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State-of-the-art Discussion and Evaluation on Artificial Intelligence Applied to Quality Assurance Using Assembly Assistance Systems

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Abstract

This research aims to present a base literature exploration study on the existing relationship between the development of deep learning-based assembly assistance systems to promote quality assurance and quality control in industrial assembly lines. The use of artificial intelligence in industry has become more common with the advance of Industry 4.0. Understanding that quality assurance is a difficult term to describe and evaluate in industrial contexts due to the difficulty of measurement methods and their limitations, an artificial intelligence approach may lead to total quality control within an assembly process by checking every step and every product assembled within a process. This study aims to understand how to develop an augmented intelligence-based assembly assistance system to guarantee the quality of a product during the assembly process.

Keywords
Innovation; Artificial Intelligence; Assembly Assistance System; AAS; Quality Assurance.

1. Introduction

Artificial Intelligence is a term used to describe computational systems used to automate human intellectual activities,focusing on problems without an algorithmic solution (Bezerra et al., 2023; Luger, 2009). The term has two main divisions: machine learning, a group of techniques that use supervised learning to develop the activities and deep learning, techniques that create algorithms to mimic human brain functioning (Data Science Academy, 2022). Recently, data-driven approaches based on Machine Learning algorithms and models have increasingly been used (de Queiroz et al., 2023). Also, the use of AI has become more common in daily activities and within the development of intelligent manufacturing systems (Bezerra et al., 2023).

The use of artificial intelligence techniques in quality assurance can permit a more efficient and more trustful approach to collect data for a quality control system since, in a practical situation, a traditional measurement model may not track a defect if its occurrence is not great enough in a set of products (Bezerra et al., 2023; Thamm et al., 2020a; Toledo et al., 2014). Focusing on assembly lines, the use of the Assembly Assistance System (AAS) for error prevention is a way to guarantee the quality of a product's assembly process, especially within low operator qualification contexts (Thamm et al., 2020b).

An AAS can be developed based on an intelligent technology (Thamm et al., 2020) to promote better quality results to an assembly line, especially with different error cases possible. Since quality has always been a difficult concept to define and measure (Rozenfeld et al., 2006; Toledo et al., 2014), proposing a different way to measure and assure quality, follows the current tendencies for industrial processes progressively incorporating technologies (de Queiroz et al., 2023), this paper evaluates the literature on how assembly assistance systems can be related to artificial intelligence techniques to promote quality into assembly lines.

2. Theoretical Background

2.1. Quality

Since there are a variety of definitions for quality based on the segment, value proposition type and the definition focus, there is no unified definition for quality. The main scholars are Armand Feigenbaum, Joseph Juran, Philip Crosby, William Deming, Kaoru Ishikawa, and Genichi Taguchi. Feigenbaum says quality can only be granted by total quality control, which is an integration system for development, maintenance, and quality enhancement of different groups within a company. For Juran, quality can be achieved through planning, controlling, and improving quality (Toledo et al., 2014). Quality planning is a process that aims to understand the needs of customers for the product being developed. Control is the stage in which what will be controlled is defined, which measure will be used, and what performance standards are expected. In improvement, the objectives and need for quality improvement projects are defined. While planning and controlling are processes, improvement is a project (Rozenfeld et al., 2006).

Crosby defines quality as the sum of the qualities obtained from the various activities and processes within a company. Deming structures the strategic importance of quality as one of the factors for increasing a company's competitiveness and defines quality planning similarly to strategic planning: the constancy of a purpose, such as a corporate vision and the definition of clear goals to guide quality actions throughout the company, maintening all employees aware of and updated on strategic quality definitions (Toledo et al., 2014).

Taguchi defines robust quality as a method for improving quality while reducing costs, this method seeks to increase products' robustness by reducing noise's effects on their performance (Rozenfeld et al., 2006). Ishikawa proposes the Japanese quality management system in which quality must always come first to an organization, which must be customer-oriented so that all decisions are made based on what the customer will benefit most. Furthermore, for the Japanese quality system philosophy, the next step of a process is a customer, so all employees participate in quality as daily actions and perform their tasks with the best level of quality to meet the requirements expected by the next process. As a result, all processes work at the optimum level of quality, generating an optimum level of quality product (Toledo et al., 2014).

For the transcendental approach, quality is an innate characteristic of the product and can only be expressed by the existence of the product and its history. For the product-based approach, quality is a precise, measurable variable and depends on the content of one or more product characteristics. This approach assumes that higher quality results in higher costs for the product (Toledo et al., 2014). For the user-based approach, it is understood that quality is a perception of the product user and, therefore, a subjective view based on personal preferences. With this idea, it is assumed that the goods that best satisfy consumers are those of the highest quality (Toledo et al., 2014). One way of understanding how to satisfy the customer is by converting the customer's requirements, that is, what the customer expects the product to contain, into technical, measurable requirements through the deployment of the quality function in a way that is possible, from these requirements, building the product in a way that satisfies the customer (Rozenfeld et al., 2006). Furthermore, it is possible to understand how the competition behaves when meeting customer requirements with their product offerings to position the new product in the market more strategically and rationally (Rozenfeld et al., 2006).

The manufacturing-based approach understands quality as conformance to specifications, by defining technical specifications based on customer requirements and enabling quality under the user's focus, it is possible to achieve quality from a manufacturing perspective (Rozenfeld et al., 2006). Excellent quality in the manufacturing approach is “doing it right the first time”, that is, following the specifications and the rigorously defined process leads to quality in the product without the need for rework or recovery of the product (da Silveira Bruno, 2016).

2.2. Quality within assembly process

An assembly line is a finite set of work elements or tasks, each having an operating processing time and a set of precedence relationships that specify the correct order of tasks (Fernandes & Filho, 2019). The main problem of assembly lines is balancing ─ assigning tasks to an ordered number of workstations (Fernandes & Filho, 2019).

From a quality perspective, it can be measured based on the inadequacy of the assembly, compared to the planned assembly, for a given product (Teale, 1987). Quality in an assembly line can also be evaluated with non-conformity indicators. Those point out non-compliance assembly according to the planned assembly which leads to the completion of an assembly process beneath conformities. Using exact methods to solve balancing problems is complex in computational approaches (Fernandes & Filho, 2019). Therefore, the use of an AAS within an assembly line can help assure the quality of its process by enhancing conformity within the assembly and promoting a more accurate way of measuring the quality for each point at the assembly process (Bahubalendruni & Biswal, 2016; Hinrichsen et al., 2016).

2.3. Quality control within industry 4.0

Industry 4.0 is a German term to designate the digital transformation of manufacturing (Klingenberg, 2017). That term denotes the integrated application of technologies in manufacturing lines, which aims to optimize processes and improve product delivery. Industry 4.0 involves a structural change in the technological basis of manufacturing, allowing flexibility in terms of product specifications, quality, design, production volume, production time and it also allows for more efficient use of resources and cost optimization (Ortt et al., 2020). All of these aspects can be encompassed as part of the total quality of a product and assembly and manufacturing line, depending on the approach used to evaluate them. From the user's perspective, having a product present on the market in different versions, as a result of greater flexibility, can follow the requirements outlined by the customer, which increases customer satisfaction, generating a higher level of quality (Rozenfeld et al., 2006; Toledo et al., 2014). From a value perspective, greater productivity and efficiency generate greater product quality while increasing these points guarantees production with lower production costs (Toledo et al., 2014).

The main technology of the fourth industrial revolution is cyber-physical systems – CPS – the interface between physical and virtual systems ─ so that everything that happens in the real world impacts the virtual system and vice versa (Klingenberg, 2017). Industry 4.0 is characterized by the cumulative aspect of technologies applied in manufacturing, which have interesting impacts on improving production and assembly systems with a gradual increase in quality based on the interaction between systems and humans (Klingenberg, 2017). Regardless of the sector, the use of integrated technologies in manufacturing implies changes in how tasks are carried out in an industry (Ortt et al., 2020).

2.4. Artificial Intelligence

Artificial Intelligence is a term that has gained greater popularity since the beginning of 2022 (Google Trends, 2023). Among the classic definitions are: the use of the computer to perform reasoning, pattern recognition, learning, or other forms of inference; a focus on problems that do not respond to algorithmic solutions; interest in solving problems using inaccurate, missing, or insufficiently defined information; reasoning that uses the significant qualitative characteristics of a situation; attempt to deal with issues that syntactically involve great semantic meaning; answers that are neither exact nor optimal but sufficient; using large amounts of domain-specific knowledge to solve problems; use of metaknowledge to gather a more sophisticated control over problem-solving strategies (Luger, 2009).

The "use of the computer to perform reasoning, pattern recognition, learning or other forms of inference" is linked to the concept of automation, in which repetitive reasoning activities, with pattern recognition, can be delegated to a computer which optimizes the use of human time and resources. Given a large enough data set, fast processors, and a sufficiently sophisticated algorithm, computers can begin to perform tasks that previously could only be performed by humans (Data Science Academy, 2022). Depending on how an Artificial Intelligence algorithm is developed, in addition to automation, the computer learns the activity so the task is optimized throug its execution (Data Science Academy, 2022). The optimization of an artificial intelligence algorithm can be observed through the increase in accuracy with each iteration it performs on the problem. Each iteration the algorithm processes a given set of data, changes the parameters and delivers results that are increasingly consistent with what is expected, thus increasing accuracy (Data Science Academy, 2022).

2.5. Quality Control in an Assembly Assistance System

An Assembly Assistance System – AAS – is a system that receives and processes information from the environment to support the performance of human activity (Hinrichsen et al., 2016). By supporting the performance of human activity, an AAS guarantees the necessary knowledge to correctly execute the activity, supporting the guarantee of one of the quality control points in an assembly process (Teale, 1987). In combination with planning work methods, AAS methods can significantly improve assembly quality and efficiency. Which can be verified based on the lower error rate of the tasks performed (Hinrichsen et al., 2016).

Also, as said before, an assembly line is a set of tasks with a precedence relationships that specify its correct order (Fernandes & Filho, 2019). Since knowledge graphs are a graph whose nodes represent entities of interest and whose edges represent potentially different relations between these entities (Hogan et al., 2021), this type of data structure can be used to represent each step of an assembly process with the nodes and each precedence relation with the edges, permitting a fastest way of implementing the precedence relations between tasks, since it functions as a digital twin for the assembly process (Simone et al., 2023).

An AAS can be classified based on the type of system support, distinguished between physical support systems, such as loading robots, and informative support systems, such as systems that display information on the next steps of the process, instructing the operator the expected execution (Hinrichsen et al., 2016). Both types are designed to increase the productivity of the operator and the assembly line and increase the quality of the process through error prevention.

2.6. The Brazilian context

Industry 4.0 is a term to identify the technological changes and innovations that allow a disruptive degree of digitalization in industrial production (CNI - Confederação Nacional da Indústria, 2023). Among the disruptive technologies for industrial application are artificial intelligence technologies embedded in industrial processes and sensors capable of processing data in real-time to evaluate important indicators of the production line.

However, to ensure the application of these technologies in industry, it is necessary to allocate resources to digitize the production line. The investment intention in the Brazilian industry, according to the CNI in November 2023, is at 55.6 points since the beginning of available data from November 2013; the highest index was 61.5 in January 2014. (CNI - Confederação Nacional da Indústria, 2023). This indicator reflects the percentage of industrial transformation and extraction companies that intend to invest in the next 6 months, according to the CNI. Still, according to the Confederation, the greater the investment, the greater the growth of the economy; therefore, knowing the investment intention helps to predict what will happen with the growth of the industry and the economy as a whole. The index of 55.6 points indicates that more than half of companies in the Brazilian industrial sector intend to make investments, which may indicate a tendency to adopt new technologies (CNI - Confederação Nacional da Indústria, 2023).

One of the important indicators in a production line is quality. In its different approaches, quality is any property of products, materials, or processes necessary to achieve suitability for their use (Toledo et al., 2014). In the manufacturing-based approach, quality is compliance with specifications, a challenge for quality is how to measure the specifications of the units produced on a production line. With the pressure for higher quality, new possibilities for investments in automation and robotization technologies in manufacturing emerge to collect quality indicators through sensors in real-time, optimizing production units (da Silveira Bruno, 2016).

3. Methodology

The present paper evaluates the current bibliography about the state of the art on the use of deep learning in industrial assembly quality assurance. It has a bibliographic exploratory objective (Silva & Menezes, 2001) as it seeks to evaluate different ways of applying intelligent systems to assess quality in assembly lines and what will be the optimal way of application at the laboratory level.

So, as described in the introduction, based on an analysis of the current literature on assembly assistance systems, this study intends to look for answers on the following questions: what is the state of the art on the development of AAS? What is its relation with artificial intelligence? How can an AAS and artificial intelligence be related to quality assurance? How to develop an AAS with artificial intelligence to enhance assembly quality?

The study's methodology involved a bibliometric analysis using the descriptors "deep learning," "industrial," “assembly,” and “quality” in the database of peer-reviewed publications of SCOPUS. The results obtained were filtered to be considered only scientific arcticles written in English. These articles were read, and we applied bibliometric techniques and qualitative classificatory analysis to identify the relationship between artificial intelligence, quality assurance, and assembly in an industrial context and how the systems proposed were developed.

4. Results and discussion

As described in the methodology, the first search obtained 95 publications without any filter and only the descriptors, which, from selecting only scientific articles written in English, reduced to 38 items found. Within the found publications, the oldest paper was published in 2017 with the title "Reducing false detection during inspection of HDD using super resolution image processing and Deep Learning" (Ieamsaard et al., 2017). This paper studied fault detection during the inspection of Hard Disk Drives, a computer component. The paper used convolutional neural networks (CNN's) to evaluate images in three channels from the production of Hard Disk Drives (Table 1).

Table 1. Bibliometric Search Quantitative Results

Quantity	Criteria
95	Search on Scopus with the key: TITLE-ABS-KEY("Deep Learning" AND "industr**" AND("assembly" AND "Quality"))
42	Filtering by type. Gathering only journal published papers.
38	Filtering by language. Gathering only English written papers.
37	Gathering only papers already published by the time the present paper was written. (There was one paper with a future release date).

As of 2019, the number of publications in this area has increased. The year featured 3 articles on the topic and the paper with the highest number of citations was published this year, "Fault Detection and Isolation in Industrial Processes Using Deep Learning Approaches" (Iqbal et al., 2019). This article presents an approach to automating fault detection using artificial neural networks (ANN's). Sample evaluation was performed using an algorithim and discusses the expected benefits of automation in fault detection and its comparison with classic and contemporary defect evaluation methods.

According to the paper, automated fault detection is interesting because it can be combined with prediction algorithms to estimate future assembly line behaviors to predict and avoid failures. One of the biggest problems cited in the arcticle is the definition of thresholds for evaluated characteristics. The main fault detection methods, until then, compared characteristics with reference threshold values to identify the existence or not of defects in a given assembly. A way of overcoming this problem is the adoption of statistical process control, which uses data from certain moments. The article uses automation with real-time data gathering from the assembly line, which can lead to a more faithful and controlled process of detecting failures and identifying patterns for failure prevention. To assess the global relevance of the topic, it is interesting to validate the profile of publications by country. The country with the largest number of publications is China with 16 english written papers. Furthermore, considering also the articles published in Chinese, there are 20 articles found on the topic (Graph 1).

The Chinese paper with the highest number of citations is the article "Stud Pose Detection Based on Photometric Stereo and Lightweight YOLOv4" (Zhang & Wang, 2022). The paper deals with the development and implementation of a simplified You Only Look Once ─ YOLO ─ algorithm for evaluating pin positioning in automobile assembly. The YOLO algorithm is an architecture used for real-time detection and tracking of multiple objects, generating coordinates for each object (Redmon et al., 2015), so that the incidence of an object in a video will not be processed more than once the which helps in evaluating metrics such as count, while the algorithm reduces replication of detections. Version 4 – YOLOv4 – is optimized for speed and accuracy in object detection (Bochkovskiy et al., 2020), in this case, the positioning of welded pins.

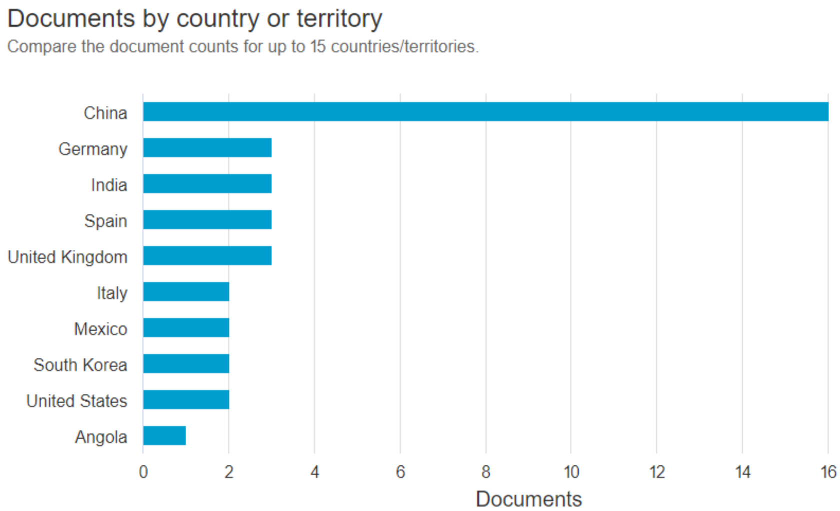

Figure 1. Quantity of articles published by country

The next countries with the highest number of published papers are Germany, India, Spain, and the United Kingdom. Of these countries, the paper with the highest number of citations is "Fault Detection and Isolation in Industrial Processes Using Deep Learning Approaches" (Iqbal et al., 2019). The most relevant paper, according to the Scopus database, is the Spanish article "Deep Learning-based Visual Control Assistant for Assembly in Industry 4.0" (Zamora-Hernández et al., 2021). This paper proposes an approach to evaluate the activities executed by operators during the assembly process in a production cell, seeking to prevent failures. The paper aims to detect and reduce errors in the execution of assembly instructions, waste of materials, incorrect use of tools, and the assembly learning curve, leading to a reduction in product failures.

Algorithms such as YOLO and fast region convolutional neural networks (Faster R-CNN) were trained to identify which tools are used in the assembly process, allow the identification of the assembled parts, and interpret the user is activity. Failure prevention is the process of improving quality and productivity by preventing the insertion of defects in a product (Mays et al., 1990). By using automation through artificial intelligence for monitoring focused on failure prevention, the proposed system directly evaluates the operator's action, which can promote an increase in operator productivity, reduction in waste, and the cost of production with failures and material waste, improving industry productivity and reducing the delivery time of products to customers. Which can promote greater efficiency and cost reduction than fault detection.

Among the Indian papers with the highest number of citations and relevance, two stand out: "An optimized Deep Learning approach to detect and classify defective tiles in the production line for efficient industrial quality control"(Kovilpillai & Jayanthy, 2023) and "Nuts&bolts: YOLO-v5 and image processing based component identification system" (Mushtaq et al., 2023) demonstrating that the application of Deep Learning techniques to assess quality in the assembly process is not restricted to a certain type of industry, and can be applied, in addition to these, in the industry food (C. Zhou et al., 2022), computing (Ieamsaard et al., 2017), furniture manufacturing (Augustauskas et al., 2021), electronics (Schwebig & Tutsch, 2020). In general, there are 3 main trends in research on the application of deep learning in the industrial assembly process. This can be assessed through bibliographic coupling, which represents papers that cite references in common and, by using similar references, can indicate trends for future work in that area.

Possible trends indicated by cluster analysis (Figure 1) are research with convolutional neural networks in the electronics industry (Schwebig & Tutsch, 2020), identification of faults in naturally irregular parts (Augustauskas et al., 2021; Jwo et al., 2021), failure process automation in the transportation industry (Figure 2) (Lu et al., 2022; L. Zhou et al., 2023).

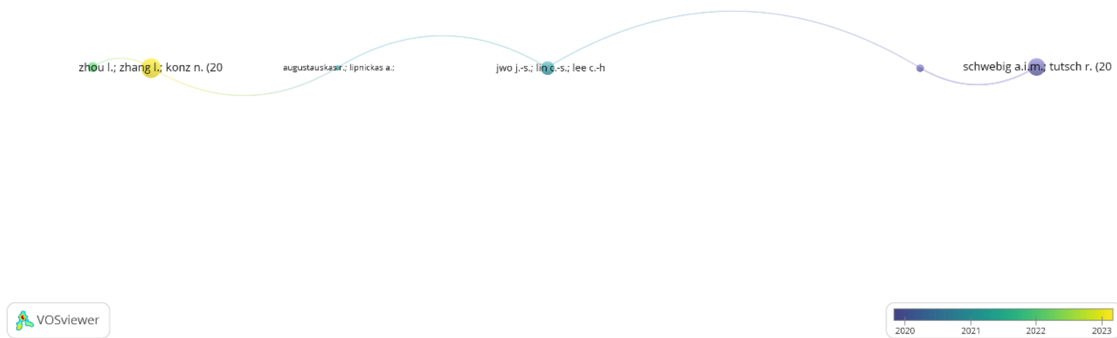

Figure 2. Bibliographic Coupling Diagram. Each link between papers means that those two papers (found on the original search made by this study) cited a group of third papers in common.

Another important indicator for evaluating how relationships between papers in the area are progressing is the co-citation analysis, which evaluates which papers are most cited together and demonstrates which bibliographies are most common for the area. Papers grouped by co-citation help to identify research strands within the topic, since papers that cite the same third party in common are more likely to have contributions with similar bases and, thus, a research strand is constructed (Figure 3).

Figure 3. Co-citation diagram. Each link between papers means that those two papers were cited together by a third paper (found on the original search made by this study).

Although 3 groups were identified (Figure 3), from the details (Table 2), it is possible to see that the paper "Deep residual learning for image recognition" (He et al., 2016) is present in groups 1 and 2. Furthermore, the papers "How transferable are features in deep neural networks?" (Yosinski et al., 2014) and "Gradient-based learning applied to document recognition" (Lecun et al., 1998) from group 2 and "Deep Learning" (Lecun et al., 2015) from group 3 are written by the same authors. Demonstrating the proximity between the research aspects of the topic.

Table 2. Co-citation bibliographic groups

Paper	Notes
Group 1	
(Mario Berger, 2012)	Book about inspection and testing with focus on electronic industry
(Goodfellow et al., 2016)	Book about the main techniques and principles of deep learning

(He et al., 2016)	Conference paper about deep learning for image recognition
(Müller et al., 2017)	Article about machine learning using Python
(Raschka & Mirjalili, 2017)	Article about machine learning using Python, sci-kit-learn and TensorFlow
Group 2	
(He et al., 2016)	Conference paper about deep learning for image recognition
(Lecun et al., 1998)	Article about artificial intelligence document recognition
(Ruder, 2016)	Article about Gradient Descending
(Simonyan & Zisserman, 2014)	Article about deep learning for image recognition
(Yosinski et al., 2014)	Article about Transfer Learning
Group 3	
(Golnabi & Asadpour, 2007)	Article about computer vision computational industrial applications
(Jia et al., 2017)	Article about computer vision industrial applications
(Lecun et al., 2015)	Article about Deep Learning theory and techniques
(Malamas et al., 2003)	Article about computer vision industrial applications

Another important analysis is the relationship between the articles´ keywords (Figure 4). Keywords are an interesting indication of how a topic will be covered in a paper and how the relationship between two terms occurs. The relationship between words in a period can indicate how the approach to the topic has evolved.

Some relationships are intrinsic to the definition of terms, for example, “Deep Learning” and “computer vision,” this is because “Deep Learning,” is a technique within the computer vision field in the same way, that “convolutional neural network” is a type of “deep neural network.” The same thing happens with “machine learning” and “Deep Learning”, which are sets of different techniques known as artificial intelligenc

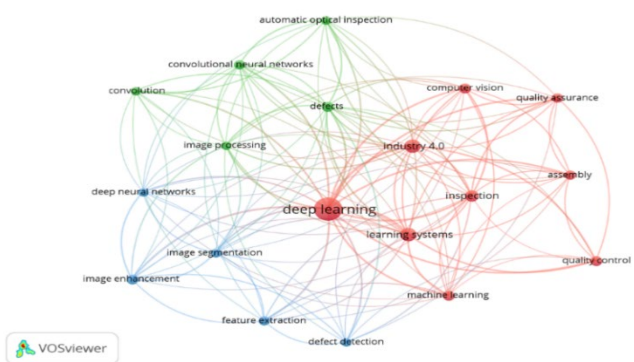

Figure 4. Keywords found on the papers gathered by the bibliometric search organized in a diagram indicating the relative frequency of each word apparition and the relation between words. Every link between two words means that they were together as keywords in a paper.

However, the links involving “quality control” help to understand how the topic is related to terms such as “learning systems”, “Deep Learning” and “inspection” so that quality control is highly related to inspection in production systems and uses learning systems and deep learning as techniques to develop quality control. The papers with these relationships deal with deep learning approaches in the detection and fault recognition (Iqbal et al., 2019), understanding quality control as detecting and preventing the propagation of faults in a production line (Bhandari & Park, 2021; Zamora-Hernández et al., 2021), on the identification and classification of defects in parts (Kovilpillai & Jayanthy, 2023) and real-time assembly monitoring and control (Torkul et al., 2022). With the plurality of definitions for the term “quality control” within these relationships, it can be understood that Deep Learning techniques can be applied in different ways and at different times in the assembly processes to obtain different quality measurements adaptable to different types of industry (Iqbal et al., 2019).

Another interesting relationship is between "automatic optical inspection", "defects," and "image processing." This relationship helps to understand how image processing can be useful in detecting defects during an assembly process by integrating an analog assembly line with an intelligent computerized system. The way image processing was used to detect defects varies according to the purpose of the paper, one of the proposals was to process images in real-time to classify images based on the existence or not of flaws (Schwebig & Tutsch, 2020), detection of objects, in which the defined objects to be identified are specific flaws in a given part (Kovilpillai & Jayanthy, 2023; Sassi et al., 2019), as well as the classification of specific defects based on the comparison between the images received and the image of a correct part (Le et al., 2022).

The relationship between "Feature Extraction" and "Inspection" can help to highlight how the inspection process of assembled parts was automated. The paper "Computer vision techniques in manufacturing"(L. Zhou et al., 2023) systematically reviews computer vision methods used in different parts of a manufacturing process. This paper explains that "Feature Extraction" is the basis of many other computer vision algorithms (L. Zhou et al., 2023) and can be used to find specific objects in images (Augustauskas et al., 2021; Kovilpillai & Jayanthy, 2023; Le et al., 2022; Liu et al., 2019; Zhang & Wang, 2022; L. Zhou et al., 2023) or to evaluate features on image edges (Shafi et al., 2023; L. Zhou et al., 2023).

It is not necessary for an AAS to be an intelligent system (Hinrichsen et al., 2016). Although, the implementation of an intelligent AAS is most commonly an image based architecture (Augustauskas et al., 2021; Bochkovskiy et al., 2020; Ieamsaard et al., 2017; Iqbal et al., 2019; Kovilpillai & Jayanthy, 2023; Le et al., 2022; Liu et al., 2019; Mushtaq et al., 2023; Zhang & Wang, 2022; C. Zhou et al., 2022), specialy YOLO since it is a video recognition architecture, wich can be well adapted for gathering information from an assembly line, since it is a dynamic enviroment.

5. Conclusion

Quality is integrated into the evaluation of a product, whether through quality assurance or through the consumers perception. There are different ways to guarantee quality in an assembly line and different ways to design a computational intelligence system. The combination of those can support quality assurance according to the perspective adopted in quality control planning.

From the perspective of innovation and technologies used in manufacturing, industry 4.0 defines the use of intelligent technologies that support manufacturing development with better efficiency and productivity, whether by a human operator or through anthropometric support systems, with the use of robotics technologies to execute tasks.

An AAS can be built in different ways. This type of system guarantees support for an assembly, which can be physical or informational. An AAS architecture may or may not use computational intelligence techniques, but an AAS is a cyber-physical system as it performs a real and virtual world interaction to support the operator in assembling, with sensors to monitorate the operator activity and information delivery to provide assembly instructions for the operators.

Furthermore, there are different intelligent algorithms to evaluate and control the quality of a process. It is possible to adapt intelligent systems to the expectations and peculiarities of a specific assembly line. Therefore, studying different approaches to develop and implement an AAS prototype in a traditional assembly line can be a contribution to the technological development of companies in the industrial sector and adaptation to Industry 4.0 and, also, understanding how the implementations of knowledge graphs can contribute to enhance the understaninment of assembly steps by an AAS and can be a step further in future investigations.

This paper contributes to bringing the main themes and author networks in this area, their recent advancements, and state-of-the-art contributions. The main limitation of our paper is that it is based on only one databases, and future improvements can take other ones as reference data. Our agenda is to develop a quality control system for assembly lines and applying it to Brazilian industries, mainly automotive and secure systems, to study the ergonomic implications of different types of deep-leaning algorithms.

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