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Smart Machine Vision System to Improve Decision-Making on the Assembly Line

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Abstract: Technological advances in the production of printed circuit boards (PCBs) are increasing the number of components inserted on the surface. This has led the electronics industry to seek improvements in their inspection processes, often making it necessary to increase the level of automation on the production line. The use of machine vision for quality inspection within manufacturing processes has increasingly supported decision making in the approval or rejection of products outside of the established quality standards. This study proposes a hybrid smart-vision inspection system with a machine vision concept and vision sensor equipment to verify 24 components and eight screw threads. The goal of this study is to increase automated inspection reliability and reduce non-conformity rates in the manufacturing process on the assembly line of automotive products using machine vision. The system uses a camera to collect real-time images of the assembly fixtures, which are connected to a CMOS color vision sensor. The method is highly accurate in complex industry environments and exhibits specific feasibility and effectiveness. The results indicate high performance in the failure mode defined during this study, obtaining the best inspection performance through a strategy using Vision Builder for automated inspection. This approach reduced the action priority by improving the failure mode and effect analysis (FMEA) method.

Keywords: machine vision; vision sensor; FMEA; smart vision inspection; screw detection; thermal paste detection

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1. Introduction

Inspections play a very important role in the manufacturing process among industries. Machine vision systems automate complex tasks for positioning inspection, identification, verification, measurement, and fault detection throughout the production chain. Unlike human inspectors, who can process only a certain amount of information at a time, machine vision systems operate continuously, performing 100% automated inspections [1]. This improves quality, increases yields, and lowers production costs [2]. High-quality and consistent product appearance and functionality [3] drive positive customer experiences and ultimately increase the product's market share.

Industries have been using automatic optical inspection (AOI) to inspect defective PCB components [4]. AOI systems generally use defect inspection methods by scanning the board and performing analysis. Methods such as matching local features to a standard image [5] and morphological image comparison are used to detect defects and obtain excellent results. However, problems with reflective materials can cause false rejections. With the increasing miniaturization of components inserted onto the surface of PCBs, the

challenges of ensuring the detection of these components are becoming increasingly complex [6]. This includes the detection and recognition of various components, such as screws, threads, gasket, and thermal paste, which are difficult to recognize through manual visual inspection [7]. As a result, the automation of inspection processes through vision systems for defect detection are increasingly required [8]. In production, it is necessary to identify defect-free products with sophisticated inspection methods [9], such as methodologies or intelligent algorithms capable of learning from data [10]. Quality inspection is a crucial process to ensure the reliability and quality of a product before it is shipped to the end consumer. Inspections are often performed visually by human operators, which can result in variations in the classification of defects due to physical and emotional inconsistencies of each operator [11,12]. This has led companies to seek out efficient inspection methods to check for defects in the early stages of production [13].

In this paper, we propose an industrial hybrid smart vision system using machine vision and vision sensors to detect the absence of screws, screw threads, the excess or lack of thermal paste, conductive pads, and chassis tabs on the surface of the main PCBs of car radios, produced for the automotive industry.

2. Theoretical Frame

Machine vision is strongly related to computer vision, enabling significant gains in efficiency and reliability of failure mode detection. It requires good lighting systems, sensors, cameras, and computer systems, such as Vision Builder for image processing [14].

With the advancement of artificial intelligence and the constant improvement of cameras and sensors, machine vision has become increasingly prevalent within industries for measuring and decision-making, helping to determine product compliance [15]. According to [16], machine vision has been used in processes with high repetition rates, benefiting several industrial activities.

2.1. Bibliometric Analysis of Machine Vision, FMEA, Vision Sensor, and Screws

A bibliometric analysis was performed to analyze the dynamics of research evolution, considering the machine vision concept for quality inspection of the manufacturing process in the context of Industry 4.0 and Quality 4.0. A final search was carried out in December 2024 on the Scopus database and Web of Science Database, with the terms “screw” or “FMEA” or “conductive” and “machine vision” or “vision sensor” or “smart inspection” used in the titles, abstracts, and keywords of the articles. For the portfolio, only articles published in English were considered.

Based on the adopted methodology, 67 articles were included in the qualitative synthesis. From the articles selected for content analysis from 2013 to 2024, quantitative analyses were developed using the Bibliometrix tool of R Studio® software, following the procedure developed by [17].

Figure 1 shows the PRISMA methodology used in the research [18].

The final search string is presented as follows:

String to Scopus database: TITLE-ABS-KEY ((“screw” OR “FMEA” OR “conductive”) AND (“machine vision” OR “vision sensor” OR “smart inspection”)).

String to Web of Science database: TS = ((“screw” OR “FMEA” OR “conductive”) AND (“machine vision” OR “vision sensor” OR “smart inspection”)).

Figure 2 shows the temporal evolution of the selected publications for the portfolio. The year 2013 was the first time a publication appeared in an indexed journal in the considered databases. The study by [19] presented a packing automation system using machine vision to improve inspection errors due to delays in the inspection process. The

authors of [20] described a model based on a combination of machine vision and deep learning to obtain localization information for controlling robotic arms.

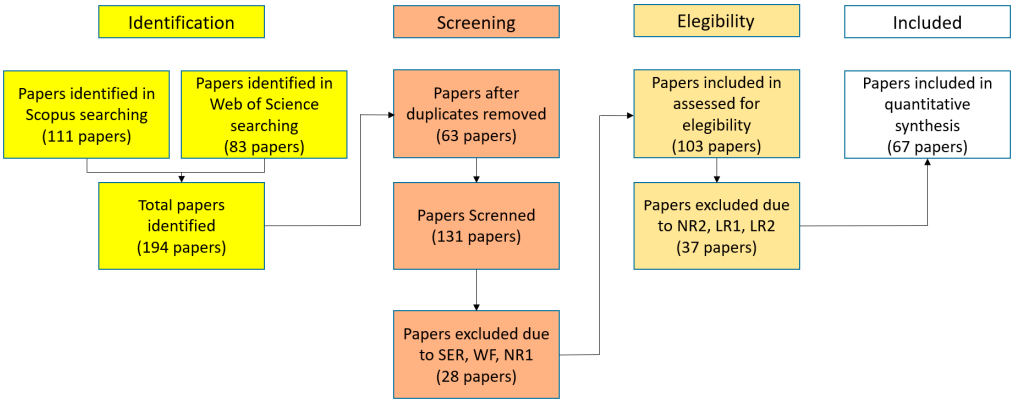


Figure 1. PRISMA methodology.

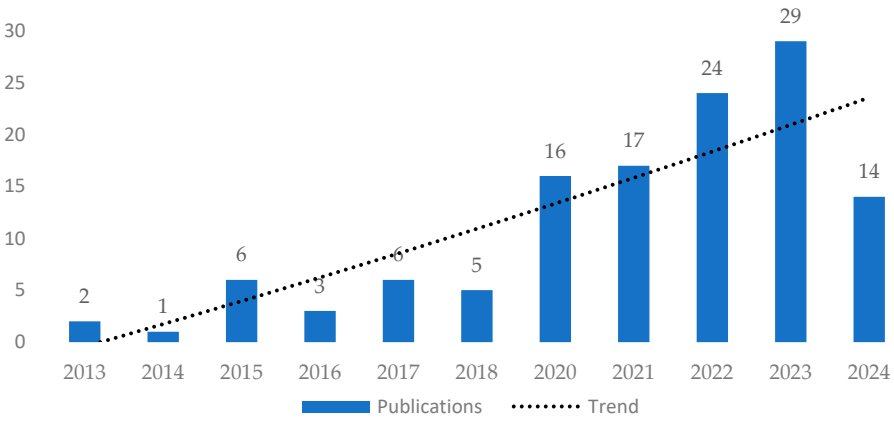


Figure 2. Temporal evolution of publications.

Since 2013, the number of publications has grown consistently. Between 2019 and 2024, publications increased by 75%. This analysis shows the growing interest in smart inspection using machine learning algorithms.

Figure 3 shows the main countries with associated studies in the research area, categorized by publications authored by only one country (in blue) and those by several countries (in red). China demonstrates strong performance with sixty-one publications, followed by the USA with thirteen, Canada with seven, India with six, and the other countries with six or fewer publications.

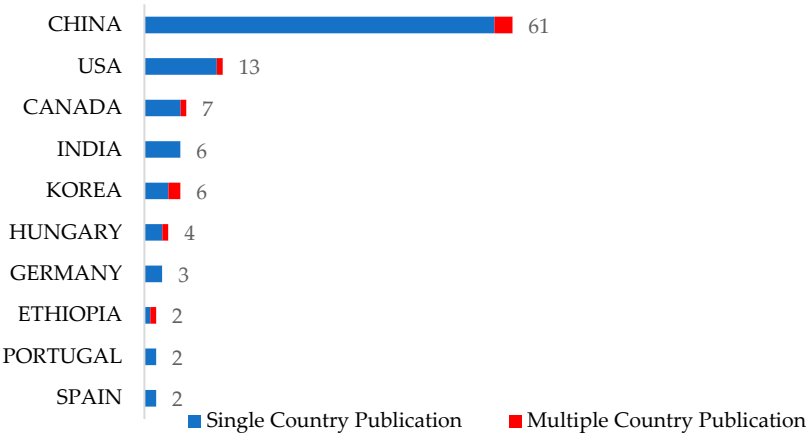


Figure 3. Publication by country.

Figure 4 shows a multidimensional scaling keyword co-occurrence network [21], using an edge betweenness centrality clustering algorithm.

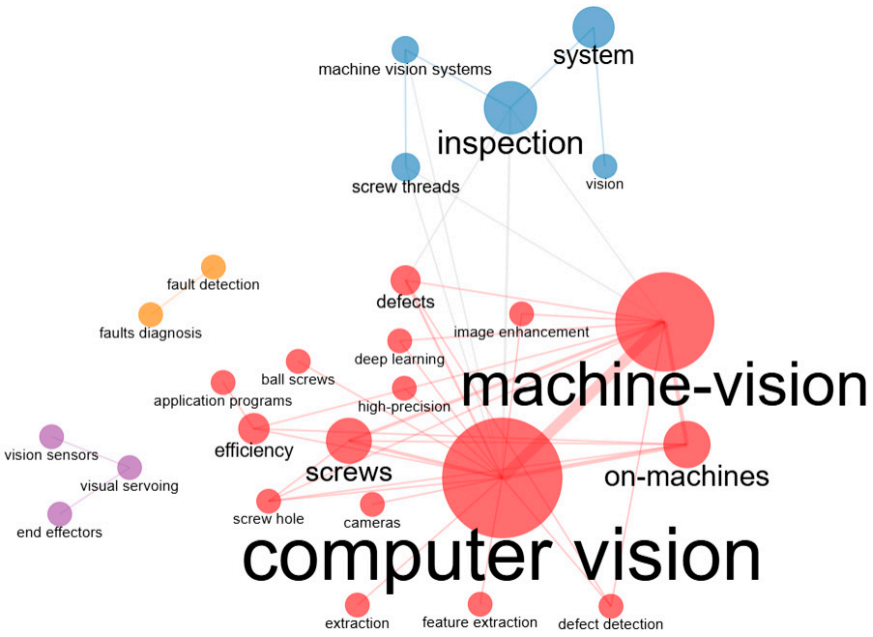


Figure 4. Keyword co-occurrence network based on the bibliometric research.

The figure identifies the main cluster of terms (in red) that address the intersection between "machine vision" and "computer vision". Surrounding the central terms, other topics, such as "screws", "defects", "defect detection", and "efficiency", appear in the co-occurrence network. It is important to note that vision sensors do not directly correlate with computer vision, highlighting the innovation of the research and implementation of this hybrid system.

Figure 5 shows a word cloud graphic that illustrates the most common expressions among the analyzed articles. From this, it is possible to conclude that the central themes involved in the area of computer vision—particularly in research that seeks to correlate the concept of inspection and screw defect detection—are the terms "machine vision" and "automation". This indicates that most of the studies in this area are focused on defining concepts and implementing new hybrid methods into existing models in the smart inspection environment to drive digital transformation.

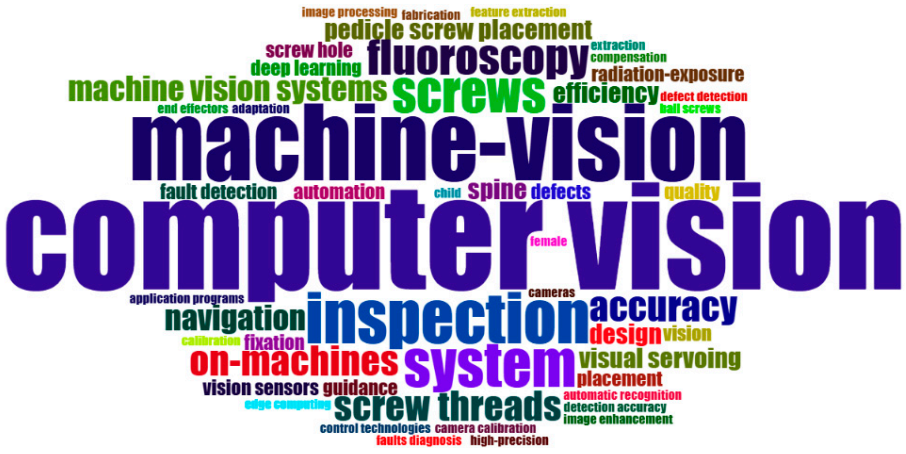


Figure 5. Word cloud of the bibliometric research.

2.2. Failure Mode and Effect Analysis (FMEA) Process

The aim of manual quality inspections is to minimize failures during production. By performing thorough inspections, it is possible to reduce defects. To address this need, the automotive industry has adopted the failure mode and effect analysis (FMEA) AIAG-VDA quality tool to help evaluate possible process defects and prevent their occurrence.

The FMEA manual describes an analysis technique designed to be applied to components. The objective is to identify all possible defects and evaluate the effects these failures will have on the other components, according to the FMEA manual.

The main objective of FMEA is to identify defects, evaluate their causes and effects, and propose solutions to prevent their occurrence. The ultimate objective is to produce a product free of defects, both during the production process and throughout its use by the customer, according to the FMEA manual [22].

Each component is examined to identify possible defects. For each defect mode, three values are assigned: the severity of the defect impact ("S"), the occurrence of the defect mode ("O"), and the ability to detect the defect before it occurs ("D"). The multiplication of these three variables generates the risk value (NPR), according to the FMEA manual, as shown in Figure 6.

Process Step	Process / Function	Requirement	Potential Failure Mode Potencial de Falha	Potential Failure Effect(s)	SEV	Special Characteristicasl "Symbology"	Potential Cause(s) of Failure	Current Process (Preventive Controls)	OCOR	Current Process (Detective Controls)	DET	NPR	Recommended Action
130	Manual Insertion + Screwing + Clinch	Conector(es) com o comprimento do terminal dentro do especificado	Connector(s) with short lead	Electrical functions not OK	6		Machine that performs the preform has failed	Operating instruction	5	Visual inspection of assembly and welding in accordance with IPC-A-610 class 3 at the next station	7	210	Need to improve
130			Connector(s) with the long terminal	Electrical functions not OK	6		Machine that performs the preform has failed	Operating instruction	2	Visual inspection of assembly and welding in accordance with IPC-A-610 class 3 at the next station	7	84	Does not require action.
130	Manual Insertion + Screwing + Clinch	Terminais dos conectores alinhados	Connector terminals misaligned	Electrical functions not OK	6		Improper handling	Operating instruction	2	Visual inspection of assembly and welding in accordance with IPC-A-610 class 3 at the next station	4	48	Does not require action.
130		Placa montada corretamente com os conectores na posição correta	Board assembled with connector(s) missing	Electrical functions not OK process interruption	6		Operator did not assemble the connector(s)	Operating instruction	2	Visual inspection of assembly and welding in accordance with IPC-A-610 class 3 at the next station	4	48	Does not require action.

Figure 6. Analysis of potential failure mode and effects.

During serial production, FMEA needs regular reviews based on lessons learned, problems, and change management using the process flow shown in Figure 7.

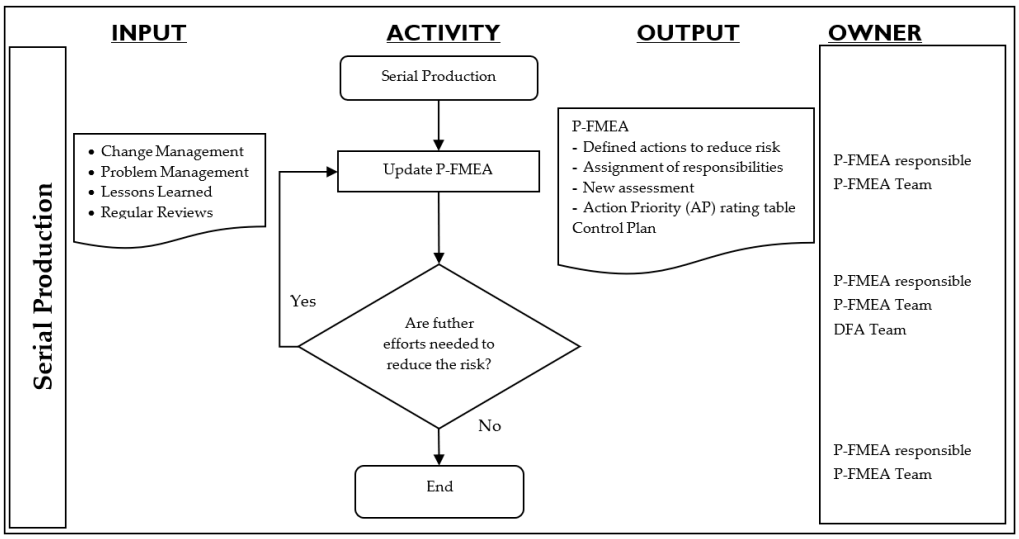


Figure 7. FMEA process flow for serial production.

The FMEA reference manual indicates that when the severity level is 6, the risk must be treated by recommended actions, as shown in Table 1, or existing project controls, according

to the FMEA manual. Every action must reduce the severity, occurrence, or likelihood of non-detection and should be assigned a person responsible and a deadline for completion.

Table 1. Severity, occurrence, detection.

Summary of General Evaluation Criteria for Severity (S)			
Rank	Effect	Impact on the Plant	Impact on Ship to Plant (when known)
6	Moderate	100% of the production run may have to be reworked offline and approved	Line shutdown up to one hour
Summary of General Evaluation Criteria for Occurrence (O)			
	Probability of failure	Criteria—Occurrence of failures	Rank
	Moderate	2 per 1000 (1 per 500)	6
		0.5 per 1000 (1 per 2000)	5
		0.1 per 1000 (1 per 10,000)	4
	Low	0.011 per 1000 (1 per 100,000)	3
		0.001 per 1000 (1 per 1,000,000)	2
Summary of General Evaluation Criteria for Detection (D)			
Rank	Ability to Detect	Detection Method Maturity	Detection Opportunity
7	Very Low	Station failure mode detection by an operator based on visual/tactile/auditory means or the use of a manual device or manual judgment.	Source problem detection
2	Very High	Detection of errors (causes) in the station based on automatic controls that will detect the error or prevent defective parts.	Error detection and/or problem prevention

Based on the detection probability table, a rank of 7 assigned to detection in the process of FMEA is a high grade and indicates that the probability of the operator detecting a possible failure is very low [22–25].

According to [6,26], the manual quality inspection process must be reliable to meet consumer expectations and the standards the automotive industry sets. However, it is common for inspections to be performed manually, which can be time consuming, tedious, and prone to human error, generating high operating costs and presenting difficulties in standardizing the results. This makes its automation desirable.

According to [25,27], in the context of industry, the existing foundation of computerized automation and a business vision focused on digital transformation gives rise to the concept of Industry 4.0. This is based on the integration of information and communication technologies, which allows new levels of productivity, flexibility, quality, and management to be reached. This enables the generation of new strategies and business models for industry through communication, integration, and connection using sophisticated software and sensors to promote advanced manufacturing technologies.

The aim of this research is to develop a new methodology using machine vision to carry out automatic inspections and increase quality reliability. According to the FMEA manual, the actions implemented by automatic controls will shift the rank from 7 (low detection capacity) to 2 (high detection capacity), as shown in Table 1, resulting in a significant increase in failure detection.

2.3. Inspection Process

Inspection processes are increasingly employing the concept of flexible manufacturing in the automotive industry, where it is possible to produce several models at the same manufacturing plant [28]. A large part of the line setup is prepared by human operators, which, in many cases, increases compliance errors, such as the incorrect replacement or feeding of components.

In [26], sensing technologies were proposed to provide reliability in manufacturing without excessive human dependence.

Several manufacturing service providers offer industries various applications for production and inspection using machine vision to meet industrial demand. These applications include component assembly, which uses vision systems to position objects at a given coordinate for the insertion or inspection of the components on the surface of the PCB. In automatic visual inspections, the inspection submits the components-specific compliance or rejection criteria, according to the pre-established parameters in the strategy for each inspected item.

2.4. Failure Modes Defined

Several failures can be detected during a production process, originating in different phases of the project, such as in the line setup, jigs, or even non-compliance with the production instructions [29,30]. Tables 2 and 3 show some failure modes in the production of the main PCB and chassis that make up the car radio.

Table 2. Failure modes—missing screw, gasket, or gap filler.

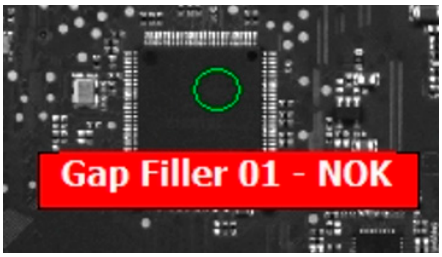
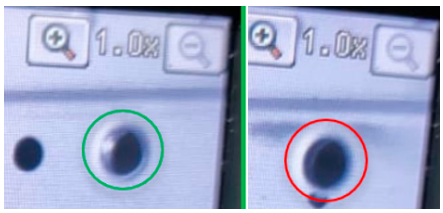
Items	Defect Type	Pictures	Process Side	Description	Inspection Type	Specification
1	Missing Gap Filler		Bottom PCBA	No evidence of gap filler (thermal paste)	Attributes	Pass/ No Pass
2	Missing Screw		Bottom PCBA	No evidence of a screw	Attributes	Pass/ No Pass
3	Missing EMI Gasket		Bottom PCBA	No evidence of a gasket	Attributes	Pass/ No Pass

Table 2 shows the failure modes inspected at the workstation, including missing thermal paste (gap filler), a missing screw, or a missing conductive pad, which are performed on the PCB surface.

Table 3 shows the failure mode of a threadless screw hole in the car radio chassis, as inspected at the workstation.

Table 3. Failure mode—threadless screw hole.

Items	Defect Type	Pictures	Process Side	Description	Inspection Type	Specification
1	Threadless Screw Hole		Side chassis	Threadless hole	Attributes	Pass/No Pass

2.5. Manual Inspection and Machine Vision

Visual inspection processes can occur in two ways—by human or automatic analysis and judgment [6]. The efficiency of manual inspection is often compromised by environmental and human factors, which can impair the human capacity for evaluation and perception, especially as fatigue increases throughout the workday [31].

According to [15], the use of intelligent processes in industry, especially through machine vision, has become one of the leading technologies used to carry out inspections. It is increasingly demonstrating its efficiency and quickly promoting the replacement of human visual inspection. Machine vision is a system that automatically collects and processes images of real objects using optical devices and sensors autonomously. Figure 8 illustrates both the manual inspection process and the automatic process through machine vision.

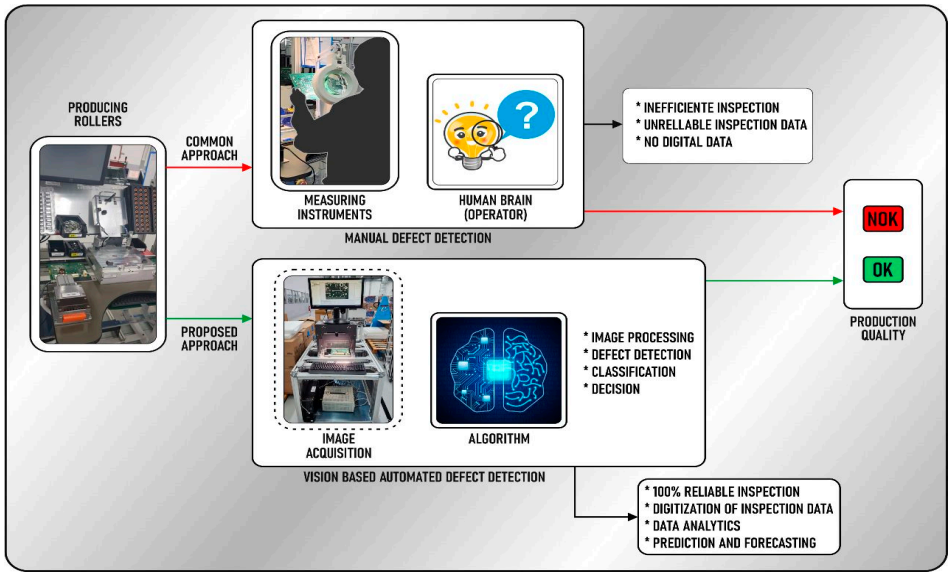


Figure 8. Comparison of manual and machine vision inspection processes.

Figure 8 shows the image capture process used to carry out inspections. In contrast, the manual process is carried out by an operator who performs the judgment process. Often, factors such as fatigue can affect the operator's judgment, affecting their ability to approve or reject the item inspected. However, machine vision is not subject to biological variations over time, meaning that it remains unaffected at every stage of inspection for which it is used [32].

3. Machine Vision System

Machine vision is best viewed as a technique that can be used to achieve various tasks. Industrial inspections, observation, monitoring, and sorting are some applications of

machine vision, although its capabilities are not limited to only these examples [11,33,34]. Several applications can be described as follows:

Industrial inspection: This is a common application of machine vision, where it is used to locate defects in a product.

Process monitoring: There are different types of machine vision cameras, and they are made to be reliable in different environments and to have a long lifespan. As a result, machine vision cameras can help observe or monitor certain situations.

Sorting: Machine vision can be used in various ways to sort objects based on color, shape, size, or other features. The software component of machine vision identifies the object, and the data obtained can be later passed on to another device to sort the object physically.

Optical measurements: Machine vision can also serve as a method to perform measurements visually. Suppose the setup is stable and the incoming images are acquired under consistent conditions. In this case, information can be extracted from the image and converted into real-world units.

Robotics: Similar to the method of obtaining optical measurements, controlling robotic movement is another common use of machine vision. Using the incoming images as a reference, data can be calculated and translated as commands to the robotic components to move or change settings.

The process of machine vision is as follows: acquisition—images are acquired from the camera; image processing—the images are digitally manipulated; and data extraction—quantitative data are extracted from the images and autonomous decisions are made based on the extracted data [32].

A vision sensor is a low-cost, small-sized camera sensor that has high-quality precision and is able to reach tight targets at long distances. The system's process is as follows: capture—images are acquired; image processing—the images are digitally manipulated; and data extraction—quantitative data are extracted from the images and autonomous decisions are made based on the defined specifications.

Figure 9 shows the framework for hybrid smart vision inspection that was developed and implemented during this study. An 8-megapixel camera was mounted to the top of the assembly fixture to detect screws, gap fillers, and gaskets. All hardware was mounted on a structure with 12-volt and 24-volt power supply levels to turn on the camera, internal lighting systems, and sensors. Keyence vision sensors, model IV-HG500GA (Keyense, São Paulo, Brazil), were installed on the left and right sides to perform simultaneous hybrid smart vision inspection after assembly to ensure the quality and reliability of the products.

The hybrid smart vision systems are designed to automatically inspect 24 items on the surface of the PCB and eight screw holes in the car radio chassis by capturing images of the PCB and the chassis placed in the inspection station. The main processes and items to be inspected are as follows:

(1) Identify the fiducial points in the image.
(2) Binarize the image.
(3) Map components based on the information provided by the golden sample image.
(4) Detect gap fillers in components.
(5) Detect screws and pads.
(6) Detect threads for screws.

The location of the PCB fiducial is the initial and most critical process since any displacement correction affects the results of every inspection. The fiduciary points are generally symmetrical, represented in a circular shape [35], as shown in Figure 10. To locate the fiducial point of the plate, the Hough transform was incorporated into the algorithm strategy. This method is used in image processing to detect parameterizable shapes, such as lines, ellipses, and circles [36].

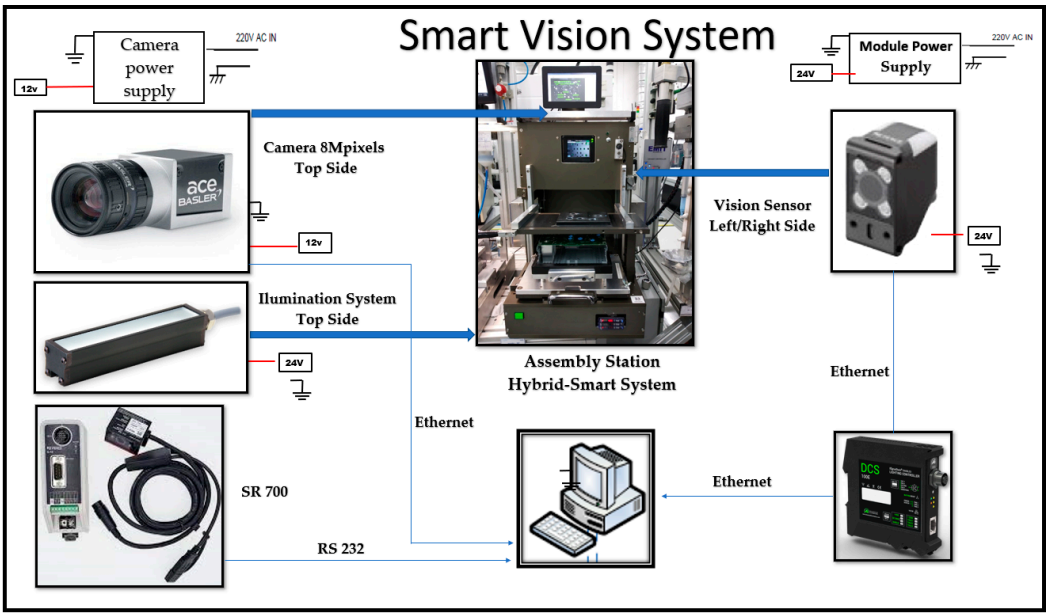


Figure 9. Hybrid smart vision inspection framework.

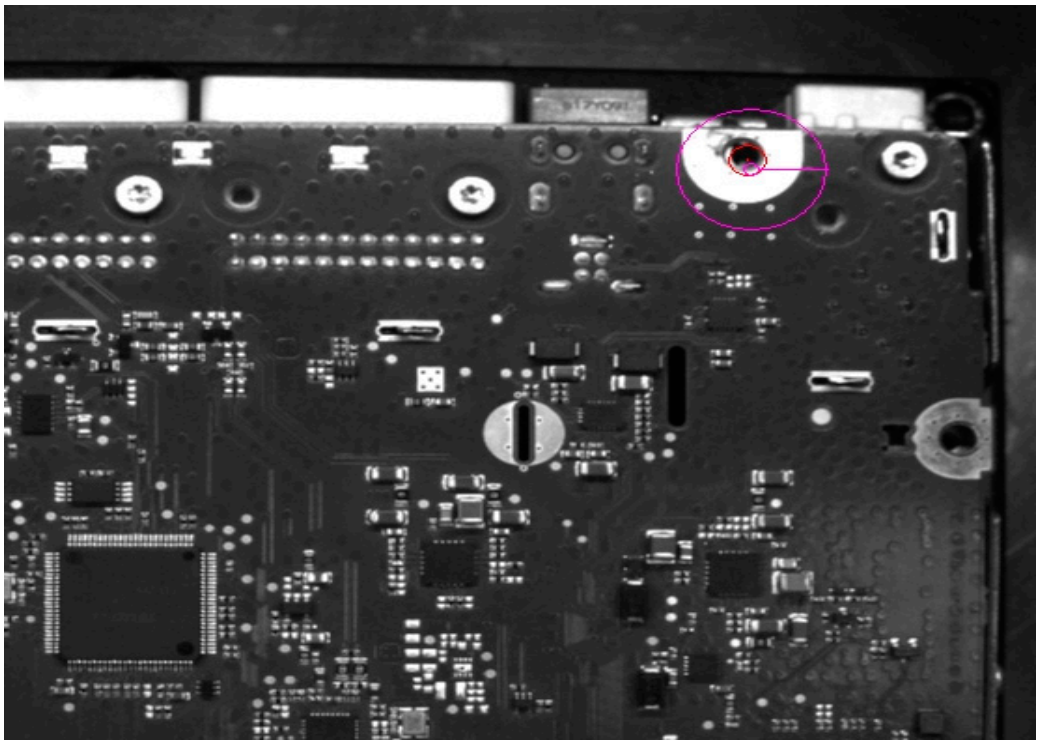


Figure 10. Fiducial reference inspection point.

After defining the fiducial of the PCB, an image of the real object is captured. An image can be defined mathematically, as a two-dimensional function $f(x,y)$, with $x, y \in \Re^2$, where x and y are the spatial coordinates that identify a given point, $f(x,y)$ denotes the gray level intensity of the image at a given point in the image, and $\Re$ is the set of real numbers [37].

A digital image is a function $f(x,y)$ discretized both in spatial coordinates and in the intensity of gray levels. It can be represented as a matrix in which the row and column indices identify an image element (pixel), and the element value identifies the gray level applied to the image [38].

After capturing the image, it is binarized, which consists of converting the various levels of gray from (0, 255) to (0.1). In this process, the pixels are defined with a value of 1, representing white, or 0, representing black, or vice versa [39], as shown in Equation (1).

$$(x, y) = \begin{cases} 1, & f(x, y) > L_b \\ 0, & f(x, y) \leq L_b \end{cases} \quad (1)$$

where b is the binary output image, f is the input image in gray levels, and L_b is the threshold chosen for pixel grouping.

As shown in Figure 11, the component mapping was developed by creating a strategy using the Vision Builder tool, with all definitions based on the customer quality specifications.

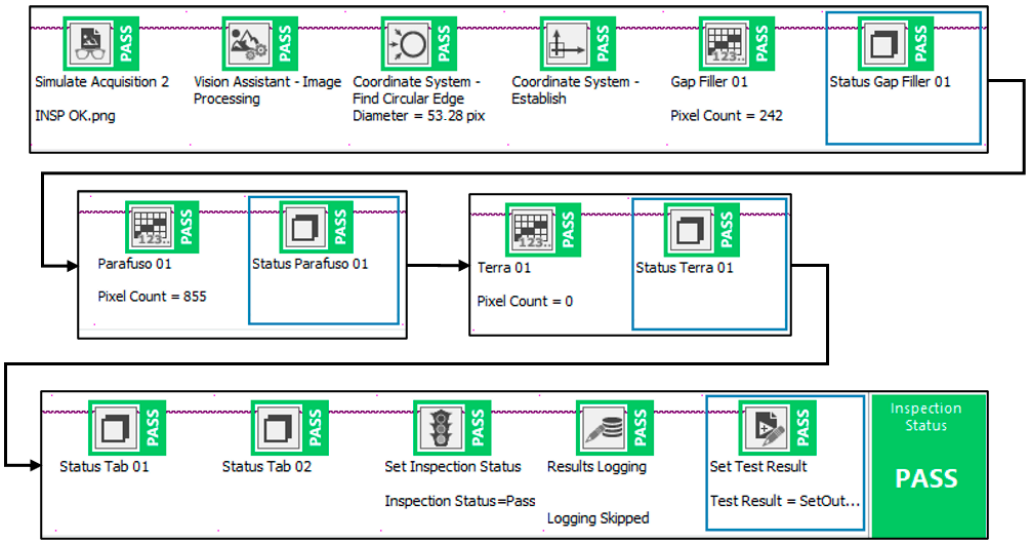


Figure 11. Inspection sequence strategy.

The luminosity criterion was defined for the inspection of the threads in the chassis to detect the metalized hole in the car radio chassis. An image sensor was used to detect the brightness intensity in the chassis hole. Since the properties of histograms do not preserve the spatial information of pixel distributions, focusing only on the number of pixels with a specific gray level [40], the effect is illustrated in Figure 12.

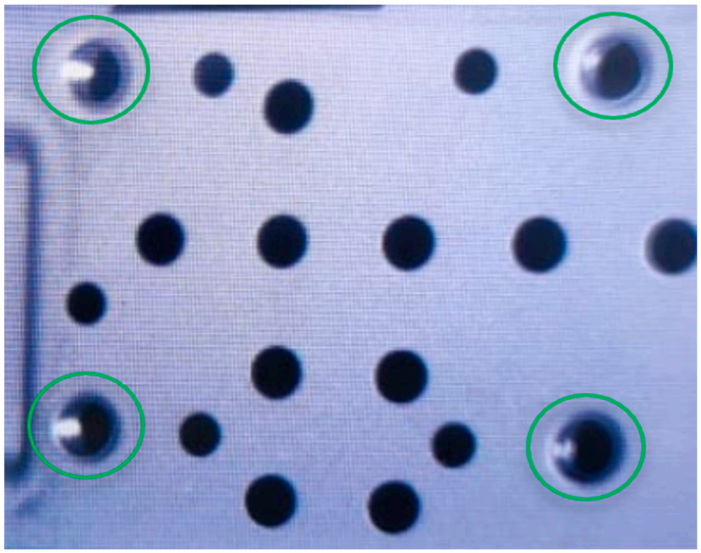


Figure 12. Chassis holes reflecting the light.

Even with different images, histograms can be identical, allowing for their use in pattern recognition [41], as illustrated in Figures 15 and 16.

4. Results and Discussion

Equation (1) accurately describes the algorithm's adaptability in processing the data during the tests carried out to evaluate the strategy.

The failure detection described in the defined failure modes had excellent results, as illustrated in Figure 13.

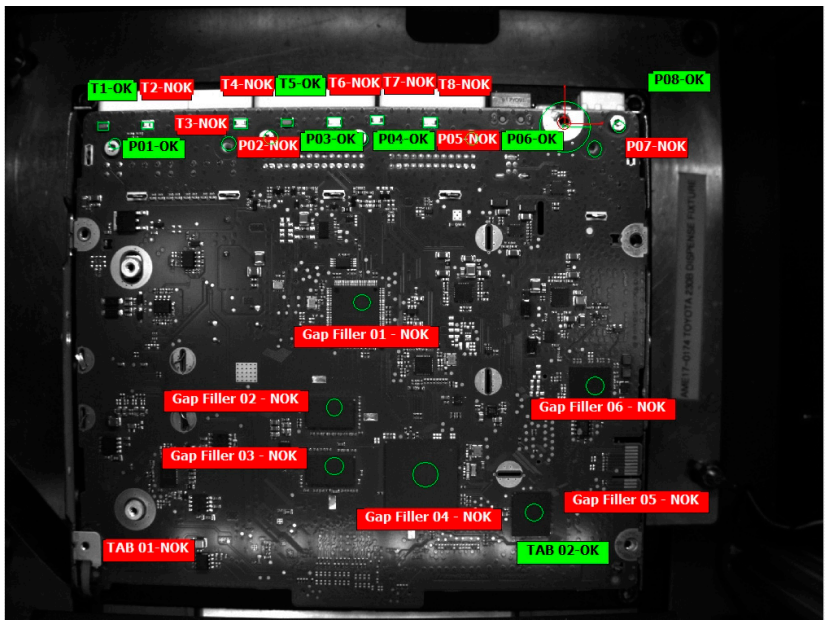


Figure 13. Defect results of PCBA inspection.

Figure 14 illustrates the system's efficiency in identifying the PCBs and chassis within the established parameters. After fine-tuning the vision system, the inspection process ensured 100% efficiency and that all items complied with the specifications.

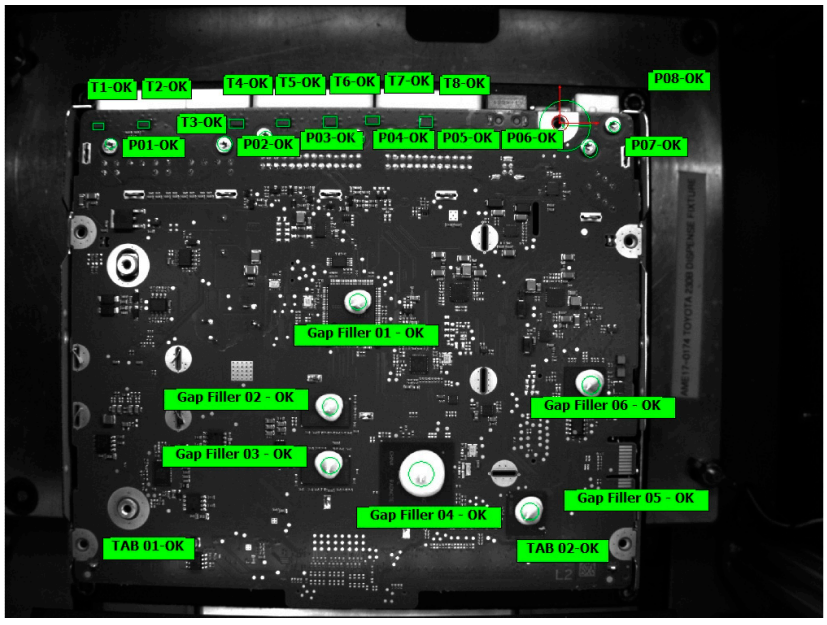


Figure 14. Approved results of PCBA inspection.

In Figure 15, the chassis image has between 25 and 245 pixels. It can be observed that the pixels with the highest brightness intensity of 1400 were significantly dispersed, with the most intense pixels at 30, 35, 200, and 220, precisely at the points where there was a higher incidence of brightness.

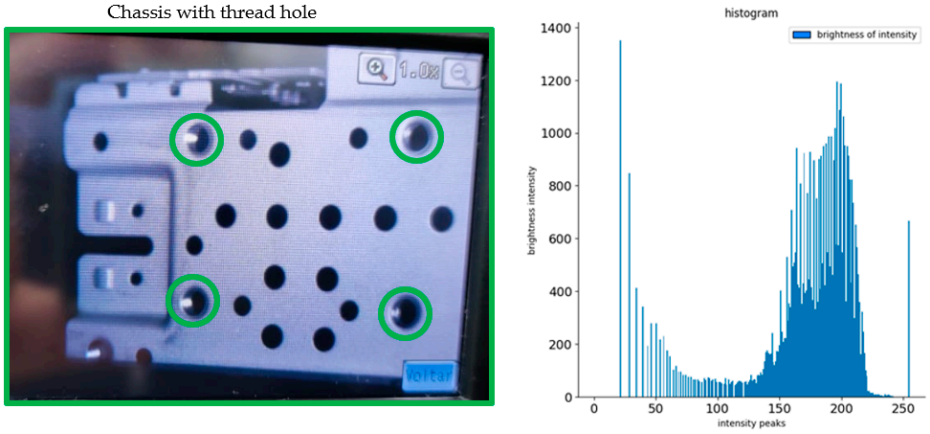


Figure 15. Approved results of a screw hole based on the reflection in the thread of the hole.

In Figure 16, the chassis image has between 25 and 230 pixels. It can be observed that the pixels with the highest brightness intensity of 1100 were significantly dispersed, with the most intense pixels at 30, 35, 200, and 210, precisely at the points where there was less incidence of brightness, resulting in a darker image.

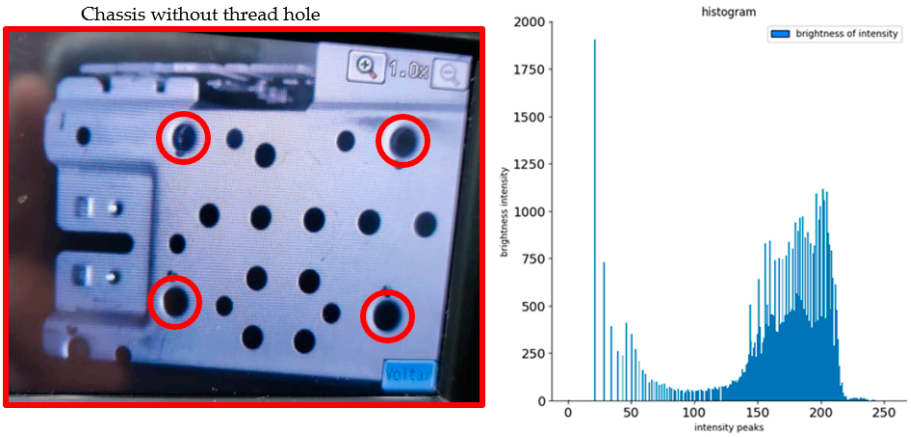


Figure 16. Defect results of screw side hole based on lack of reflection in the thread of the hole.

5. Conclusions

This research analyzed a new hybrid smart vision inspection method designed to improve the operator's decision-making abilities. The main proposal is to combine the inspection of flaws using machine vision techniques to detect defects in the absence or excess of thermal paste, conductive pads, screws, and threads for screw holes. Additionally, a smart vision sensor is used to simultaneously identify the threads of screw holes in the chassis without increasing the cycle time.

Industries face pressure to provide quality products to the automotive consumer market. Automatic inspection is directly linked to quality control, since defects, such as PCBs without conductive pads, can mean a loss of product efficiency and a decrease in the quality of the final product. This highlights the need to create methods for developing a hybrid smart vision system to inspect 24 items and eight threads of screw holes in the product chassis, using a machine vision system integrated with a vision sensor.

We conclude that after implementing the new system, we increased the reliability of the products as follows: (1) the FMEA risk priority number was improved; (2) real failures that were approved by manual inspection due to the operator's mistake were reduced; (3) traceability control was improved based on saved images; (4) the production output was maintained with additional automatic inspections; and (5) real failures were eliminated.

This research was applied in the real automotive industry; consequently, in addition to the technical achievements, the involved team was recognized by customers for the improvement in process and quality.

However, due to the influence of hardware conditions and algorithms, the research described in this paper still has the following limitations in practical applications. These limitations need to be addressed in future studies on the use of machine learning and deep learning algorithms to enable autonomous learning inspection processes.

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