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Review

Machine Vision—Moving from Industry 4.0 to Industry 5.0

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Abstract: The Fourth Industrial Revolution combined with the advent of artificial intelligence brought significant changes to humans' daily lives. Extended research in the field has aided in both documenting and presenting these changes, giving a more general picture of this new era. This work reviews the application field of the scientific research literature on the presence of machine vision in the Fourth Industrial Revolution and the changes it brought to each sector to which it contributed, determining the exact extent of its influence. Accordingly, an attempt is made to present an overview of its use in the Fifth Industrial Revolution to identify and present the changes between the two consequent periods. This work uses the PRISMA methodology and follows the form of a Scoping Review using sources from Scopus and Google Scholar. Most publications reveal the emergence of machine vision in almost every field of human life with significant influence and performance results. Undoubtedly, this review highlights the great influence and offer of machine vision in many sectors, establishing its use and searching for more ways to use it. It is also proven that machine vision systems can help industries to gain competitive advantage in terms of better product quality, higher customer satisfaction, and improved productivity.

Keywords: machine vision; computer vision; Industry 4.0; Industry 5.0; industrial revolution; artificial intelligence

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1. Introduction

After the onset of industrial revolutions, it took several years of transition from one era to the next for each to leave its mark and progress. One hundred years passed between the first three industrial revolutions: Industry 1.0 (1784), Industry 2.0 (1870), and Industry 3.0 (1969). Moreover, 40 years passed from the Third to the Fourth Industrial Revolution (Industry 4.0 (2011)), while it is very likely that less than 40 years will pass before the transition to the Fifth Industrial Revolution (Industry 5.0) [1]. There are differences in the demands between time periods, but all focus on the aim of satisfying and serving human daily needs as best as possible. However, the trends, as well as the problems that had to be resolved with each revolution, dynamically change, forcing research to move towards new methodologies and technologies and integrate them in all sectors of daily life.

With the emergence of artificial intelligence (AI) and its integration into various intelligent robotics, the Fourth Industrial Revolution, also known as Industry 4.0, managed to trigger changes. Its need has been emphasized in multiple situations, such as that of the COVID-19 pandemic, entering every area of human life, with Industry 4.0 being more and more involved in production processes [2].

Industry 4.0 is an emerging concept that is multidisciplinary and complex [3]. Leveraging not just one, but a patchwork of technologies that can work individually as well as in combination, Industry 4.0 strives to achieve a more general digital transformation with high expectations both in the production of products and services in real-time [4]. This effort is mainly based on advanced computers with fast processors able to store, manage, process, and analyze a large amount of data, spending less time and resources than ever before.

Based on the above, Industry 4.0 offers a range of technologies to allow the remote use of devices via mobile phones or computers (Internet of Things—IoT) [5], the 3D printing of models (3D printing), processing and storage in central units (cloud computing), the automation of production and decision-making processes based on huge volumes of information (AI), smart networks, and augmented and virtual reality (AR and VR), leading to a new concept of smart industrial production based, in general, on the integration of production systems and resource planning systems [5]. In this way, smart automation and robotic machines, storage systems, and production facilities could communicate, actuate, control, and monitor each other autonomously [6]. Therefore, traditional production methods are replaced by new methods with more intelligent production, as machines are considered to have properties such as self-awareness, self-prediction, self-comparison, self-configuration, self-maintenance, organization, and resilience [7].

Industry 4.0, therefore, is coming to replace traditional manufacturing methods based on machine vision. Machine vision, being an AI technology, aims to overcome traditional production methods and help towards the implementation of the "smart" factory logic adopted by this technological period, as well as to confront the problems that may arise, eliminating all possible costs and, at the same time, triggering scientific and research interest. After all, Industry 4.0 belongs to a dynamic strategy of intelligent production, which allows computers and machines to "see" the world through the extraction, processing, and analysis of visual knowledge [8–10]. Industry 4.0 tends to limit human intervention, as well as any biased decision making in quality control [11], to upgrade decision-making and production processes, offering immense help in problems of traceability, classification, detection, identification, etc.

Industry 5.0 is going to use the creativity of specialized people so that they can cooperate better with intelligent and precise machines [12]. Industry 5.0 marks an era where the goal is for machines and human resources to work together to the best of their abilities for the best possible exploitation of the advantages of both technologies and service provision to increase production at a rapid pace. Thus, everything traditional, but also autonomous, will be modernized by integrating technologies such as *machine vision*.

To this end, machine vision is a supporting technology that is increasingly involved in various sectors. Thus, it deserves the necessary attention towards defining both its role in the Fourth Industrial Revolution, and its involvement in the emerging Fifth Industrial Revolution. Comprehensive insights about its progress, development, and its existence in general should be offered.

Based on the above, the contribution of this work includes a comprehensive overview of the scope of machine vision in Industry 4.0 and Industry 5.0 that has not yet been reported in any previous works to the best of the authors' knowledge, providing comparative results. Three research questions were raised to guide the research, justify the conclusions, and raise concerns about subsequent research questions and gaps at a research and scientific level. PRISMA-ScR was used to conduct a scoping literature review, fully covering the importance of machine vision in the periods under investigation. In addition, all research findings were analyzed and visualized for a more comprehensive comparison, and each research question was answered and discussed in detail, as defined by the proposed methodology.

The rest of the paper is organized as follows. Section 2 is an introductory section, including the fundamentals of machine vision and the specific periods under investigation. Section 3 includes the research questions, as supported by the chosen methodology, as well as the details of the conducted research and the characteristics of the collected papers. Section 4 presents the results of our scoping review. Section 5 includes a summary of the highlights of the conducted research. Finally, Section 6 concludes the paper.

2. Foundations

In this section, an overview of the contribution of machine vision to several sectors of human life over the years takes place. Industry 4.0 and Industry 5.0 are defined, and related works on the subject are overviewed to underline the contribution of this work.

2.1. Machine Vision

Vision is considered one of the most important human senses; it helps people perceive everything around them differently. The value and importance of vision has always been invaluable. For this reason, researchers since the 1980s have been working on providing machines with this ability, to see and perceive their surroundings, creating a research field widely known as “machine vision”. Machine vision systems can provide numerous automation options to variable manufacturing industries in a fast, efficient, and constant manner. Therefore, the term “machine vision” was directly linked to industry in general but more specifically to electrical engineering and robotics. Later, the term “computer vision” was introduced, but it was not long before both terms were merged into a common scientific field, that of AI, offering countless considerations for their use.

Machine vision, being a scientific subfield of AI, specifically tries to reproduce the sense of vision for machines through algorithms, covering areas even wider than human vision, namely from gamma rays to radio waves [13]. This reproduction is carried out in computers or robots. With the help of image sensors, digital visual data are obtained in diverse modalities such as images, videos, multidimensional images, etc., and along with supporting technologies such as image processing algorithms and communications, machine vision systems are created [14].

Machine vision systems in industry mostly consist of numerous cameras, which are placed according to existing requirements on assembly lines for product observation and data collection. They also provide the ability to read labels and automatically sort products without human intervention. Humans may be prone to errors due to tiredness and lack of adequate expertise. Consistency of automations combined with reduced human participation results in decreased errors and greater accuracy of detection, identification, supervision, measurements, etc. According to Javaid et al. [15], one of the reasons why the need for machine vision is crucial is because machines, systems, and robots have the ability to observe, communicate, and work with more precision, providing more opportunities.

The first milestone for machine vision was in the 1950s, where Gibson developed optical flow of two-dimension imaging towards statistical pattern recognition [16]. In the 1960s, Roberts was the first to formally study 3D machine vision in his PhD thesis at MIT [17]. In the 1970s, Marr from MIT developed an approach for scene understanding through computer vision, marking the beginning of real-word object tracking and low-level vision tasks such as detection and segmentation [18]. The development of both smart cameras and optical character recognition systems, in the 1980s, triggered the wide use of machine vision in ever increasing applications, starting from industrial ones, aiming to read letters and numbers to facilitate shorting and other product-related tasks. In the 1990s, machine vision invaded the industrial environments; companies started to sell commercial machine vision systems, while further technological advances were made from that time onwards, in terms of sensor functions, control architectures, and automation. The latter, along with the decrease in acquisition costs for machine vision systems, making them accessible to everyone, offered enhanced possibilities for machine vision systems to further advance. Therefore, since the early 1990s, machine vision has been developing rapidly. It has been closely connected to the cognitive field of machine learning and vision algorithms performed in real-time, providing significant results in a multitude of critical applications.

In the 1990s, thousands of factories worldwide included machine vision systems in their production lines to automate many of their operations.

Over the years, both machine vision algorithms and systems have been playing a key role in increasing industries’ financial analytics incrementally in every report or sales survey. In 2017, the share of financial transactions in North America increased by 14.6% compared to the turnover of the previous year. After 5 years, in the year 2022, the global machine vision market was estimated at USD 16.89 billion, while it is estimated to grow by 11.3% within the next seven years (2023–2030), as illustrated in Figure 1 [19].

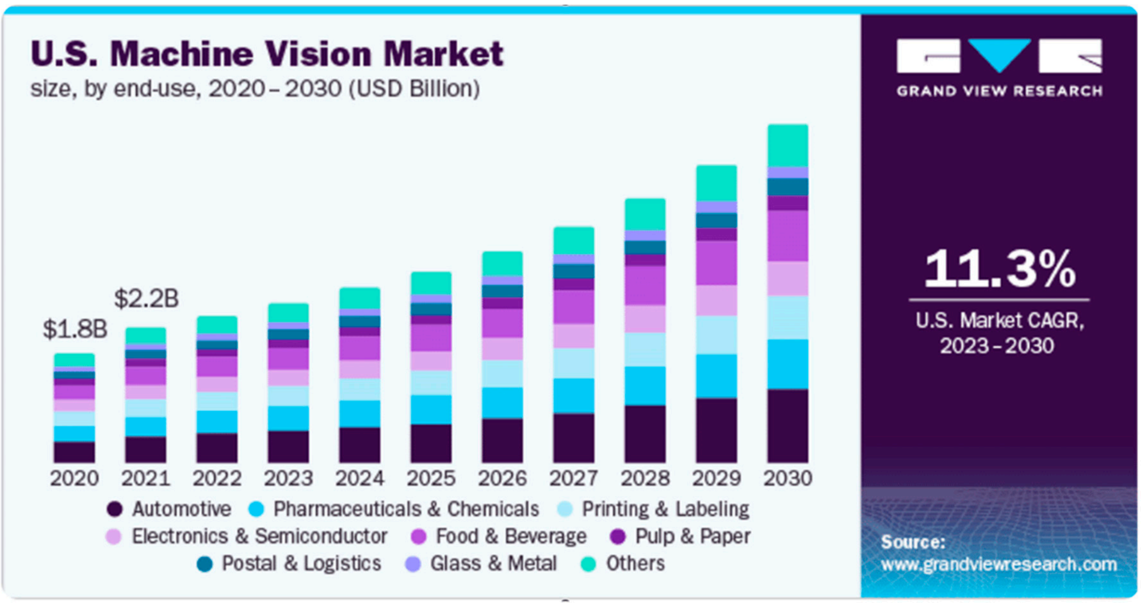

Figure 1. US machine vision market [19], available at https://www.grandviewresearch.com/industry-analysis/machine-vision-market (accessed on 5 February 2024).

More recently, machine vision combined with the advancements of the Industrial Internet of Things (IIoT) brought significant changes in the industrial settings. The IioT network can efficiently collect and analyze data from several machines, leading to high-quality production at reduced costs. In addition, when machine vision is embedded in industrial devices connected to IioT, images collected by machines can be used in operation monitoring, computation, and intelligent decision making [20–27]. In particular, machine vision both individually and in combination with other technologies helps to perform a specific task at a time. In the industrial field, the use of machine vision is for the purpose of solving problems of detection, classification, identification, material quality, control, monitoring, maintenance, storage, etc. In fact, the correct exploitation and processing of data coming from connected objects/elements in the production line enables fast, flexible, and more efficient product management, providing products of higher specifications at the lowest possible cost [28].

In order to understand the contribution of machine vision, it is worth presenting its use through specific examples. One example would be its use in problems that require classification and detection, using a deep learning model. In [29], for real-time tile detection in a production line, a deep model was trained with 30,000 images. The model returned better results for tile quality assessment compared to manual processes. Another example could be that of the identification and detection of the textures, decorations, and other characteristics of an ancient building studied in [30]. The manual process would require a lot of time and effort. The authors suggested an approach using a machine vision system, deep learning, and a convolutional neural network to classify building images, resulting in high detection accuracy rates. It is also worth mentioning the effort to build a visual detection platform, where, by photographing certain products, it is possible to directly match them with cloud storage data [31]. In fact, in the context of its transition to production mode, a method of directly creating matching templates using 3D cloud product models is also proposed [31].

Detection of defective materials on the production line can also be performed by using machine vision. Bianconi et al. [32] tested their algorithm on nine image datasets including seven material classes (carpet, concrete, fabric, fused lamination, leather, paper, and wood) of regular and defective samples, outperforming traditional detection methods.

Maintenance of machinery is also a big issue in industrial production. Predictive maintenance can be performed by combining machine vision and neural network models [33].

Low-cost cameras can efficiently support predictive maintenance in industry, at an ever-decreasing cost.

The ability to monitor manual work is also an important aspect of smart industry based on machine vision. Oyekan et al. [34], in the assembly processes in a production line, employed an RGB-D camera, such as a Kinect camera, along with machine vision techniques to acquire big data in real time, towards improving the production line and enabling a more flexible construction.

A factory's warehouse stocking and inventory operations are largely completed manually by warehouse personnel with a high workload and high risk of error rates. A machine vision-based inventory consisting of a surface detection model of stacked products combined with a quantity calculation algorithm managed to perform better than the traditional manual way of working [35]. Another smart warehouse 4.0 approach suggests the combination of machine vision with the Internet of Things (IoT) [36].

Finally, quality control of production products is an important, time-consuming, but also crucial process for the entire production line. Machine vision managed to automate quality control in a reliable and effective way. A typical example is its use in the automotive industry in quality control of catalytic converters [37], but also in non-contact quality control of welded joints in welding productions in various industries [38].

To this end, it is evident from all aforementioned examples that machine vision is a technology whose size and scope of use in industry are enormous, and its contribution seems to be decisive for many areas of human life.

2.2. Industry 4.0

The Fourth Industrial Revolution, also known as Industry 4.0, was first introduced in 2011, promoting a new idea, that of a 'Smart Factory', where autonomy in all its aspects would be one of its main characteristics [39]. In fact, production systems would be able to make intelligent decisions in real time. It also came to shape the developments in the social as well as the working sector. The human workers could interact more with technology, which was more open, augmented, and also virtual [6]. The need for more human-centered approaches in the context of this era was evident [40]. Figure 2 illustrates industrial revolutions from the first to the fourth, along with their main characteristics.

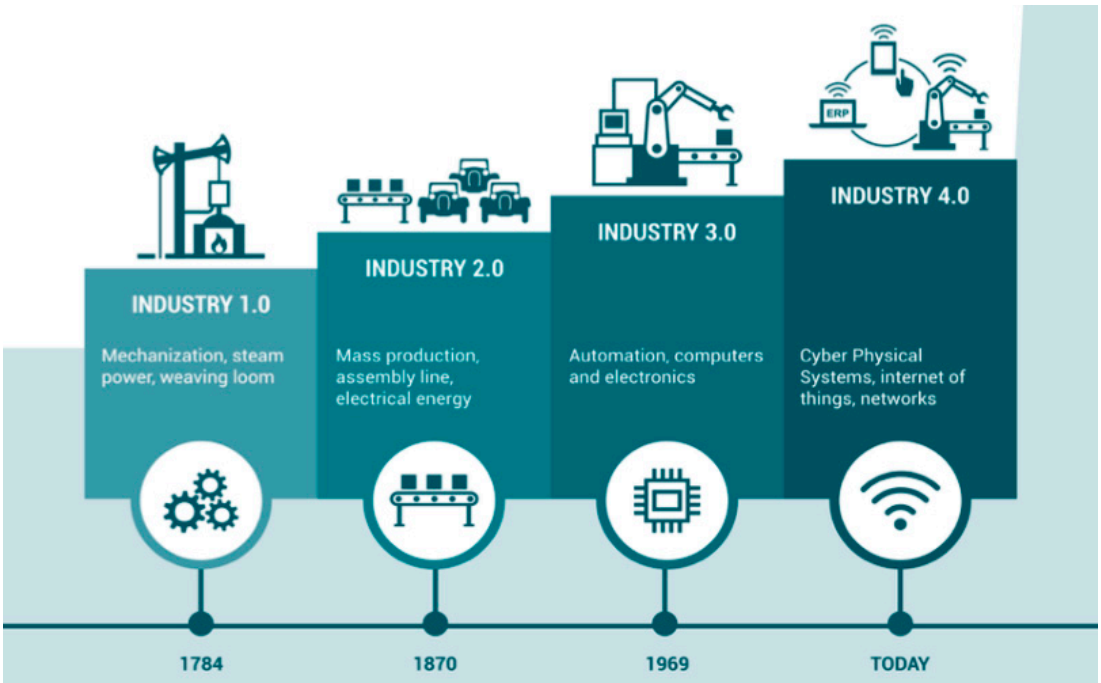

Figure 2. The four industrial revolutions [41] are available at https://www.finite.com.au/blog/2018/11/fourth-industrial-revolution/ (accessed on 5 February 2024).

In Industry 4.0, automation seems to play a decisive role. The appearance of robots combined with many novel technologies came to meliorate all aspects of human life, including industrial automation. The concept of human–robot collaboration (HRC) is critical in modern smart manufacturing. In particular, it was stated that the new vision of this era is a production environment that mainly includes machine-to-machine communication, networking, productivity, and intelligence without human intervention [42]. Moreover, this new era includes reducing production costs, saving time, and increasing production and precision in the quality of final products, while ensuring maximum worker safety in dangerous industrial environments [43].

The main possibility of this era, however, is the constructive cooperation of computers and machines, so that after storing, managing, and processing a large amount of information, they allow efficient decision making without human intervention [44]. With AI, robotics, IoT, AR and VR, 3D printers, neural networks, cyber-physical systems, cloud computing, and many other technologies, new possibilities and perspectives are emerging, towards changing the concept of time [45], as well as the spiritual and living standards of humans in a more autonomous and intelligent era.

2.3. Industry 5.0

While one would expect that the end of one era would bring the beginning of another, this is not the case with the era of Industry 5.0. Already, within ten years of the advent of Industry 4.0, the European Commission brought to the fore and talked about Industry 5.0, outlining a series of implementation strategies from investment, marketing, and governance dimensions to promote it [46]. Until now, the response from other governments and industries is still limited. However, academia quickly embraced Industry 5.0; the Journal of Manufacturing Systems, the International Journal of Production Research, and the IEEE Transactions on Industrial Informatics established related special topics to encourage Industry 5.0 research in 2021. The Technical Committee (TC) on Digital Manufacturing and Human-Centered Automation also highlighted its relevance to Industry 5.0 [47]. Future technologies of Industry 5.0 (Figure 3) are summarized in the following:

- Personalized human–machine interaction technologies that interconnect and combine the advantages of both humans and machines.
- Bio-inspired technologies and smart materials, which enable recyclable materials with built-in sensors and improved features.
- Digital twins and simulation to achieve modelling of entire systems.
- Technologies related to transmission, storage, and analysis of data, with data processing and system interoperability.
- Artificial intelligence to detect losses in complex dynamic systems, leading to actionable insights.
- Environmentally friendly technologies (energy efficiency, renewable energy sources, storage, and autonomy).

Based on the above, it appears that the advent of Industry 5.0 is not just a technology-driven revolution, but is driven by values that will lead to purposeful technological transformation [48].

In Industry 5.0, operators and robots come together and collaborate to implement complex projects in a variety of scenarios with heterogeneous and dynamic conditions. Humans can work interactively with robots, by assigning them to repetitive or dangerous tasks. Less physical work and more safety are therefore guaranteed for human workers [49].

In the development of these models, a decisive and unique role is played by machine vision as a means of sensing, providing reception and processing of visual information about the environment, analysis of images of the workplace, transfer of relevant information to the control center, and decision making. In this way, the task of recognizing the actions of a human operator, in order to apply the extracted knowledge towards an effective human–robot cooperation system, becomes important [50].

Figure 3. The future technologies of Industry 5.0 [46].

A typical example of the above collaboration between humans and robots is provided by Wagner et al. [51] for an Industry 5.0 application of an end-to-end edge system based on machine vision. More specifically, a machine vision system is presented, which relies on cloud services for data storage and training of AI-based models, for the application of bin collection in industrial facilities. The system is intended to work with Universal Robots Collaborative Robots, namely cobots. In industry, bin collection refers to picking and moving objects (bins) to predetermined locations within the cobot's work area. In the case study of Wagner et al. [51], the robot is constantly encountering objects it has never seen before; thus, it needs to learn them. The new objects are displayed to the robot by the human operator, posing an incremental learning challenge, towards automatically labeling the new training data to avoid time-consuming and expensive labeling processes.

Typical development of an object detection system involves training a model on a dataset in the cloud. After the model is successfully trained, it is used on an edge device in the production line. However, there are several cases where the system should learn new objects in the production line, without forgetting the previous ones [52]. Wang et al. [52] in their study used 100 photos to train the model and 25 photos for each old object. The proposed system, by retraining on a small set of samples, managed to achieve high-quality performance using all-in-one and stepwise learning.

Extended Reality (XR) includes various technologies (augmented, virtual, and mixed reality). Mixed reality in particular is a key technological component of Industry 5.0. The results of the use of augmented reality are improved customer experience, advanced training (industrial and academic), immediate ability to diagnose faults in industries, and improved safety in industrial settings [53].

2.4. Related Works

Although there are various works in the literature that mention the use of machine vision in Industry 4.0 and Industry 5.0, nevertheless, there are no works that compare these two periods in depth with the technology in question in focus. In particular, most referenced works for both periods focus on different issues or innovations, but not specifically on the use of machine vision. Some works discuss the issue of the smooth coexistence of full automation with human presentation [54,55], while others refer to all the technologies involved from one era to another to present the new transformation towards an era of great promise for humans [56,57]. Additionally, there are works that refer to all the challenges and opportunities that are going to arise from the coming together of these two eras [58]. The latter observation is mainly because Industry 5.0 is a period that it is expected to make its appearance, using many technologies of Industry 4.0, but without showing or explicitly mentioning their use in all sectors yet.

To this end, not having reference research on the presence of machine vision in both industrial eras, an attempt was made in this work to carry out an extensive bibliographic review, to present the involvement of machine vision in Industry 4.0 as well in Industry 5.0 and present an in-depth comparison. Our research was conducted on eighty-seven related papers on Industry 4.0 and seven on Industry 5.0. We thoroughly focused on Industry 4.0 and on the sectors that machine vision was applied to, and correspondingly did the same for Industry 5.0 in order to better understand the evolution of the involved technologies as well as the differences between the two industrial revolutions.

3. Materials and Methods

3.1. Research Questions and Protocol

The present review aims to provide a specific view and more general conclusions regarding the involvement of machine vision in Industry 4.0 and 5.0, based on existing works, towards urging the scientific community towards further reflection.

The research questions (RQs) that guided the research are formulated as follows:

- RQ1: In what sectors of Industry 4.0 did machine vision contribute?
- RQ2: What is the use of machine vision in Industry 4.0?
- RQ3: How did machine vision start to contribute from Industry 4.0 to Industry 5.0 and how it is expected to further contribute to Industry 5.0 in the future?

The application of machine vision in Industry 4.0 is found in various sectors of industry, and for this reason, we chose to conduct a scoping review method instead of a systematic review; the systematic review method is considered a more valid approach to a question concerning research into the appropriateness or effectiveness of a specific practice, while the scoping review method is exploratory and examines a broad question and is considered a more valid approach for identifying certain characteristics and mapping, reference, or discussion of these features [59]. The present study was developed using the PRISMA methodology [60] and specifically PRISMA-ScR, which is an extension for scoping reviews [61]. PRISMA has become one of the most cited reported guidelines in the literature and was adopted in this work due to its ability to produce a transparent and thorough scoping review that can easily be replicated, providing confidence in the extracted results.

3.2. Research Methodology

The literature selection criteria were based on the requirement that the selected works include references to machine vision, with a primary focus on the context of Industry 4.0 and the anticipated developments in Industry 5.0. Selected papers were conference papers or journal articles published up to the date of our search query (21 May 2023), written in the English language. The latter selection was due to the fact that journal articles contain completed research, have undergone extended review by experts in the field, and are the most cited document types. While journal articles typically stand first in the hierarchy of recognition, conference proceedings follow as the second most cited document type, presenting valuable insights in specific fields of interest. Moreover, papers in the English language were selected as being of a more general scientific interest due to language limitations from the authors. Papers that did not meet the eligibility criteria were excluded. The research works that were not supported by any scientific background or were published without evaluation were also excluded. Finally, grey literature, such as reports, working papers, government documents, white papers and evaluations, works that did not explicitly refer to the selected time period, as well as works with a more general use of machine vision, were not included in our research.

The research for related papers was conducted in the bibliographic databases of Scopus and Google Scholar. More weight was given to Scopus since it contained papers, articles, and reports from important libraries in the scientific and research field such as Springer, IEEE, Elsevier, etc. In addition, the possibility that Scopus gives for more complex and precise searches with the criteria we set has the effect of prevailing in the number of selected documents [62]. The first query posed to Scopus on 21 May 2023, was as follows:

`TITLE-ABS-KEY (‘‘machine vision’’ AND (‘‘industry 4.0’’ OR ‘‘4.0’’ OR ‘‘industry 5.0’’ OR ‘‘5.0’’))`

The search on Google Scholar was conducted on the same day as Scopus, using the following keywords:

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All_in_title:  Machine vision and Industry 4.0
All_in_title:  Machine vision and Industry 5.0
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Due to the fact that the results related to Industry 5.0 were almost zero in the first Scopus research, in a subsequent step, the Scopus searches were formulated more precisely. The queries were as follows:

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TITLE-ABS-KEY(‘‘MANUFACTURING INDUSTRY’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY (‘‘METRICATION’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY (‘‘MINING INDUSTRIES’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘MACHINING’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘MECHATRONIC ROBOTS’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘METALLURGICAL INDUSTRY’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY (‘‘CONSTRUCTION INDUSTRY’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘AUTOMOTIVE INDUSTRY’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘MEAT INDUSTRY’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘MANUAL WORK’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘HEALTHCARE’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘PHARMACEUTICAL COMPANIES’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘AGRICULTURE’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘SPORTS’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘ROAD NETWORK’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘3D PRINTING’’ AND ‘‘INDUSTRY 5.0’’)
TITLE-ABS-KEY(‘‘EDUCATION’’ AND ‘‘INDUSTRY 5.0’’)
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We also used a more general query:

`TITLE-ABS-KEY ((‘‘MACHINE VISION’’ AND ‘‘INDUSTRY 5.0’’) AND (‘‘COMPUTER VISION’’ AND ‘‘INDUSTRY 5.0’’))`

3.3. Data Synthesis

Initially, it was necessary to carry out a mapping of the data, in order to ensure the selection of appropriate papers. The mapping was performed based on the criteria below:

- The year of publication.
- The type of source (journal articles and conference papers).
- The article publisher.
- The reference language.

Then, weight was given to keywords related to the topic under study. During this process, the following aspects were taken under consideration:

- Conceptual approach: An idea or attempt or implementation of using the specific technology of our topic, i.e., machine vision, as mentioned in the various studies.
- Area of interest: Specific field or area, where the contribution of machine vision through specific efforts/applications is mentioned.
- Period of use: In what period was the technology of interest developed/implemented/used (Industry 4.0 or 5.0)?
- Purpose of using machine vision: What is the reason for using this particular technology?

In order to synthesize the final results, it was necessary to group the studies based on the reference topic and the reference periods. Any studies that simply referred to machine vision or simply to Industry 4.0 or 5.0 were not included in the conducted research, so they were excluded from the count, but their number was recorded. Various demographics such as year, type of source, sector, and purpose of use were also weighted for both periods to provide a more complete picture of the data. An attempt was made to group the results so that, through analysis and diagrams, there would be a better visualization and understanding of them.

All paper abstracts were thoroughly examined so that none were excluded by their title, lest we lose valuable information on the subject. In addition, duplicated papers were examined in order to ensure consistency in the statistics and results, which were based on percentages and numbers. Finally, for the conclusions and each research question, an attempt was made to provide data and information from various sources, so that there is a more complete picture of the subject under study.

The results from Scopus were retrieved in Bibtex format and later saved in a CSV file. By using the Publish and Perish tool, the files from Google Scholar were retrieved in the same format. For bibliography management, the Zotero open-source bibliography reference manager was used. Any processing of the results and the illustrations of diagrams were carried out in version 2401 of EXCEL in Microsoft 365.

4. Results

4.1. Research Data

A total of 331 documents were retrieved for the present study (321 from Scopus and 10 from Google Scholar). Initially, a check was carried out for the existence of any duplicate records. After the first approach, 151 documents were excluded due to the following reasons: they did not relate to the topic, were not written in English, were not scientific papers, were simply discussion papers, or they were not accessible. In the end, the number of records was limited to 180. During the second screening, and with a more thorough look, 86 more papers were removed, since they did not comply with the specific research questions we posed and constituted a more general framework of the subject of interest. The remaining 94 research papers were ultimately included in our scoping review. The research process is illustrated in Figure 4.

Figure 5 captures the annual interest in machine vision in Industry 4.0. Apparently, there has been an increase in research interest in the subject in the most recent years. The subject was first time introduced in 2015 with only one reported paper, followed by two in 2016, four in 2017, and seven in 2018, while from 2019, the number of papers started to rise exponentially, with seventeen in 2019, twenty-nine in 2020, twenty-seven in 2021, thirty-nine in 2022, and five until the end of May 2023.

The corresponding annual distribution of papers on machine vision in Industry 5.0 is depicted in Figure 6. As can be observed, there has been an increase in research interest in Industry 5.0 in the last couple of years. More specifically, machine vision in Industry 5.0 was first introduced in 2018 with one paper referring to the subject, two papers in 2019, five in 2020, seventeen in 2021, sixty-four in 2022, and sixty-one already by the end of May 2023.

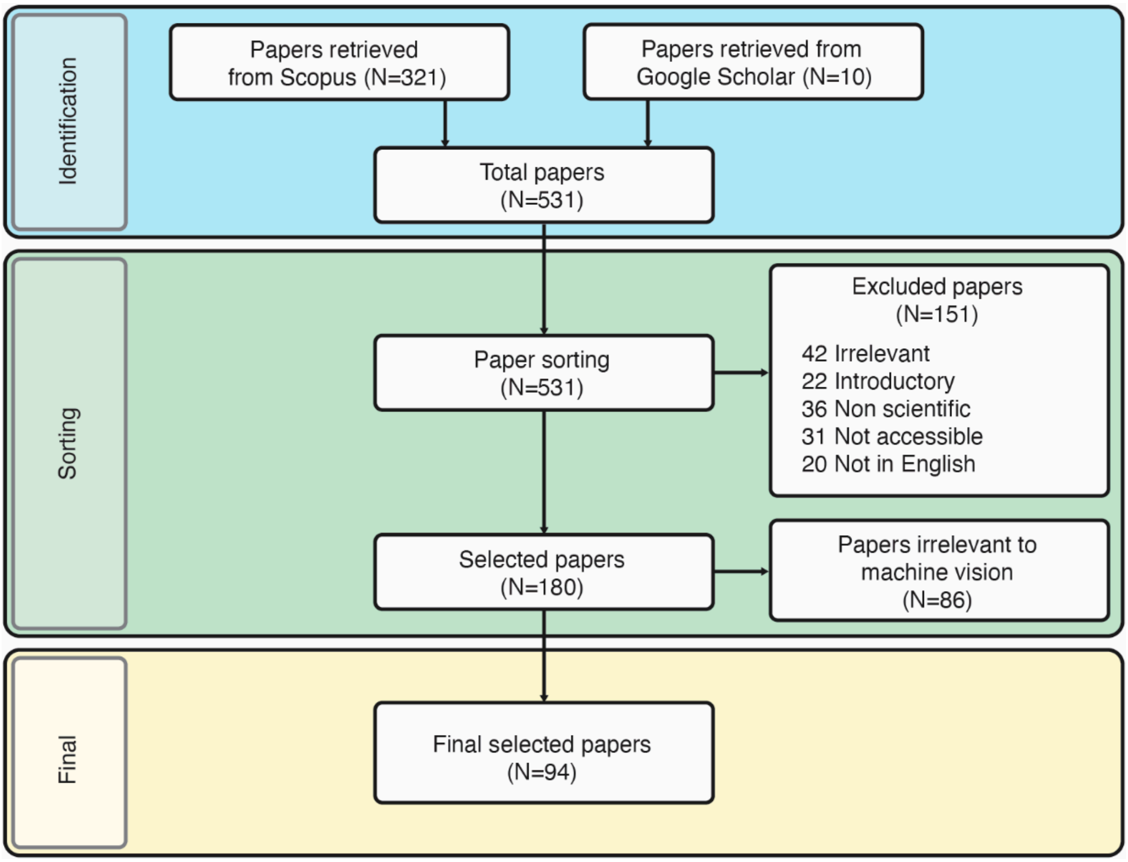

Figure 4. Selection of research data.

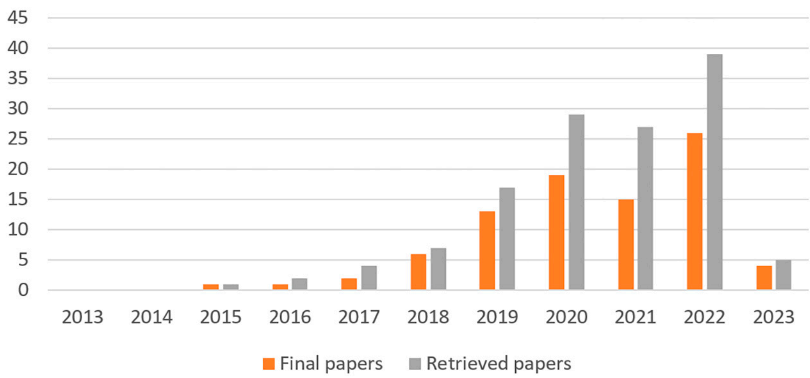

Figure 5. Total retrieved papers and final selected papers on machine vision in Industry 4.0 per year.

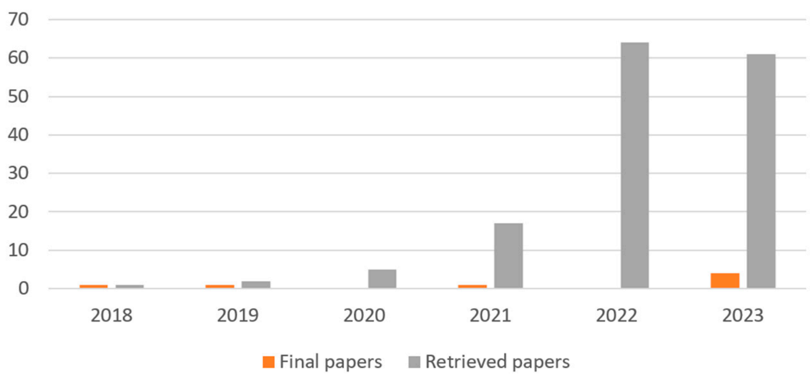

Figure 6. Total retrieved papers and final selected papers on machine vision in Industry 5.0 per year.

From the retrieved papers and for reasons either of inaccessibility or due to the more general interest of the papers not focusing on the subject under study, the final papers were distributed as follows. For Industry 4.0, there was one paper in 2015, one in 2016, two in 2017, six in 2018, thirteen in 2019, nineteen in 2020, fifteen in 2021, twenty-six in 2022, and four until May 2023. Accordingly, for Industry 5.0, there was one paper in 2018, one in 2019, none in 2020, one in 2021, none in 2022, and four until May 2023.

Figure 7a illustrates the number of papers on Industry 4.0 per publisher that were ultimately included in the scoping review. Elsevier and Springer each contain 20.69% (18 papers each) of all relevant papers. Other publishers that appear very often are IEEE with 19.54% (seventeen papers) and MDPI with 8.05% (seven papers). Finally, 27 papers (31.03%) have been published by various other publishers, showing that the interest is not only limited to specific publishers, but it is more general. Figure 7b depicts the same information for Industry 5.0; MDPI ranks first with 28.6% (two papers), followed by various other publishers with 14.28% each.

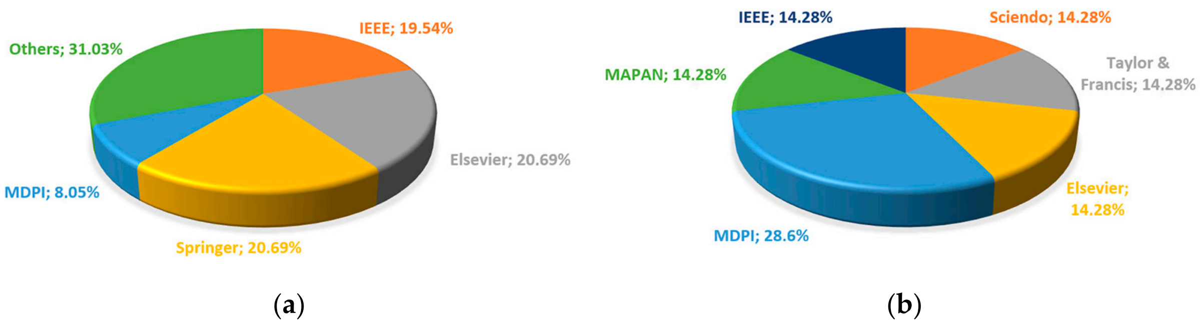

Figure 7. Distribution of final selected papers per publisher referring to machine vision in (**a**) Industry 4.0; (**b**) Industry 5.0.

4.2. Data Characteristics and Synthesis of Results

The findings pertaining to the research queries are analyzed below, accompanied by relevant diagrams. These visual aids serve to facilitate a comprehensive analysis and a more intricate portrayal of the responses to the research queries, along with comparisons between the two industrial revolutions. The following analysis concerns eighty-seven papers related to Industry 4.0 and seven papers related to Industry 5.0. Details of the referenced papers for both industrial revolutions are included in Tables 1 and 2 at the end of this section.

Regarding the first research question (RQ1) about the sectors where machine vision contributed during Industry 4.0, the results are included in Figure 8. Most machine vision applications in Industry 4.0 concern Industries/Factories, with a great percentage referring to the manufacturing and automotive industries. Next come Robots, using machine vision for the execution of specific tasks. The agricultural sector and education follow. While the above-mentioned sectors are the most popular, there are several more sectors that took advantage of machine vision enhancements and contributed to Industry 4.0: Construction Sector, Metrology, Infrastructure Projects, Telecommunications, Stores, Printing Companies, Transportation, Sports, Mechatronics, Architecture, as well as entertainment.

Regarding the second research question (RQ2) about the reasons for using machine vision in Industry 4.0, the results are summarized in Figure 9. According to the figure, we observe that, in the largest percentage of applications, 9%, corresponding to 25 reference works, machine vision is mainly used for quality control, while with 24% and 21 reference papers, it is used for monitoring some object/product. Moreover, it can be used for detection purposes (21%), e.g., defect or anomaly detection in a product. Then follows the recognition task with 10%, e.g., the identification of a certain variety of products, for product separation, etc. Other applications refer to product counting for inventory purposes, as well as for specific tasks of classification and evaluation.

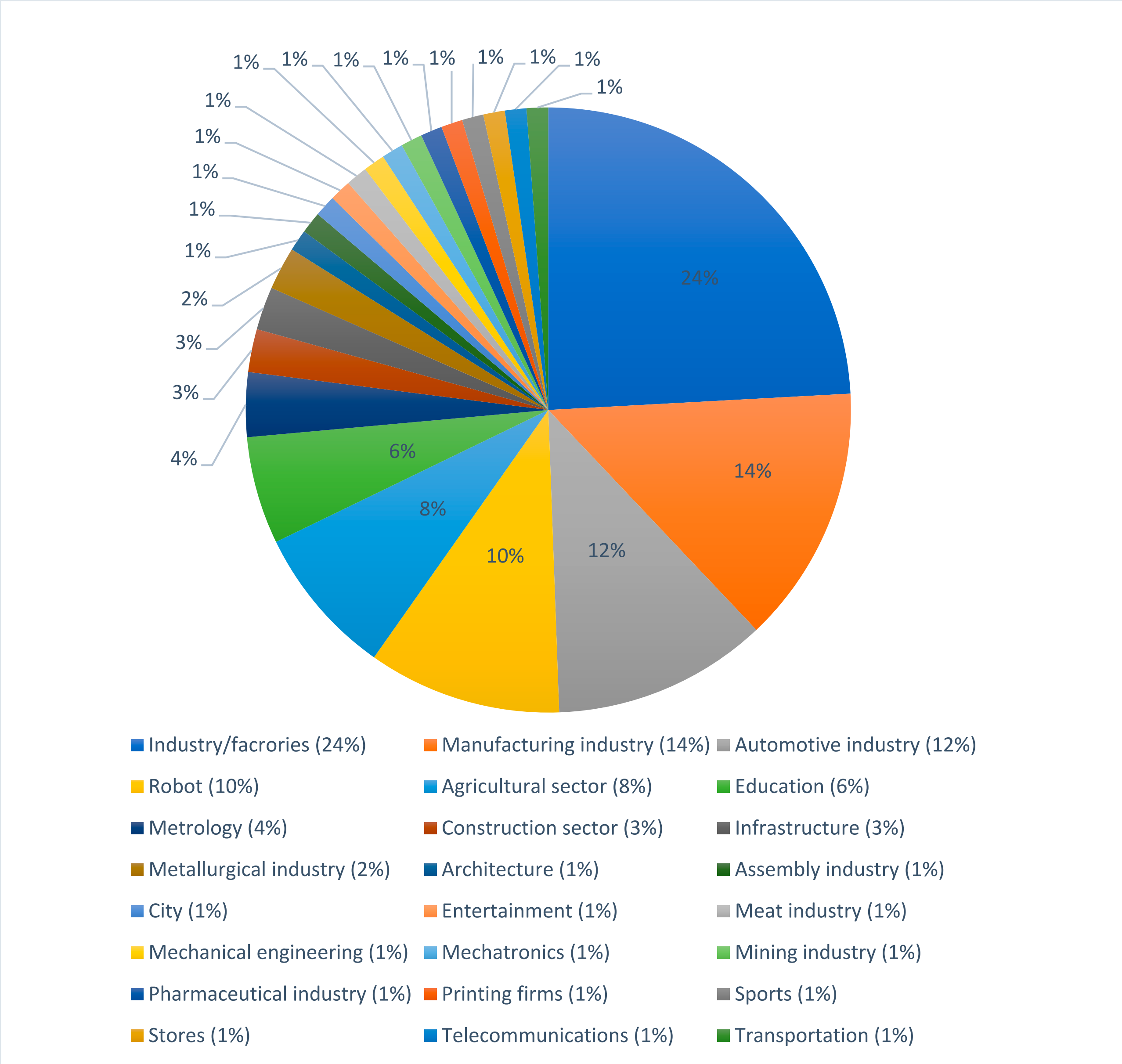

Figure 8. Application sectors of machine vision in Industry 4.0.

Regarding the last research question (RQ3), referring to the contribution of machine vision in Industry 5.0, results are presented in Figure 10. At this point, it should be clarified that the search was carried out in the form of "Specific Sector" and "Industry 5.0" (e.g., `ABS(''MANUFACTURING INDUSTRY'' AND ''INDUSTRY 5.0''))`, as well as a general query (e.g., `ABS(''MACHINE VISION'' AND ''INDUSTRY 5.0'')` and `ABS(''COMPUTER VISION'' AND ''INDUSTRY 5.0''))`. Searches were performed for 17 different sectors, for which the use of machine vision in Industry 4.0 had already been reported, and a total of 150 results were obtained. Out of these results, only seven mentioned/proposed the use of machine vision in Industry 5.0, two in the Manufacturing sector (29%), two in the Health sector (29%), two in Industries/Factories sectors (29%), and one in the Agricultural sector (13%).

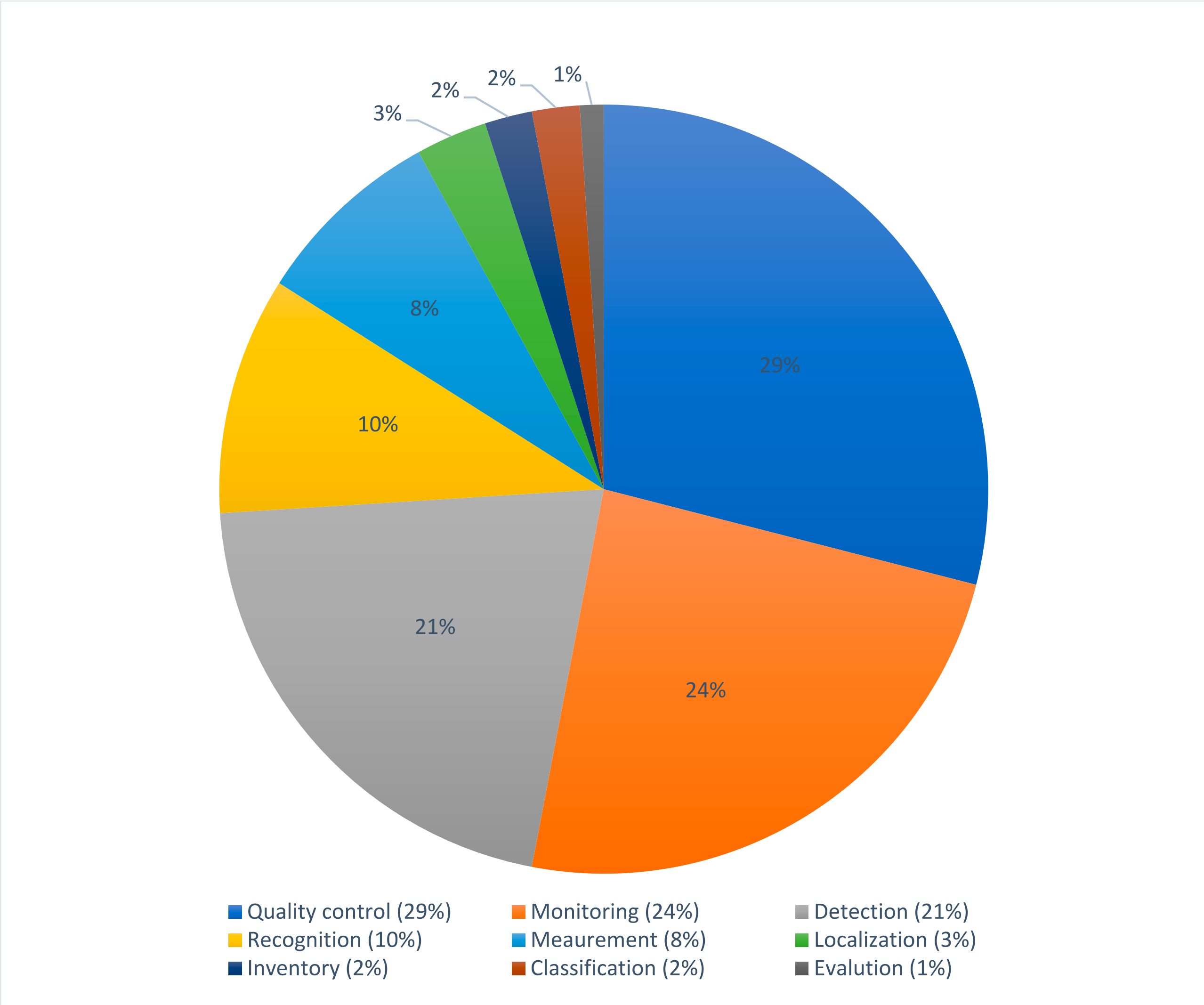

Figure 9. Use of machine vision in Industry 4.0.

Regarding the reasons for using machine vision in Industry 5.0, seven different uses were reported, grouped into four main categories, as can be observed in Figure 11:

- Camera observation and image processing using machine learning by cooperative robots (cobots).
- Advanced training, instant fault diagnosis, and improved safety using Extended Reality (XR).
- Detecting objects and training robots to recognize them.
- Imaging (which will lead to a reduction in the cost of magnetic resonance imaging (MRI) scans).
- Remote monitoring and examination of patients with eye diseases and remote ophthalmic surgery.
- Data collection (in agriculture).
- Automatic part recognition (in shipbuilding).

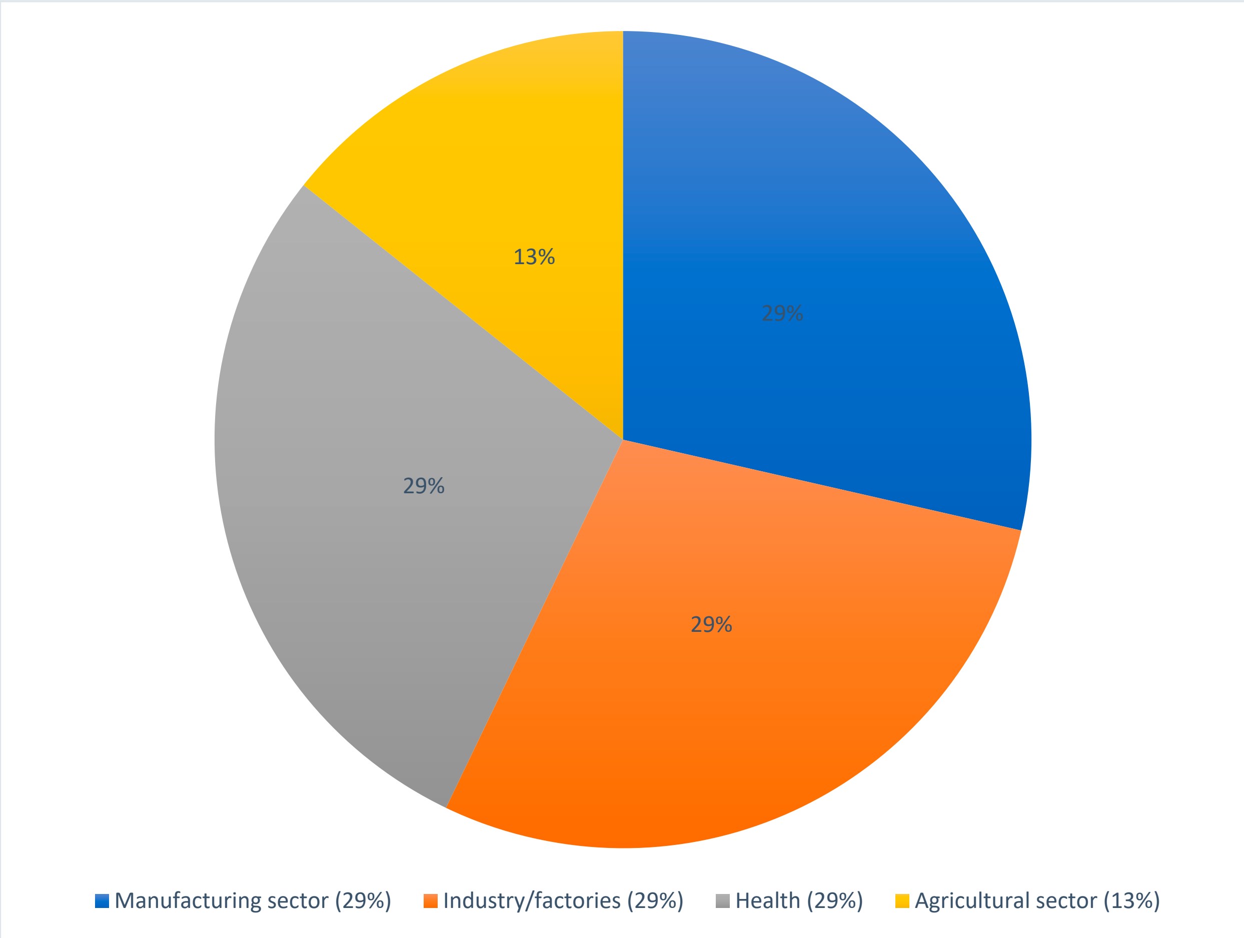

Figure 10. Application sectors of machine vision in Industry 5.0.

Table 1. Details of 87 referenced articles regarding the use of machine vision in Industry 4.0.

No.	Ref.	Year	Publisher	Document Type	Application Task	Sector
1	[29]	2023	Springer	Article	Detection	Manufacturing industry
2	[63]	2023	Elsevier	Article	Monitoring	Industry/factories
3	[33]	2023	National Institute of Science Communication and Policy Research	Article	Monitoring	Industry/factories
4	[32]	2023	Springer	Conference Paper	Detection	Industry/factories
5	[35]	2022	Springer	Article	inventory	Industry/factories
6	[26]	2022	Elsevier	Article	Monitoring	Telecommunications
7	[38]	2022	MDPI	Article	Quality control	Metrology
8	[64]	2022	Elsevier	Article	Measurement	Metrology
9	[65]	2022	Elsevier	Article	Monitoring	City
10	[66]	2022	Springer	Article	Quality control	Industry/factories
11	[67]	2022	ASTM	Article	Localization	Robot
12	[68]	2022	ASME	Conference Paper	Quality control	Assembly industry
13	[69]	2022	Springer	Conference Paper	Monitoring	Mining industry
14	[70]	2022	International Institute of Informatics and Cybernetics	Conference Paper	Monitoring	Education
15	[71]	2022	IEEE	Conference Paper	Detection	Automotive industry
16	[72]	2022	Elsevier	Conference Paper	Detection	Manufacturing industry
17	[73]	2022	Springer	Article	Quality control	Manufacturing industry
18	[74]	2022	ASME	Conference Paper	Quality control	Stores

Table 1. *Cont.*

No.	Ref.	Year	Publisher	Document Type	Application Task	Sector
19	[75]	2022	Springer	Conference Paper	Quality control	Manufacturing industry
20	[76]	2022	IEEE	Conference Paper	Monitoring	Agricultural sector
21	[77]	2022	Hindawi	Article	Quality control	Industry/factories
22	[78]	2022	Hindawi	Article	Quality control	Manufacturing industry
23	[79]	2022	IOP	Conference Paper	Quality control	Industry/factories
24	[80]	2022	Elsevier	Article	Measurement	Manufacturing industry
25	[81]	2022	Springer	Conference Paper	Monitoring	Robot
26	[82]	2022	Hindawi	Article	Localization	Automotive industry
27	[83]	2022	Springer	Conference Paper	Evaluation	Robot
28	[84]	2022	MDPI	Article	Quality control	Education
29	[85]	2022	Springer	Conference Paper	Recognition	Robot
30	[86]	2022	IEEE	Conference Paper	Localization	Automotive industry
31	[87]	2021	MDPI	Article	Quality control	Pharmaceutical industry
32	[36]	2021	Production Engineering Institute	Article	Recognition	Printing firms
33	[88]	2021	MDPI	Article	Quality control	Agricultural sector
34	[89]	2021	IEEE	Conference Paper	Classification	Agricultural sector
35	[90]	2021	IEEE	Conference Paper	Detection	Robot
36	[91]	2021	IEEE	Conference Paper	Detection	Transportation
37	[92]	2021	Nova Science Publishers, Inc.	Book Chapter	Detection	Industry/factories
38	[93]	2021	MDPI	Article	Quality control	Industry/factories
39	[94]	2021	IEEE	Conference Paper	Monitoring	Manufacturing industry
40	[95]	2021	IEEE	Conference Paper	Quality control	Automotive industry
41	[96]	2021	TANGER Ltd.	Conference Paper	Detection	Metallurgical industry
42	[97]	2021	Estonian Academy Publishers	Article	Monitoring	Robot
43	[11]	2021	Elsevier	Conference Paper	Monitoring	Industry/factories
44	[98]	2021	Springer	Conference Paper	Quality control	Automotive industry
45	[99]	2021	Elsevier	Conference Paper	Classification	Agricultural sector
46	[34]	2020	Emerald	Article	Monitoring	Industry/factories
47	[100]	2020	IEEE	Conference Paper	Recognition	Agricultural sector
48	[101]	2020	Oxford University Press	Article	Monitoring	Meat industry
49	[102]	2020	Springer	Article	Quality control	Manufacturing industry
50	[103]	2020	MDPI	Article	Measurement	Industry/factories
51	[104]	2020	IEEE	Conference Paper	Detection	Industry/factories
52	[105]	2020	IEEE	Conference Paper	Monitoring	Automotive industry
53	[106]	2020	IEEE	Conference Paper	Monitoring	Sports
54	[8]	2020	Springer	Article	Recognition	Manufacturing industry
55	[107]	2020	Elsevier	Article	Monitoring	Mechanical engineering treatment
56	[43]	2020	Institute of Industrial and Systems Engineers, IISE	Conference Paper	Monitoring	Education
57	[108]	2020	Universidade Federal do Ceara	Article	Quality control	Agricultural sector
58	[109]	2020	Editorial Institution of Wrocaw Board of Scientific	Article	Monitoring	Robot
59	[110]	2020	Elsevier	Conference Paper	Quality control	Industry/factories
60	[111]	2020	SPIE	Conference Paper	Detection	Infrastructure
61	[37]	2020	Elsevier	Conference Paper	Quality control	Automotive industry
62	[112]	2020	Springer	Conference Paper	Recognition	Industry/factories
63	[113]	2020	Springer	Conference Paper	Quality control	Construction sector
64	[114]	2020	Springer	Article	Measurement	Industry/factories
65	[115]	2019	IEEE	Conference Paper	Quality control	Manufacturing industry
66	[116]	2019	IEEE	Conference Paper	Measurement	Automotive industry
67	[117]	2019	Springer	Article	Quality control	Automotive industry
68	[118]	2019	Chinese Society of Agricultural Engineering	Article	Inventory	Infrastructure

Table 1. *Cont.*

No.	Ref.	Year	Publisher	Document Type	Application Task	Sector
69	[119]	2019	IEEE	Conference Paper	Detection	Automotive industry
70	[120]	2019	IEEE	Conference Paper	Detection	Manufacturing industry
71	[121]	2019	IEEE	Conference Paper	Measurement	Education
72	[122]	2019	Elsevier	Conference Paper	Detection	Metrology
73	[123]	2019	Elsevier	Conference Paper	Recognition	Industry/factories
74	[124]	2019	Elsevier	Conference Paper	Monitoring	Robot
75	[125]	2019	Chamber of Textile Engineers	Article	Quality control	Manufacturing industry
76	[126]	2019	Elsevier	Conference Paper	Detection	Construction sector
77	[127]	2019	Elsevier	Conference Paper	Quality control	Education
78	[128]	2018	EDP Sciences	Conference Paper	Detection	Metallurgical industry
79	[129]	2018	OSA-The Optical Society	Article	Quality control	Industry/factories
80	[130]	2018	Springer	Book chapter	Recognition	Mechatronics
81	[30]	2018	SPIE	Conference Paper	Recognition	Architecture
82	[131]	2018	MDPI	Article	Monitoring	Industry/factories
83	[132]	2018	-	Conference Paper	Monitoring	Entertainment
84	[133]	2017	EDP Sciences	Conference Paper	Detection	Robot
85	[134]	2017	Danube Adria Association for Automation and Manufacturing, DAAAM	Conference Paper	Measurement	Industry/factories
86	[135]	2016	Elsevier	Article	Detection	Agricultural sector
87	[136]	2015	Elsevier	Conference Paper	Detection	Industry/factories

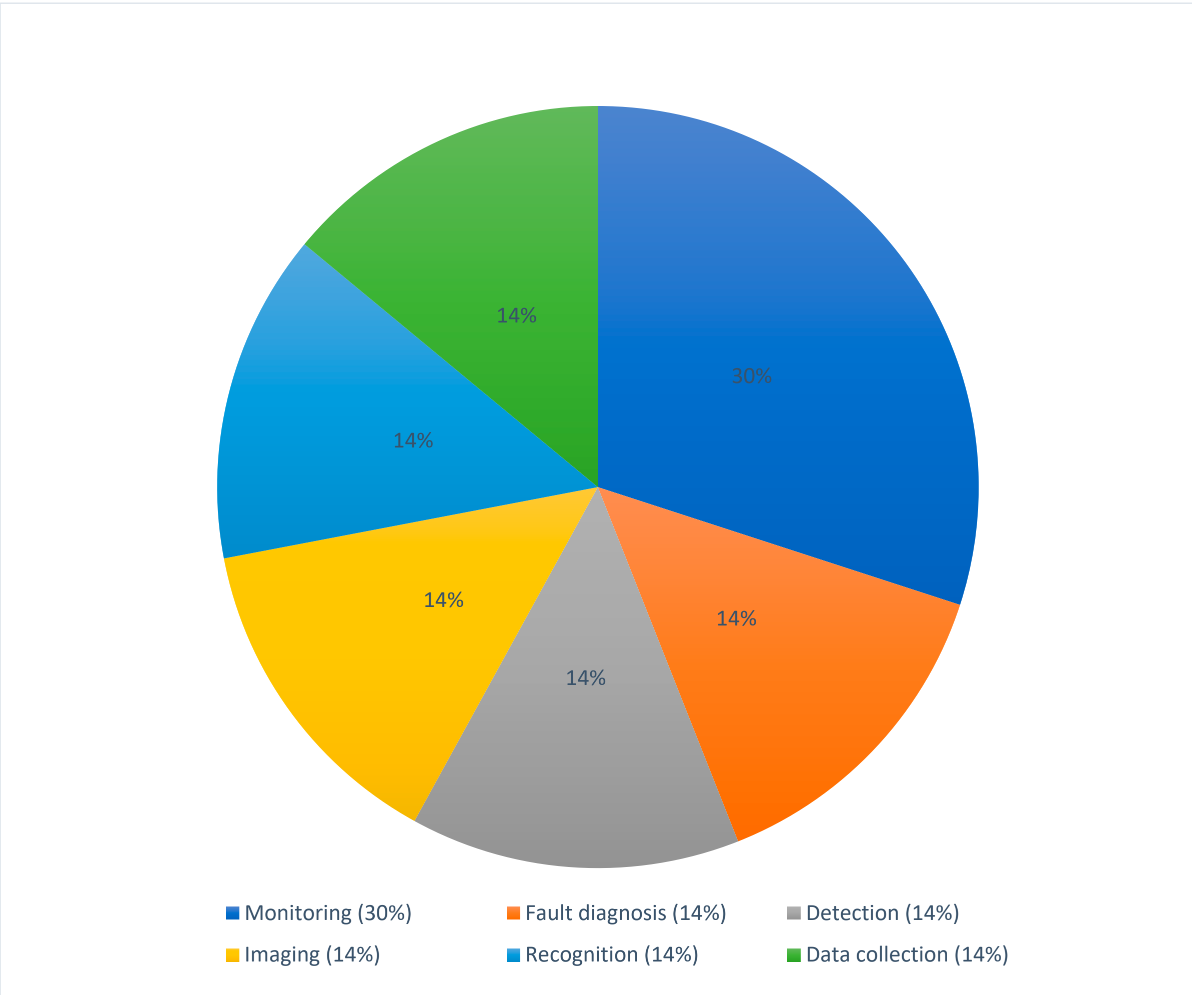

Figure 11. Use of machine vision in Industry 5.0.

Figure 12 presents the co-occurrence map of the keywords of the selected articles regarding the use of machine vision in Industries 4.0 and 5.0. As can be observed, Industry 5.0 is not among the 14 more frequently used keywords appearing within the keywords of the selected articles, indicating its nascent stage. Industry 4.0 and machine vision are linked together strongly, along with smart manufacturing, deep learning, image processing, object detection, and machine vision systems. Machine learning, quality control, computer vision, and AI are also linked to the main research subject, indicating their contribution to both industrial revolutions, as analyzed in the upcoming section.

Details of all referenced articles regarding the use of machine vision in Industry 4.0 and Industry 5.0 are provided in Tables 1 and 2, respectively.

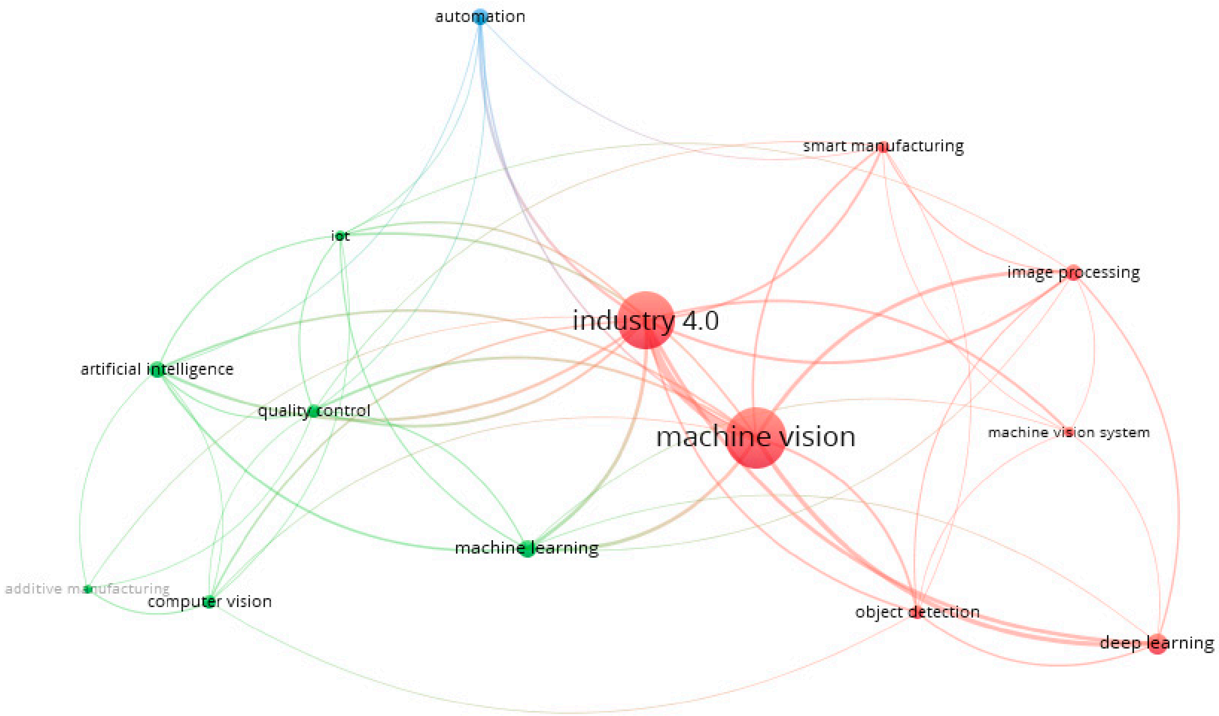

Figure 12. Co-occurrence map of keywords of the selected articles regarding the use of machine vision in Industries 4.0 and 5.0. Node size reflects co-occurrence frequencies and link thickness indicates co-occurrence relationships.

Table 2. Details of 7 referenced articles regarding the use of machine vision in Industry 5.0.

No.	Ref.	Year	Publisher	Document Type	Application Task	Sector
1	[53]	2023	Taylor & Francis	Article	Advanced training (industrial and academic), immediate ability to diagnose faults in industries and improved safety in industrial processes	Manufacturing sector
2	[51]	2023	Elsevier	Conference Paper	Detecting objects, and training robots to recognize them.	Industry/factories
3	[137]	2023	MDPI	Article	Imaging (MRI cost reduction)	Health
4	[138]	2023	MAPAN	Article	Remote monitoring and examination of patients with eye diseases and remote ophthalmic surgery	Health
5	[139]	2021	IEEE	Article	Recognition	Industry (Shipbuilding)
6	[140]	2019	MDPI	Concept Paper	Camera observation and image processing using Machine Learning by the robot	Manufacturing sector
7	[141]	2018	Sciendo	Article	Data collection	Agricultural sector

5. Discussion

5.1. General Research Findings

According to the results of the conducted study, it is revealed that the use of machine vision in both Industries 4.0 and 5.0 covers and is expected to cover a huge range of fields, for various reasons, as discussed in the following. However, the main application sector in both cases is the wider industrial sector, including manufacturing and automotive industries, while the most popular uses are for monitoring and quality control. All assumptions are based on the data included in Tables 1 and 2.

More specifically, one of the main findings of this work indicates that the applications of machine vision in Industry 4.0 vary; yet, according to the findings, reported applications are almost evenly distributed. Quality control in general is a use where human workers are struggling to balance between precision, tiredness, expertise, and time. Our research revealed that with a percentage of 29%, quality control is the most popular task in Industry 4.0 to be performed with the help of machine vision. Almost as important is the monitoring function, applied in 24% of the cases, followed by object detection with 21%. The role of machine vision in Industry 4.0 is characterized as decisive since its contribution can upgrade and develop several fields of human daily life. Its appearance in general in industries and factories can be characterized as necessary; note that a percentage of 24% of the literature refers to general industrial applications without including the percentage of specific industries that were considered separately, such as the automotive industry. By considering all industries together, the latter percentage reaches 50%. The reason for that is that the use of machine vision can cover all industry-related operations (quality control, monitoring, detection, recognition, measurement, inventory, identification, classification, evaluation, storage, etc.). However, since, among all sectors, the automotive sector was the one with the most applications, it is natural that the most frequent use of machine vision refers to a specific application related to this sector.

Industry 5.0 is an era that many would expect to be the continuation of Industry 4.0; yet, it comes to play its role in parallel, giving enhanced possibilities and options. In Industry 5.0, the use of machine vision aims to enter areas crucial to human life, although this attempt is still in early stages. One would expect that the evolution of Industry 5.0 would include full robot control over automated tasks or even full control over production lines of both manual tasks and processes. Nevertheless, none of the above characterizes this era. In Industry 5.0, robots are meant to cooperate with humans, *not to replace them*, and are envisioned to work together cooperatively towards increasing the efficiency of production, as depicted in Figure 12 [140]. The aim of this era seems to be cooperation in an environmentally friendly context. In Industry 5.0, machine vision still plays and is expected to play a decisive role in several sectors, as foreseen from the present report. Early findings indicate its contribution to the manufacturing industry/factories (percentage of 58%), the health sector (29%), and the agricultural sector with 13%. The lack of references in other sectors up to the date of this report indicates that machine vision in Industry 5.0 may be still at an early stage; however, its involvement is expected to expand in all relevant sectors of Industry 4.0 and more.

At this point, the limitations of this research should be noted. Limitations are mainly related to the maturity of the publications as well as the databases from which the information was retrieved. Only scientific literature was included due to the need for greater reliability of the information. In addition, because the supporting technologies in one of the two search periods, i.e., Industry 5.0, are at an early stage, the search results were limited, and as a consequence, any comparison between the two periods would be non-equal. The latter limited the discussion for the sectors and applications that use machine vision in Industry 5.0. Yet, the trend is obvious, and further work on the subject can be foreseen.

5.2. Contribution of Machine Vision in Industry 4.0

5.2.1. Main Uses and Application Sectors

In what follows, all application sectors and main uses of machine vision in Industry 4.0 are identified.

In the field of the *automotive industry*, the assistance of machine vision is reported to be of great importance. Every mechanical or electrical part or component produced in this field needs to pass quality and performance tests before any construction is completed. The cost invested each time is huge and any human error or defect could cause irreparable damage both in terms of money, human lives, and the reputation of the company/brand. For this reason, the funds invested in the automation of such processes are huge. According to the findings, the first priority in Industry 4.0 is the use of machine vision for quality control [37,75,94,98], with a percentage that even reaches 29%. This is followed by monitoring and detection of surface anomalies with a rate of 24% and 21%, respectively.

An important area that encompasses machine vision in many tasks in Industry 4.0, with a percentage of 10% according to our findings, is *Robots*. Usually, Machine Vision Inspection (MVI) systems are used for component quality inspection, monitoring, manufacturing and assembly supervision, as well as for robot guidance [70]. By acquiring visual perception, robots are more capable of efficient motion planning as well as of manipulative actions in a workplace, even in less orderly spaces or in unstructured conditions [81]. In fact, from the findings of this work, monitoring is also a high-priority task in this field. Another important application of machine vision in robots is the one that focuses on object detection, especially for robots that need to work in procedures that require object manipulation by robotic arms [90]. More generally, machine vision application tasks such as product accuracy assessment [83], localization [67], and recognition [75] are also included in Industry 4.0. It is worth mentioning, even at an early stage, the effort made for the automated assembly process with the help of machine vision-based robots. However, problems related to the way of placing the cameras are one of the factors that affect the accuracy of the procedures, as well as the high costs. Unfortunately, the scientific knowledge of automated assembly power supply is not yet ready compared to other manufacturing sectors or assembly operations. Also, the framework that supports this type of work is not yet available, but it is expected to give further impetus to the 'smart' industry in the coming years [124].

The *manufacturing industry* is another sector that gives significant value to the use of machine vision. In the manufacturing industry, problems such as tool wear come to add further stress and maintenance costs to industries in cases of general damage. The time spent on corrections and repair actions is often detrimental, and in many cases, locating the source of the problem can cause long delays. In cases where machine vision was employed in Industry 4.0, the methods followed were intact, and managed to have high measurement speeds and even carry out the measurements online, providing high accuracies [80]. Based on the findings of this research, quality control is the priority application, since, in the manufacturing sector, the quality of the products is decisive. Detection is also a fundamental task, such as detection, e.g., of surface irregularities [72], measurement, e.g., wear measurement [80], recognition, e.g., of materials [8], and monitoring [94].

The *agriculture sector* is another sector that takes advantage of machine vision. In the field of agriculture, Industry 4.0 comes to contribute dynamically, by promoting autonomy and novel technologies, introducing the corresponding Agriculture 4.0. Monitoring of agricultural conditions (territorial variables, hydro-meteorological), counting, sorting [89], harvesting [76], monitoring and detection of defects in terms of quality control, cultivation, disease control, and more agricultural tasks were automated by employing machine vision [108]. Especially in cases where the decision to accurately estimate the crop load (yield prediction) before each harvest is crucial, machine vision systems in Agriculture 4.0 played a significant role. The latter is also important for storage and transportation procedures.

Machine vision was also of interest in *educational applications* in the period of Industry 4.0, according to the findings of this study. The need to convey both the concept of machine vision and its importance has prompted educational institutions and students to join experiments—attempts to use machine vision to further enhance its use.

In the *construction industry*, suggestions to improve technical constructions in terms of Industry 4.0 include treating them as cyber-physical systems. The estimation of the surface roughness when cutting hardened steel with specific tools [113] using machine vision is a typical example. Also, constructions with panels, as well as modular constructions, are of great interest in the construction of commercial buildings and high-rise buildings. The main tasks for using machine vision in the construction sector are detection and quality control.

A serious aspect of advanced industry and Industry 4.0 is *manufacturing metrology*, also showing an interest in machine vision applications. Anything manufactured with metrology systems must meet specific criteria, so inspection and measurement play a key role. The most common applications of machine vision in this field are related to quality control, measurement, and monitoring.

An additional sector that took advantage of machine vision during Industry 4.0 is the *metallurgical industry*, characterized by increased requirements for quality, economy, and efficiency of technological processes [96]. Intelligent systems significantly helped the upgrading and development of this sector. Automation of parts of processes in heavy industry also followed the trend of Industry 4.0, employing machine vision and artificial intelligence. The use of machine vision in this field, according to our report, is mostly designated for monitoring and detection.

The intervention of machine vision during Industry 4.0 in *infrastructure projects*, specifically in the road network, is also noteworthy. The condition of a road network is a critical parameter for safety issues. Machine vision was employed towards providing a solution for the aforementioned problem, reporting significant success rates and thus giving incentives for further improvement or suggestions in the future [111]. The integration of machine vision systems in road navigation on specific road models is an additional application. According to our investigation, the processes of interest in this field are related to detection [111] and inventory [118].

An interesting application of machine vision systems in Industry 4.0 is related to *LED displays*. In Industry 4.0, smart e-business manufacturing includes ways to detect product defects from an industrial robot to improve the quality and efficiency of the automatic production process. LED screens, with their wide use in the field of electronic production, constitute a large part of the developed applications. Bright spots, light leakage, white spots, foreign objects, markings, Binary Large Objects (BLOBs) (a geometric shape), black spots, uneven color, scratches, bubbles, and creases are the possible defects of an LED screen that need immediate treatment in case of non-smooth operation [120]. With the aim of deep learning technology and measurements aided by machine vision, the offered reinforcement and flexibility in detecting defects raise the level of intelligence of industrial production. The same concerns the use of 3D printers, which in many cases provide solutions and assist in various Industry 4.0 sectors. The quality of the printed products is a key issue. For this reason, the detection of errors before the final product is delivered and used is essential, and in Industry 4.0, it is implemented with the aim of machine vision [142].

Another sector is that of *mining industries*. Machine vision with the help of deep learning neural networks is prominent in mining industry applications; the processes of foam flotation and concentration of large amounts of lead developed by Bendaouia et al. [69] led to efficient results, establishing the use of machine vision technologies in this sector in the future.

In the health sector, and specifically in *pharmaceutical industries*, machine vision also contributed to automating processes in the frame of Industry 4.0. Several clinical applications, an important part of the pharmaceutical industry, having great financial and clinical benefits, do not necessarily meet all quality standards. Thus, machine vision techniques, 3D printing, and machine learning are used for better automated quality control and error detection to overcome deficiencies in Ordering and Distribution Facilities (ODFs), processing of medicines, etc. [87].

The *meat industry* was also upgraded in Industry 4.0 by using machine vision automations. In the last 25 years, both primary and secondary meat processing has seen obvious changes. The development of manual tasks in meat processing units has started to be replaced in some cases by machine vision-based robots, limiting the workforce involved in the process, as well as the costs. Smart meat factories are already present.

Another area that the advent of machine vision has entered during Industry 4.0 is that of *sports*. The main process being automized is that of monitoring. In fact, a typical example is the sport of shooting. For example, in the sport of shooting, by monitoring eye characteristics, an attempt was made to characterize the performance of the athletes by taking into account special conditions and their behavior. The monitoring of the eye's iris with machine vision techniques could also be used towards the evaluation of employees in production lines in the future, as well as other applications.

However, there are cases where, beyond the use in automated operations, machine vision can play a decisive role in manual operations, in factories and industries, as in *Assembly Industries*.

In the field of *Architecture*, the contribution of machine vision is also evident, providing significant results. Identification and detection of textures, decorations, and other features of buildings are some typical applications in this field. The manual process would require a lot of effort and time by domain experts, especially for ancient buildings that have numerous paintings and textures.

Another sector where machine vision contributed to Industry 4.0 is the field of *entertainment* [132]. The contribution of machine vision to cybersecurity is also noteworthy. Industry 4.0 imposes inspections in short time intervals for any attacks on production lines as well as on the general systems of modern industrial infrastructures. For this reason, machine vision using advanced methods aims to identify defects in production lines by recognizing objects, events, and behaviors that do not fit the original way of the process [82].

The integration of Industry 4.0 was also evident in mechanical processes such as tool wear monitoring. The integration of a vision system into a drilling machine aided the automatic detection of tool wear. Machine vision systems and Cyber-Physical Systems (CPS) play a key role involving different software and hardware elements [107] that could enhance the mechanical sector [110]. According to Industry 4.0, mechatronics and related fields are fundamental for stimulating the development of the digitalization of industry [130]. The recognition of products, of specific standards, etc., is a process of great interest for all sectors, either for quality control or for various measurements.

In Industry 4.0, machine vision combined with machine learning could enable the manufacturing industry to distinguish between materials and machinery and to be able to make quick decisions. Support Vector Machines (SVMs), k-nearest neighbor (k-NN), random forests (RF), decision trees (DT), etc., are common machine learning models used as supportive algorithms. In order to develop reliable algorithms that could be extended to similar procedures, ten-fold cross-validation techniques [8] are also employed to test the accuracy of algorithms. The introduction of the Internet of Things (IoT) in Industry 4.0 and the extended use of cloud servers have further enhanced the available resources providing numerous possibilities for big data collection and real-time processing applications [115].

5.2.2. Practical Applications

In what follows, results of machine vision in Industry 4.0 are referenced, covering indicative applications in the previously identified sectors.

Frustacie et al. [37] developed a machine vision system for in-line quality checks of the assembly process of a catalytic converter, enabling a paradigm of Industry 4.0 and Smart Manufacturing. Gözükırmızı et al. [71] presented a machine vision application for the automotive industry for detecting surface anomalies on electric motors. The authors claim that such automation systems are core features of the Industry 4.0 concept, which is led by the automotive industry. The automotive and aerospace industries are the beneficiaries of the developed framework presented by Evangelista et al. [105]. The authors developed a framework to set up industrial inspection robots, including full coverage of the part to be inspected and simultaneous quality assessment of the part. In [119], the authors present a machine vision application for the automotive industry to automatically detect, analyze, and measure the size of the defect of automobile cluster pointers, resulting in real production lines reporting accuracy of up to 99.4%. Ferreira et al. [116] introduced an automotive industrial implementation based on machine vision in combination with a user-friendly interface and a secure cloud environment, for solving problems related to the control and calibration in the maintenance and manufacturing of logistic racks. More generally, in the automotive sector, machine vision is employed to observe human workers (body movements, Health and Safety (H&S) compliance) as well as guide vehicles with the aim of enhancing quality and correcting errors/defects in real-time. The dominant goal is to deliver constructions with zero defects at the human system level [94].

In the manufacturing sector, Lee et al. [133] presented an automatic loading/unloading system based on visual inspection. Another application of machine vision in the manufacturing sector is reported in [109]; the proposed system was based on a Cognex camera mounted on a Universal Robot (UR) robotic arm, managing to distinguish the arm from the rest of the robot's body. Despite its poor precise positioning conditions, the developed system managed to significantly support multiple industrial processes at the Industry 4.0 testbed. An application of machine vision in the industrial production of textiles was reported in [78] by Li et al. The authors developed a lightweight vision-based segmentation model capable of fabric defect detection in real time in the production line.

Typical applications of machine vision in the agricultural sector within Industry 4.0 are reported in [88,143–146], focusing on mango cultivation. Mango is a fruit that needs special handling due to its short period of natural ripening on the tree, as well as its low endurance after harvest. Therefore, harvesting, storage, and transportation need to occur in a timely manner; in such cases, prediction of harvest time and yield estimation play a vital role for the correct and direct management of production. Additionally, with the use of machine vision, it became possible to count fruits or nuts on a tree, from images collected by RGB cameras mounted on ground vehicles, by applying deep learning methods for tree fruit detection, as reviewed in [147], towards a more advanced and 'intelligent' precision agriculture. Another application task in agriculture that benefits from the employment of machine vision is that of classification and ranking. Sorting a fruit into the correct category is a manual and time-consuming process that machine vision can be used to fully automate. Al Haque et al. [89] used machine vision combined with a Convolutional Neural Network (CNN) to classify and identify rotten bananas, with a high accuracy of up to 98.3%. Another approach in agriculture is maturity level classification. In [99], maturity assessment was implemented for bunches of fresh oil palm fruits, by using machine vision and an artificial neural network (ANN) with a back-propagation algorithm, reaching 98.3% accuracy. In [135], the authors deal with the detection of citrus fruits that fall due to some disease as well as the stages of decay before the fruit falls. In cases where destructive diseases are heavily affecting plants, the detection of falling fruits, with the help of machine vision, is a method of assessing the presence and severity of the disease with a major importance. Accordingly, the detection of defective areas in a fruit or vegetable is something that machine vision can also handle. An example is that of the detection of calyx and stem scars, both for defective and healthy tomatoes, in order to improve the production process and produce products without defects, reported in [100].

In the educational sector, a machine vision-based implementation of Industry 4.0 was reported in [43]. The proposed system included simulation, VR, analytics, automation, and 3D printing to integrate a small-scale production and inspection line of 3D-printed parts. In the same context, the experimental production system [83], namely SMART, developed from the SmartTechLab laboratory based on the concept of Industry 4.0, was developed to train, update, and implement methodologies for use in modern industrial and collaborative robots. A similarly notable effort was a Learning Factory, presented in [127], based on low-cost machine vision so that the students would develop an implementation of a quality control system. Learning Factories provided a promising environment for developing the competencies required by a future workforce to implement and integrate technologies related to digitized manufacturing environments and cyber-physical systems. Calderon et al. [121] employed machine vision towards a useful intervention in the development of educational board games aimed at special education institutions. Specifically, teaching mathematical operations to visually impaired children with an automated tutor based on machine vision and machine learning algorithms gave 100% error detection and a 94% performance rate. The game was characterized as low-cost, fast, and non-intrusive. According to the present review, in the field of education, machine vision is employed for monitoring [70], quality control [127], and measurement issues [121].

In the construction sector, spotting holes and inspecting proper screw operation with automatic Light-Gauge Steel (LGS) machines was also an advancement of Industry 4.0; Martinez et al. [126], with the help of an algorithm able to detect holes and the use of a machine vision system, implemented screwing operation properly, ensuring the quality of the screwing 59% more accurately than the fastest available algorithm that time. Huang and Lin [128] proposed a machine vision and machine learning system in the metallurgical industry, to improve product quality, helping to detect surface defects such as scratches, spots, shallow pits, edge defects, etc., as well as processing the elements such as size, diameter, thickness, height, etc. An application of machine vision in the meat industry is that of cutting meat. By making use of laser scanners enabling a 3D cutting image, with the help of weight control (to adjust volume and density) of a computer and machine vision techniques, the cutting process can be implemented with higher precision. For this specific process, the cutting knife managed to perform 700 cuts/min with an accuracy of $\pm$0.5% [101].

5.3. Contribution of Machine Vision in Industry 5.0

5.3.1. Main Uses, Application Sectors, and Foreseen Use Cases

In what follows, all application sectors and main uses of machine vision in Industry 5.0 are identified, highlighting all related prospects.

Machine vision in the *manufacturing industry* has already been a subject of interest and therefore has been investigated since the beginning of Industry 5.0. In the manufacturing industry during Industry 5.0, humans work while robots observe the process through a camera (Figure 13). By monitoring the human and the environment and by analyzing human intentions, the algorithms are capable of estimating the human's next move. To understand human intention, a sensor can be used to retrieve brain signals (electroencephalograms, EEGs), using near-infrared functional spectroscopy in a wireless communication channel. The EEG sensor is in the form of a non-invasive headset and does not need a time-consuming setup and calibration process. Once the robot estimates the human intention, it will try to help by guiding the next step of the task.

In the *health sector*, the high costs of several procedures remain a suppressive factor. Nevertheless, after the digital transformation that will be completed in Industry 5.0, it seems that, with the use of digital technologies, AI, machine learning and the cloud, procedures will be made less complicated. For example, ophthalmic surgery, in the future, is expected to be assisted by robots. In addition, there will be the possibility of remote surgery and remote monitoring of the patient in real time (e.g., scanners with AI to take various images of the eye and with the use of deep learning to classify the disease), remote re-examination of patients to evaluate their progress of treatment, and the use of robots to reduce the working load of optometrists. Also, it seems that, in the future, a bionic eye could be built based on a high-resolution camera [138]. Moreover, the high costs of MRI scans are expected to be exceeded by introducing big data, Cloud Computing, and the developments running in the field of AI [137]. Medical personnel will be facilitated in predicting future diseases, such as diabetic retinopathy, glaucoma, and age-related muscle recurrence in ophthalmology [148].

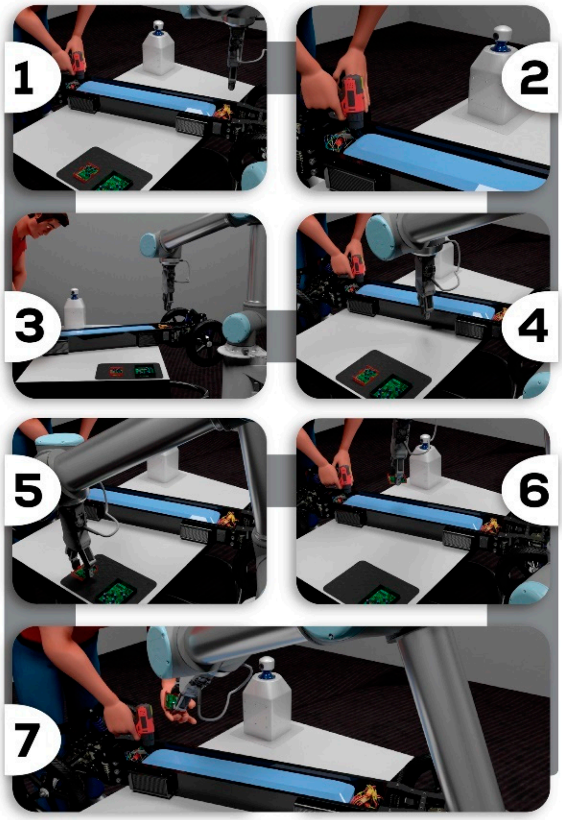

Figure 13. Industry 5.0 hypothesis. Robots are working collaboratively with humans to enhance production in seven steps [140]: (1) the robot observes the human to understand the process; (2) the robot analyzes the intentions of the human using visual cues from a camera; (3) the robot picks up an object not currently useful for the worker; (4) the robot moves the object away from the workbench to help the human; (5) the robot picks up an object useful for the worker; (6) the robot brings the object to the human; (7) the robot hands the object to the human when he needs it.

In the field of *Agriculture*, the contributions of machine vision and AI are also expected to be of key importance. It seems that the analysis of big data with machine learning algorithms will help to exploit the large amount of data that will be collected, at all stages of the supply chain [141], from aerial vehicles, mobile platforms, cameras, and sensor networks, towards making decisions about improvements throughout the supply chain.

In addition, in the *construction sector,* and specifically in the shipbuilding industry, machine vision could contribute to the construction or repair of a ship, with the automatic identification of components, using an optical recognition subsystem with a digital camera or barcode to read data from quick response (QR) codes or 2D barcodes [139].

It is estimated that AI and the use of augmented and virtual reality tools, which can be used to guide the employee, will provide professional employment to people with reduced mental abilities. In addition, the collaboration of humans with mobile robots and exoskeletons, which will take on tasks of physical strength, will allow people with less physical strength to claim jobs of such requirements. Finally, the digitization of human resources is also expected, towards the selection of appropriate personnel for each position, through remote work, even if living in remote areas.

5.3.2. Supporting Technologies

All aforementioned foreseen contributions of machine vision in Industry 5.0 are based on the capabilities of current developments in both hardware and software accompanying machine vision systems. Key hardware developments include camera technology, AI, and chipsets. The latter developments increase the typical machine vision benefits of cost saving, competitiveness increase, and product quality improvements. Notable technologies that are expected to affect the landscape of machine vision applications in Industry 5.0 towards boosting its adaptation are listed as follows. (1) *High-resolution cameras* in some cases are superior to the human eye, at 45 megapixels and more, and are able to track objects of high speed without distortions. (2) Newly introduced *event-based vision sensors* (EVSs) are capable of high-speed data output with low latency by restraining the data output to changes of luminance from each pixel, along with data on coordinates and time. Focusing on movements, they can be applied in a wide variety of fields, ideally for gesture tracking, e.g., hand movements, promoting the machine-human collaboration as defined by Industry 5.0. (3) Newly introduced *sensor technologies* that can enhance the capabilities of conventional cameras include point cloud machine vision and hyperspectral machine vision, to provide details such as depth and what cannot be seen in the optical spectrum. (4) *AI* is a key enabling technology towards efficient decision making. Nowadays, generative AI is at the forefront, presenting advancements in natural language processing (NPL) that have not yet been fully employed in the industrial sector. Large language models (LLMs) are expected to provide new opportunities in Industry 5.0, by taking advantage of large volumes of data to cover contextual needs within the industry, e.g., for customer service, provision of guidance to workers, supervision, and problem solving by domain-specific models, offering a powerful tool for human workers to elevate their knowledge. (5) Advanced powerful *chipsets*, e.g., the AM69A flagship AI vision processor from Texas Instruments, are able to control up to eight cameras.

6. Conclusions

This work is the first scoping review of the contribution of machine vision in Industry 4.0 and Industry 5.0, based on PRISMA-ScR. The aim is to highlight all advancements of the two industrial revolutions based on machine vision, including several application sectors and specific tasks. Similarities and differences between Industry 4.0 and 5.0 are highlighted, and the future potential contribution of machine vision in the upcoming Industry 5.0 is indicated.

In Industry 4.0, machine vision entered several areas of human life, trying to help as much as possible, towards automation, production increase, time saving, quality improvement, and many other functions, indicating the beginning of the smart factory era. The use of technologies that support machine automation as well as industrial mechanisms is based on new technologies and can perform complex tasks and help to increase production, save time, as well as address cost issues. Machines are smarter, more flexible, faster, fully collaborative, and often able to process data in real time and perform autonomous decision making. The latter, however, caused an additional concern regarding the general future of machine–human interaction, about who will ultimately be the one who will be in control of things.

Industry 5.0 is an era that many would expect to be the continuation of Industry 4.0; yet, it comes to play its role in parallel. While still ongoing research deals with interconnected technologies to improve productivity and efficiency following the principles of Industry 4.0, early research has started indicating a novel industrialization phase. The focus is now moving towards human–machine collaboration rather than automation and integrated technologies. Industry 5.0 emerged as a new era where it imposes the ultimate synergy between humans and machines that use the human spirit and creativity to increase the efficiency of any process. In Industry 5.0, machine vision, combined with other technologies, still aims to help, giving more options for humans regarding the way they work, by respecting the environment and their needs. Machine vision plays an essential role in both industries, and its contribution is gradually increasing; its role is progressive from one era to another, taking advantage of the developed knowledge to fulfill the different set goals.

Industry 5.0 may seem to demand even smarter factories; nevertheless, emotional intelligence as well as human creativity are innate processes, where under no circumstances will a robot be able to reach these levels by itself. Thus, it seems that in Industry 5.0, the replacement of man by robots is not promoted in any case; yet, it promotes their cooperation. Man is the one who will plan things, and take on the parts that require emotion, as well as spontaneous adaptation to new challenges, since to an extent, the robot is not able to improvise. This collaboration is expected to contribute to a reduction in social inequalities and give the possibility of employment to personnel who possess intellectual potential and abilities but have been excluded or limited from options in the market, due to lack of physical strength or inability to move to the workplace.

Industry 5.0 is expected to increase productivity and operational efficiency, be environmentally friendly, reduce work injuries, and shorten production time cycles. It has been mentioned that Industry 4.0 is based more on technology, while Industry 5.0 is based more on the value of the goals that are set each time. The latter gives another perspective on how a goal can ultimately be achieved and which parameters will determine the final outcome. Also, while in Industry 4.0, the focus is on the quality of products and the use of various digital technologies with the aim of increasing profits, Industry 5.0 aims at the integration of human creation and sustainable development, two important elements that Industry 4.0 did not include, and the provision of personalized products rather than mass production. We would say that both machines and robots in Industry 5.0, with the help of machine vision, will be capable of observing, learning, and acting according to humans. Early research results indicate that this collaboration will be able to perform incredibly well in several sectors of human life where the human eye will not be able to cope or in tasks where excessive detail is required.

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