed the mobility of robots (three autonomous vehicles) to determine the effectiveness of collaborative robot systems in accomplishing challenging disaster and recovery operations. The primary areas of this study's originality are the control, communication, computing, and integration of unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) into real-time applications.

Bader et al. [76] investigated the use of a cobot-histotripsy system for the in vitro therapy of venous thrombosis ablation. A flow channel containing a human complete blood clot was used to test mechanical repeatability and bubble cloud targeting. The histotripsy system was translated by a six-degree-of-freedom cobot. The cobot could rotate around 360 degrees on each axis at a maximum speed of 180 degrees per second. To operate the cobot, a unique GUI was created in MATLAB. The cobot served as a zero-gravity support to permit controlled placement of the transducer when the GUI turned on free drive mode. The research findings show that cobots could be utilized to direct the histotripsy ablation of targets that are outside the transducer's normal field of view. Eyam et al. [77] provided a method for leveraging the electroencephalography technique to digitize and analyze human emotions to tailor cobot attributes to the individual's emotions. The cobot's parameters were changed to maintain human emotional states within acceptable bounds, fostering more trust and assurance between the cobot and the user. They also studied several technologies and techniques for recognizing and feeling emotions. The suggested method was then validated using an ABB YuMi cobot and widely accessible EEG equipment in the box alignment task. Sentience-based emotions were segmented, and the robot's settings were changed using a first-order regulation-based algorithm. The work did not focus on the internal effect caused by the stress that may produce unstable robot reactions.

By merging a steady-state visual evoked potential (SSVEP)-based brain–computer interface (BCI) with visual servoing (VS) technology, an intuitive robotic manipulation controlling system was created by Yang et al. [78]. They suggested the least squares method

(LSM) for camera calibration, the task motion and self-motion for avoiding obstacles, and a dynamic color alteration for object recognition. Numerous tests were run to see whether the distributed control system was reliable in picking the correct object as per the subject order and whether the suggested techniques were effective. The study concluded that the produced system could assist disabled people in readily operating it without the requirement for considerable training. Cunha et al. [79] presented the outcomes of the use of a neuro-inspired model for action choice in a human–robot collaborative situation, using dynamic neural fields. They tested the concept in a real-world construction setting in which the robot Sawyer, working alongside a human worker, chose and verbalized the next component to be installed at every stage and produced the suitable way to install it. The 2D action execution layer enabled the simultaneous visualization of the constituents and action.

3.3.5. Vision Systems in Cobots

Visual inspection in industrial applications generally can be divided into manual visual inspection and automated visual inspection. The disadvantages of manual visual inspection are that it can be monotonous, laborious, fatiguing, subjective, lacking in good reproducibility, costly to document in detail, too slow in many cases, and expensive. On the other hand, automated visual inspection shows it is more reliable if programmed accurately (although it is not expected to be error-free). It poses minimal to no safety concerns, but some operational conditions must apply.

Collaborative robots are becoming increasingly perceptive to their environment because of developments in sensors, cameras, AI, and machine vision. These advanced robots can operate more safely and effectively in specific types of workplaces due to their enhanced visibility [80]. The little end effectors and payload can nevertheless be dangerous even though they are intended for safe interaction with human staff [81]. In completely automated packing and loading systems, the cobots must be able to identify items, determine their posture in space so they may be grasped, and design pick-and-place trajectories that avoid collisions. To determine an object's posture, it is often not enough to just record raw sensor data. The data must be processed using specialized machine vision techniques [82].

Computer vision enables cobots to have a highly developed sense of perception and knowledge of their surroundings. A cobot's inbuilt sensors, including proximity, LiDAR, motion, torque, and 2D vision, all work together to make it safer on its own. Systems that employ 3D depth cameras and computer vision algorithms enable cobots to operate alongside people and have complete knowledge of their environment [83]. The summary of the state-of-art research on vision systems employed in cobots is provided in Table 6.

Table 6 summarizes the deep learning-based vision systems employed in the cobots for collaborative environments to work with human workers. A stable intelligent perceiving and planning system (IPPS) for cobots was developed by Xu et al. [84], using the deep learning method. A well-designed vision system was employed to provide a novel method of observing the environment. A hand-tracking approach, fingertip marking method, new grasping method, and trajectory planning method were also suggested. The perceivable image was utilized as input to the deep learning neural networks to implement planning. For intelligent robot planning, a vision system was created with the help of two 3D RGB cameras, a depth camera, and an eye tracker. The RGB object images from the perception process were used as the input for a convolutional neural network, and the output was the type of object that was grasped. It can be said that IPPS has undergone real-world testing and has proven to be capable of realizing intelligent perception and planning with high efficacy and stability that can satisfy the needs of intelligence. Jia et al. [85] present a deep learning-based technique for autonomous robot systems to detect computer numerical control (CNC) machines and recognize their operational status. First, a system called the SiameseRPN was suggested to recognize the target CNC device and human–machine interface (HMI). The collected, pre-processed HMI images were then utilized as sources for working status recognition. To determine the target CNC device's operational status, a unique text recognition technique was created by fusing projection-based segmentation with a convolutional recurrent neural network (CRNN). When compared to the benchmark method Faster-RCNN, the proposed method was 16.5% more accurate.

Table 6. Summary of the state-of-art research on vision systems employed in cobots.

No.	Author(s) and Year	Robot Type	Sensing Tool	Task Type	Workspace Type	Technique	Remarks
1.	Xu et al. [84], 2021	Seven DoF manipulator and three-finger robot hand	Two 3D RGB cameras, one depth camera, eye tracker	Hand tracking, environment perceiving, grasping, and trajectory planning	Collaborative	Convolutional neural network	The experiments demonstrate a decrease in planning time and length as well as a posture error, suggesting that the planning process may be more accurate and efficient.
2.	Jia et al. [85], 2022	DOBOT CR5 manipulator	Webcam with 1920 × 1080 pixels	Text recognition, working status recognition	Autonomous	Siamese region proposal network, convolutional recurrent neural network	Compared to broad object recognition, text detection and recognition are much more susceptible to image quality. Lettering may also appear blurry when an image is taken due to camera movement.
3.	Xiong et al. [86], 2022	UR5	3D camera, Basler acA2440-20gm GigE (Basler AG)	Port surgery	Collaborative	Machine vision	Throughout simulating port surgery, the cobot effectively served as a reliable scope-carrying system to deliver a steady and optimized surgical vision.
4.	Comari et al. [87], 2022	LBR iiwa has seven degrees of freedom	Laser pointer, monochrome 2D camera	Raw material feeding	Collaborative	Computer vision	The suggested robotic device can load raw ingredients autonomously into a tea-packaging machine while operating securely in the same space as human workers.
5.	Zhou et al. [88], 2022	UR5e, Robotiq 2F-85 gripper	PMD 3D camera and See3Cam 2D camera	Printing and cutting of nametags, plug-in charging	Collaborative	Point-voxel region-based CNN (PV-RCNN)	Presented a broad robotic method using a mobile manipulator that was outfitted with cameras and an adaptable gripper for automatic nametag manufacture and plug-in charging in SMEs.
6.	Ahmed Zaki et al. [89], 2022	RV-2FRB Mitsubishi industrial robot and Mitsubishi Assista cobot	Intel Realsense D435 3D stereo cameras	Industrial tasks	Collaborative	Computer vision	The implemented system, which was built on dynamic road-map technology, enables run-time trajectory planning for collision prevention between robots and human workers.
7.	Zidek et al. [90], 2021	ABB YuMi	Dual 4K e-con, Cognex 7200, and MS Hololens cameras	Assembly process	Collaborative	Deep learning (CNN)	The work discussed in this paper introduces a CNN training approach for implementing deep learning into the assisted assembly operation.
8.	Olesen et al. [91], 2020	UR5 manipulator, Schunk WSG 50-110 gripper	Intel RealSense D415 Camera, URG-04LX-UG01 scanner	Mobile phone assembly	Collaborative	CNN, YOLOv3 network	The suggested method deals with the assembly of sample phone prototypes without engaging in actual manufacturing procedures. However, the overall success rate was achieved as 47% only.
9.	Amin et al. [92], 2020	Franka Emika robot	Two Kinect V2 cameras	Human action recognition, contact detection	Collaborative	3D-CNN and 1-D CNN	The human action recognition system achieved an accuracy of 99.7% in an HRC environment using the 3D-CNN algorithm, and 96% of accuracy in physical perception using 1D-CNN.
10.	Bejarano et al. [93], 2019	A 7 DoF dual arm ABB YuMi robot	Cognex AE3 camera	Assembling a product box	Collaborative	Machine vision	The design, development, and validation of the assembly process and workstation are shown.

Xiong et al. [86] developed a cutting-edge robotic device that can identify ports and automatically position the scope in a strategic location. They carried out an initial trial to evaluate the accuracy and technical viability of this system in vitro. A cobot can locate a marker attached to the surgical port's entrance using its 3D camera and machine vision program. It can then automatically align the scope's axis with the port's longitudinal axis to provide the best possible brightness and visual observation to save the time and effort of specialists. Comari et al. [87] proposed a robotic feed system for an automatic packing machine that incorporated a serial manipulator and a mobile platform, both of which featured collaborative characteristics. To identify targets for the cobot near stationary plant components and to examine raw materials before loading operations, a vision system with a laser pointer and a monochrome 2D camera were used. To create trustworthy target objects for manipulating raw materials and interacting with static components of the fully automated production cell, appropriate computer vision techniques were used in this work. Zhou et al. [88] created a deep learning-based object detection system on 3D point clouds for a mobile collaborative manipulator to streamline small- and medium-sized enterprise (SME) operations. Robust detection and exact localization problems were addressed by the development of the 3D point cloud method. The mobile manipulator's position in relation to workstations was calibrated using the 2D camera. Utilizing the deep learning-based PV-RCNN, the identification of the targeted objects was acquired, and the localization was carried out utilizing the findings of the detection.

The implementation of a commercial collision prevention platform was proposed by Ahmed Zaki et al. [89] in order to carry out simultaneous, unplanned industrial operations including robots, cobots, and human workers. A robotic cell was deployed with two robotic manipulators. An Intel Realsense D435 camera-based 3D vision system was used to detect and recognize the products to be chosen. The implemented technology made it possible to control the two robots' real-time trajectory planning, allowing for simultaneous use of both robots even while the items to be collected were being placed onto the conveyor belt relatively closely together. A CNN training based on deep learning was employed for the aided assembly operation by Zidek et al. [90]. The approach was tested in a SMART manufacturing system with an aided assembly workstation that used cam switches as the assembling product of choice from actual production. The authors trained two CNN models (single shot detection and mask region-based CNN) using 2D images created from 3D virtual models as the training data and created a communication framework for cobots that aided in assembly operation. Olesen et al. [91] examined the advantages of integrating a collaborative robot for mobile phone assembly with a cutting-edge RGB-D imaging system and deep learning principles. To get around the difficulties in gripping the cellphone parts, a multi-gripper switching approach was put into place employing suction and several fingertips. The system employed a YOLOv3 model to identify and locate the various components, and a separate CNN to precisely adjust each component's orientation during phone assembly.

A hybrid vision safety solution was suggested by Amin et al. [92] to increase productivity and security in HRC applications by enabling the cobot to be aware of human actions by visual perception and to differentiate between deliberate and unintentional touch. The authors collected two distinct datasets from the subjects which included contact and visual information. For human action recognition they utilized 3D-CNN and for physical contact detection they utilized 1D-CNN algorithms. The authors investigated the effectiveness of these networks and provided the outcomes with the help of the Franka Emika robot and vision systems. In order to assemble a product package, Bejarano et al. [93] suggested a HRC assembly workspace made up of the ABB YuMi robot. The IRB 14000 gripper, which is outfitted with a Cognex AE3 camera, was utilized to perform image acquisition and recognition. This study also outlined the benefits and difficulties of using cobots by using an actual example of collaborative contact between a cobot and a human worker that could be used in any industrial plant. They concluded that the cobot was able to carry out a collaborated assembly process within allowable precision, coexistence, and simultaneity characteristics without endangering a human involved directly in the process.

From the above literature, a cobot now processes a substantial portion of 3D video information and responds swiftly due to sophisticated machine-vision methods and its underlying bespoke computer capability. When it notices obstacles close to its workspace, it will immediately stop moving to protect its human coworkers from damage.

4. Discussion

Robots are now able to collaborate closely with people thanks to new technology. In the previous two decades, there existed a wall separating the human workspace from where the robot was located. In the next five years, this will change because the robot will be capable of coexisting with humans in our living environments, including our homes, workplaces, and industries, and they will be ready to do so safely and securely. A new generation of robots that have sensing elements all over them, meaning their joints are independently operated, have started to appear in the last five years. As a result, if a person approaches a robot and touches it, the robot will halt as it would recognize that a person is nearby. The collision rate has been successfully decreased and the success rate has been improved with reinforcement learning comparatively without RL [63]. The work time for a robot is more than that of a human. According to Weiss et al. [64], there are presently just a few areas where cobots are used in the workplace. Cobots have not yet effectively overtaken career opportunities; rather, their use has been focused on automating simple parts of team projects. Even though robots excel at routine and tedious jobs, human workers still manage unexpected and unscheduled duties better than their computerized coworkers. In a way, people continue to be the system's most adaptable resource. HRC may be superior to solely robotic processes by utilizing the heterogeneous benefits.

The preceding section discussed the findings in five different tables (Tables 2–6). In Table 2, the discussion on the related works with the non-collaborative workspace-type robots with five articles shows that only a few of the studies that implemented cobots were not able to carry out the collaborative tasks due to safety concerns. For non-collaborative tasks, AI was employed where performance in terms of effectiveness and efficiency has improved. Table 3, which discussed 17 articles, provided a summary of the state-of-art research on collaborative workspace-type robots, where a lot of research has been carried out in making the robots do collaborative tasks of numerous kinds for industrial application. All studies employed AI methods, such as deep learning and reinforcement learning, for the design of cobots in performing several industrial activities with improved execution. The summary of the state-of-art research on industrial robots employing machine learning in Table 4 with four articles shows that the implementation of collaborative workspace robots by utilizing machine learning techniques is showing better output. Table 5 with the summary of cobot-related works without AI with five articles has shown the poor quality of performance in their output. The summary of the state-of-art research on vision systems employed in cobots with 10 articles is provided in Table 6. It shows the influence of deep learning on improving performance.

In addition, the robot's usage in collaborative research works in the last five years from Tables 2–6 is given in Figure 5.

From Figure 5, the use of robots in collaborative research work has been increasing between 2018 and 2022. Cobots provide robustness, reliability, and data analytical skills to adaptable and collaborative technology, enhancing human abilities and contributing positively to the cobot's enterprise customers.

The tasks performed by the robot in collaborative research works are given in Figure 6.

According to Figure 6, most studies utilized collaborative robots to perform the assembly tasks followed by pick and place tasks. The development of cobots is aimed at sharing a workstation with people in order to improve a workflow (co-existence) and scalable automation for different activities with human involvement (collaboration). Nevertheless, in any kind of task human behavior can be unexpected, making it challenging for robotics to interpret a person's intentions. Therefore, it is still difficult for some people and robots to work together in industry sectors.

From the analysis of the literature, it can be safely stated that quite a number of recent articles have shown the expanding role of AI on cobots. In addition, the implementation of AI on cobots has resulted in better performance as clearly stated in Section 3.

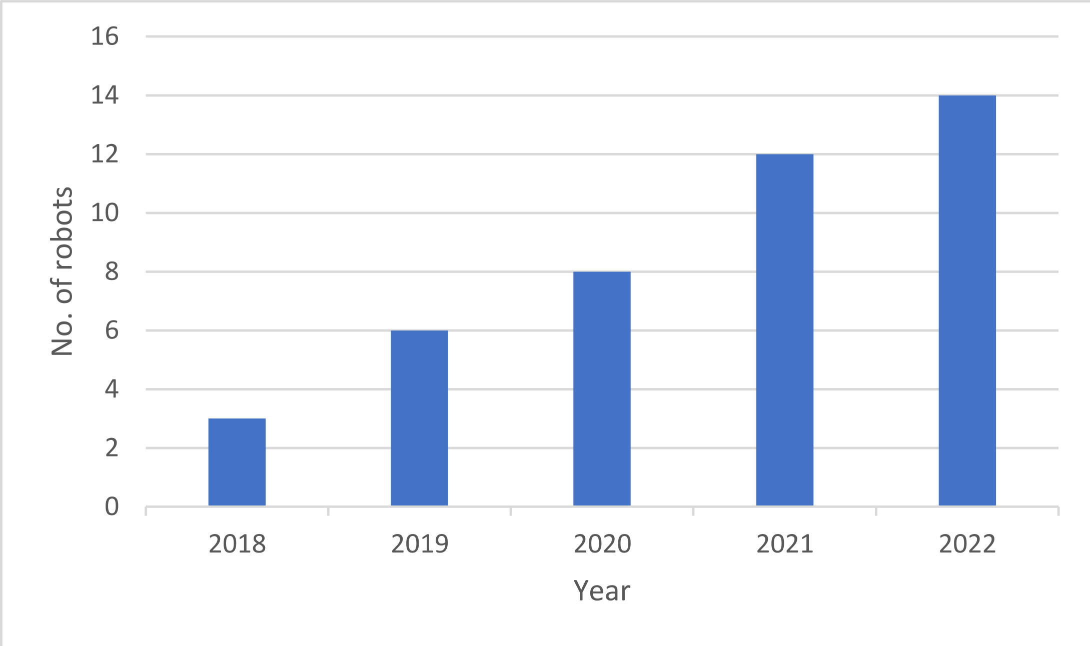

Figure 5. Robot usage in collaborative research works between 2018 and 2022.

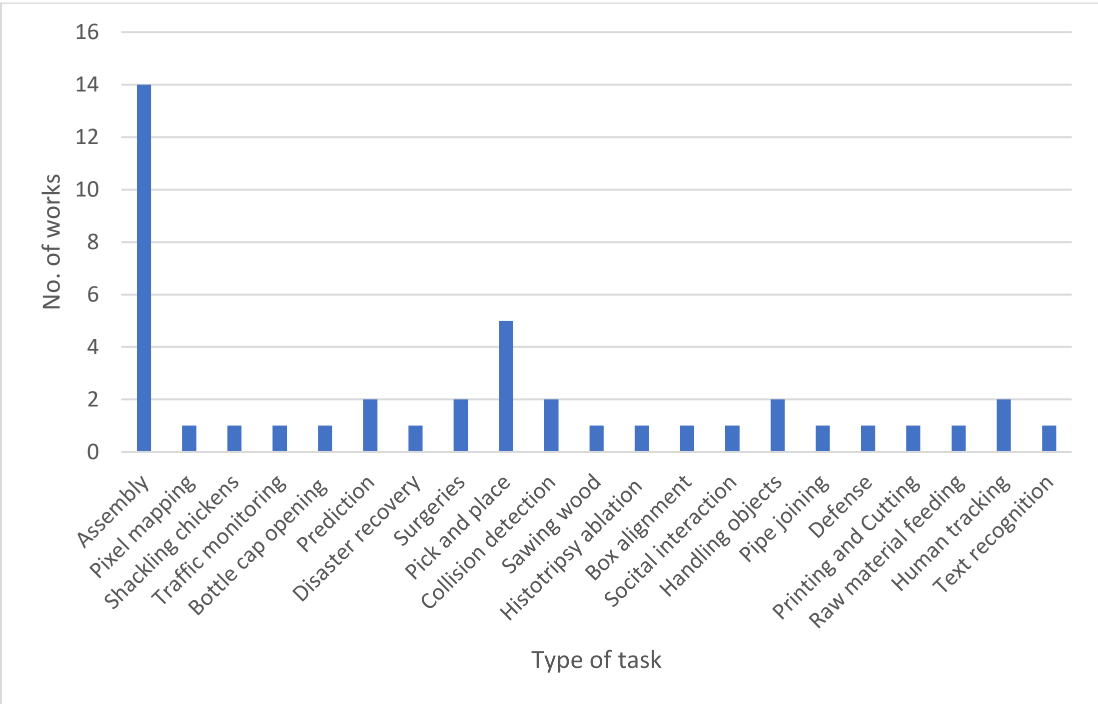

Figure 6. Tasks performed by the robot in collaborative research works.

5. Recommendations and Future Directions

The published research shows that the investigations have mostly concentrated on a particular set of fixed tasks. For dynamic circumstances with several kinds of tasks, an in-depth study is lacking. Additionally, such collaboration techniques depend on static feature-based techniques or robots that are controlled by humans. Most of the decisions are still made by the supervisor, who is still a human being, and thus the robots providing services are not cognitive. To execute the activities effectively and safely, it can be difficult to develop healthy cooperation between robots and workers. Although, if any of the commands are incorrect or missed, the cobot likely will not be able to complete the task successfully on time. In this instance, assistance from a human worker is needed, which calls for the person to be aware of the cobot's prior activities [47].

Existing deep learning techniques are not time-efficient and do not offer the essential adaptability for cobots in complicated circumstances, in which real-time robotic application is not possible. It is required to make strides in several areas, notably online deep learning for dispersed teams of cobots and human operators communicating with one another, to bring up the data-driven control systems to the next generation level. The exchange of knowledge regarding prior actions and experiences across numerous cobots is not taken into account by current technologies in order to enhance and speed up learning. To ensure each cobot will learn from both its own and the experiences of other cobots, necessitates unique distributed sensor signal processing and data aggregation across the numerous wirelessly networked robots.

The degree of autonomy in robots has recently been increased in the industrial and service sectors by using machine learning methods, which have seen a growing success rate. Most significantly, techniques utilizing reinforcement learning or learning from demonstration have produced impressive outcomes, such as training robots to carry out difficult tasks by examining the range of potential behaviors in the environment or following human instructors. However, the application of these strategies in automated robotic coding is constrained.

Reinforcement learning successfully automates the trial-and-error method by enabling the robots to continuously interact with their surroundings, which is not possible during the normal operating stage of an actual production unit. In simulated situations, RL necessitates highly precise and computationally costly simulators, so reconciling the associated gap between the simulation model and reality is regarded as an unanswered problem.

The sophisticated machine-vision methods with the use of deep learning enable cobots to have a highly developed sense of perception and knowledge of their surroundings. With these capabilities, these advanced robots can operate more safely and effectively in specific types of workplaces due to their enhanced visibility.

5.1. Advanced Autonomous Algorithms

For cobots to fully realize their enormous potential for manufacture in high-mix, low-volume production situations, cutting-edge algorithms are required. Cobots should be capable of operating without clear instructions in new circumstances. In situations where its surroundings are well known, the cobot's movement planning algorithm enables it to reach a position of the object, while collision-avoiding algorithms enable responsive behavior in environments where its surroundings are dynamic. These algorithms rely on the contextual information supplied by the cobot's sensors as it moves.

5.2. Safety Devices

It is imperative to understand, create, and verify an environment where the cobot can perform its tasks and safely coexist with humans. Several ISO-regulated requirements must be fulfilled aiming to create a stable and safe environment, such as safety-rated stop monitoring, hand guiding (teaching by demonstration), speed and separation monitoring, power and force limiting, and so on.

A technical challenge to the wider usage of robots is safety barriers. Cobots are created to meet safety standards with inherent safety designs that permit the cobot to communicate safely with human beings and handle things carefully in its workplace. Cobots incorporate adaptive elements, namely joint torque sensors, to absorb the force of unintended hits, reducing the momentum exposed to possible accidents. The development of cobots also makes use of a wide range of external sensing devices (vision systems) such as cameras, lasers, depth sensors, and so on, fusing the data obtained to enable accurate vicinity and action recognition between humans and robots.

The majority of cobots integrate the following security features, among others: firstly, when a robot detects a human entering its functional workspace, it immediately stops moving. This is known as safety-rated stop monitoring. To recognize the presence of people, it is frequently implemented by utilizing one or more sensors. Secondly, it has a hand-guiding capability that enables a human to securely train the robot to adhere to a predetermined operating trajectory. In the event of an unexpected touch, the robot will immediately decrease its force to avoid hurting the human. The safety and health of people working with robotics have been a topic of active research in recent years, and progress has been made.

6. Conclusions

It was found that based on our review of the state-of-the-art publications, various cobots have been widely applied in various areas. These areas include communication robots in public areas. These logistic or supply chain robots move materials inside a building and articulated or industrial robots assist in automating tasks that are not ergonomically sound, such as assisting individuals in carrying large parts, or assembly lines. Since the cobot and robot can both undertake similar tasks, the differences between the two approaches were demonstrated to highlight their usage and to show which is better than the other in certain scenarios. The advantages and disadvantages of cobots were discussed. Several metrics can affect the performance of the cobot, including different sensing, preprocessing techniques, and control methods. This work presents an overview of robot and cobot types, sensing or simulation tools, the task and where it can be achieved, and the types of control technology based on AI. Many reviewed studies implemented machine learning and deep learning techniques for managing the cobot task. In addition, this review discussed the outcomes of the selected papers, including the accuracy, safety issue, time delay, training process, and robot ability. Finally, this systematic review provided recommendations and future direction for the interaction between the cobot and the ever-advancing AI domain.

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