IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 27, Issue 6. Ser. 10 (June 2025), PP 34-42
www.iosrjournals.org

Computer Vision System for Automatic Measurement of Boxes with Final Product in Production Lines

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Abstract:
This work proposed the development of a computer vision system for the automatic measurement of boxes with final products in production lines, with the objective of increasing the accuracy, agility and standardization of industrial measurements. Using image processing algorithms and camera calibration techniques, the system achieved an accuracy of over 97% and an average processing time of less than 0.5 seconds per case, demonstrating high efficiency and reliability. In addition, the tests carried out pointed to a robustness above 95% in different lighting conditions and line movement, evidencing the potential for practical application in real industrial environments. The results obtained validate the approach and suggest that the developed system is a promising solution to meet the demands of automation and quality control in Industry 4.0.
KeyWords*: Computer Vision, Industrial Automation, Product Quality, Production Line.*

Date of Submission: 08-06-2025 Date of Acceptance: 20-06-2025

I. Introduction

In the field of computer science, Computer Vision is the subdiscipline specifically focused on the computational interpretation of visual data. Historically, it is one of the first problems proposed, in the 1950s, for the development of AI, then as a derivation of cybernetics (CARDON, COINTET, MAZIÈRES, 2018).

Computer Vision has proven to be an effective resource for the industry, especially in production processes and quality control. However, the high cost of this implementation represents a difficulty for companies of different sizes and segments. In view of this situation, the advancement of this technology has become more present in the industry, enabling automated systems to comply with assembly sequences according to precise instructions, avoiding operational errors. With this condition, more investments in innovation can be generated, as shown by data from the Ministry of Development, Industry, Commerce and Services, based on the report that shows that in 2023, 59 companies in the Manaus Industrial Pole (PIM) invested R$ 1.48 billion in 425 projects aimed at research, development and training, encouraged by the regulatory framework established by the Manaus Free Trade Zone Information Technology Law (Law No. 8,387/1991). Some of these investments include the use of smart cameras on the assembly line, allowing not only to verify that all steps of the process are being executed correctly, but also to prevent risks and speed up production (BRASIL, 2024).

This study aims to demonstrate the operation of a system created to verify the quality in a production process, using a computer vision model. This system can be employed on the production line to ensure quality and automatically detect improper assemblies on the production line or at quality control points.

The general objective of this study is to develop and implement a computer vision system that allows the automatic measurement and quality verification of products in production lines, in order to ensure that the assemblies meet the specifications requested by customers. This system seeks to reduce human errors, optimize production time and minimize costs, contributing to the continuous improvement of production processes and customer satisfaction.

The developed system, designed to be implemented in a cardboard packaging company, aims to ensure that the assembly of the products strictly meets the specifications requested by customers. This is accomplished through the automatic verification of measurements and quality standards, ensuring that each product manufactured meets the established criteria. In this way, the system eliminates the need for manual measurements carried out by employees, reducing the margin of error and providing savings for companies. In addition, it contributes to the reduction of raw material waste, optimizes production time and reduces operating costs, resulting in more effective quality control.

II. Bibliographic Reference

The theoretical framework based on conceptualizing the computer vision revolution in the industry: automation and quality measurement, defining computer vision, referencing pattern recognition, and listing the OpenCV (Open Source Computer Vision Library).

2.1 The Computer Vision Revolution in Industry: Automation and Quality Measurement

With the advancement of technologies, Artificial Intelligence (AI) has become a crucial element in the industry, especially in the automation and optimization of production processes. According to the Future of Jobs Report 2025, AI and information processing are the technologies that will most impact business by 2030, resulting in 86% of changes in the work environment (WORLD ECONOMIC FORUM, 2025). The adoption of AI has promoted significant growth in the modernization of industrial processes, with 72% of companies already implementing this technology in their operations, according to a study by McKinsey (2024).

The growing demand for AI and Big Data-related skills reflects the transformation of companies towards smart technologies (WORLD ECONOMIC FORUM, 2025). Before the introduction of computer vision systems, the measurement and inspection of products on production lines was carried out manually, with operators using traditional instruments such as rulers, calipers, and micrometers. Although this practice was consolidated in the market, it impacted the quality of the final product. Automation, in turn, allows the reduction of human errors, improves production time, and increases the quality of products, in addition to minimizing labor costs (EGA, 2023).

The implementation of automated solutions, such as computer vision, has demonstrated a significant advance in the operational efficiency of companies. AI-based automation is predicted to reduce human participation in tasks by up to 15% by 2030, with 81.5% of this change attributed to replacement by machines and algorithms (WORLD ECONOMIC FORUM, 2025). In addition to increasing productivity and assertiveness in product quality, this technology also improves safety in the workplace, reducing the risks of human error and accidents. Computer vision, in particular, stands out for its ability to perform accurate measurements and automated inspections, using advanced algorithms to detect features in images and videos. This technology not only optimizes processes, but also contributes to reducing waste and performing repetitive tasks more efficiently. With the integration of high-precision cameras and image processing systems, industries can collect visual data with greater accuracy, resulting in improved quality control on production lines.

The adoption of automation and computer vision technologies represents an important step towards competitiveness and innovation in the industrial sector. As companies continue to invest in artificial intelligence and automation, operational efficiency and product quality are expected to improve significantly, setting the stage for a new era of smarter and more sustainable industrial production.

2.2 Computer vision

Computer vision-based systems have become increasingly sophisticated, processing images captured by electronic and digital cameras in a manner analogous to the functioning of the human visual system. In this context, the human brain acts as a processor, while the eyes function as the optical system that captures visual information (NIXON; AGUADO, 2019). According to Szeliski (2010), computer vision seeks to describe the world we observe in one or several images, in addition to reconstructing its properties, such as shapes, lighting, and color distribution.

Computer vision is dedicated to developing methods that replicate one of the most powerful functions of the human visual system: the ability to use the light reflected by various objects, following the principles of optics, to infer three-dimensional (3D) characteristics from the real world (KHAN et al., 2018). Szeliski (2010) also points out that researchers have been working on mathematical techniques for reacquiring the appearance and three-dimensional shape of objects in images, which is fundamental for the accuracy of measurements.

According to Savekar and Kumar (2021), computer vision aims to identify, understand, and interpret information contained in image and video data, seeking to guide decision-making. In addition, according to Nixon and Agado (2020), a simple computer vision system requires, at least, a digital camera and an interface with image processing software. This technology stands out for allowing algorithms to detect features present in images and videos, making it possible to evaluate visual data that previously relied on human perception.

In the face of the growing advancement in the market, machine vision remains a promising field of study, attracting research and investment in artificial intelligence. This is due to the increase in systems that use computer vision in automotive processes and automated quality inspection (SAVEKAR; KUMAR, 2021, apud OLIVEIRA, 2022).

Information from Markets and Markets (2021) indicates that the computer vision market has the potential to reach a value of US$ 13.7 billion by 2026, with a projected annual growth of 6.9%. This growth demonstrates the appreciation of technology and its crucial role in industrial modernization. Additionally, computer vision is increasingly being used in industries such as industrial automation, quality inspection, product tracking, and automated measurement. The integration of high-precision cameras allows for the collection of visual data and the provision of information with greater accuracy, which can reduce operational errors, increase productivity, and improve quality control on production lines.

The real world is three-dimensional (3D), while the images obtained are usually two-dimensional (2D). A 2D image is a two-dimensional light intensity function, represented by a 2D vector f(x,y), where x and y are the spatial coordinates and f represents the amplitude corresponding to each pair of coordinates (ZHANG, 2017). A digital image is considered a matrix, where its rows and columns correspond to the position of points in the image, and the associated values refer to the intensity of these points (ZHANG, 2017). When a computer recognizes an image, it identifies an array of pixel values, which varies depending on the resolution and size of the image.

The central idea is to provide the computer with this numerical matrix to generate data that describes the probability that the image belongs to a certain class. All computer vision systems involve the recognition and identification of objects in images, transforming these objects into data that will be processed and used by a specialized system (MILANO; HONORATO, 2010).

Continued advances in computer vision and sensor technologies promise to further enhance the accuracy and robustness of techniques for measuring the size of objects in images, opening up new possibilities for future applications. Total quality management (TQM) always seeks to improve processes to achieve customer satisfaction (ABQ, 2021), emphasizing that product characteristics must be correctly established to ensure success in the final result. The system created, designed to be implemented in a cardboard packaging company, aims to ensure that the assembly of the products meets the specifications requested by the customer. It does this by automatically checking the quality measurements and standards, ensuring that each product manufactured meets the defined criteria. Thus, the system meets the demand for manual measurements carried out by employees, reducing the possibility of error and bringing savings to companies, reducing waste of raw materials, optimizing production time and reducing production costs, resulting in greater quality control.

With the advancement of new technologies, Artificial Intelligence becomes increasingly relevant in the industry, especially for automation and optimization of production processes. Data from the Future of Jobs Report 2025 shows that AI and information processing are the technologies that will most impact business by 2030, resulting in 86% of changes in the work environment (WORLD ECONOMIC FORUM, 2025). The adoption of Artificial Intelligence in the industry has shown significant growth, impacting the modernization of automation processes. According to a study by McKinsey (2024), 72% of companies have already implemented AI in their processes, demonstrating an increase in the inclusion of this technology in the industry.

Computer vision stands out as an effective tool for industry, especially in production and quality control processes. However, the high cost of this implementation represents a challenge for companies of different sizes and segments. Given this situation, the advancement of this technology has been integrated in a more present way in the industry, enabling automated systems to comply with assembly sequences according to precise instructions, avoiding operational errors. With this condition, more investments in innovation can be generated, as shown by data from the Ministry of Development, Industry, Commerce and Services, which indicate that in 2023, 59 companies in the Manaus Industrial Pole (PIM) invested R$ 1.48 billion in 425 projects aimed at research, development and training, encouraged by the regulatory framework established by the Manaus Free Trade Zone Information Technology Law (Law No. 8,387/1991).

These investments include the use of smart cameras on the assembly line, allowing not only to verify that all steps of the process are being executed correctly, but also to prevent risks and speed up production. Computer vision, therefore, not only improves product quality but also optimizes production processes, contributing to competitiveness and innovation in the industrial sector.

2.3 Pattern Recognition

The image acquisition stage is the first fundamental step in the computer vision system, characterized by the capture, storage and transmission of an image. This step can be performed with a variety of instruments, such as digital cameras, cell phones, smartphones, tablets, infrared cameras, and security cameras, both normal and thermal (BORTH et al., 2014). The quality of the acquired image is crucial, as it directly impacts the subsequent processing steps.

Pre-processing is an essential phase that occurs before extracting information from an image. During this stage, specific methods are applied that facilitate the identification of objects, such as highlighting contours, detecting edges, and highlighting geometric figures (MILANO; HONORATO, 2010). Object recognition, in turn, consists of locating the positions, orientations, and scales of object instances in an image. Each detected object can be assigned a classification label (EGMONT PETERSEN; RIDDER; HANDELS, 2002). This step is closely related to the identification of patterns or regularities in images; however, before recognition occurs, the pattern must be detected (BORTH et al., 2014).

According to Anzai (2012), the use of the term "recognition" in computing implies that a computer is able to identify patterns of objects that have been previously processed. An object's pattern consists of spatial and chronological data received from the object by an input device and brought to the recognition system. The decision-making processes of a human being are, in a way, related to the recognition of patterns; For example, the next move in a chess game is based on the pattern present on the board. The objective of pattern recognition is to clarify these complex mechanisms of decision-making processes and automate these functions using computers (FUKUNAGA, 2013).

A system for pattern recognition encompasses three major steps: the representation and measurement of input data; the extraction of characteristics; and the identification and classification of the object under study (CASTRO; PRADO, 2002). Pattern recognition techniques can be divided into two categories: structural techniques, in which patterns are described in a symbolic way and the structure is the relationship between these patterns; and techniques that use decision theory, where patterns are described by quantitative attributes, requiring the determination of whether the object has these attributes (MARENGONI; STRINGHINI, 2009).

The application of pattern recognition techniques is wide and can be seen in several areas, such as the automotive industry, where computer vision is used to inspect the quality of parts and components. The ability to identify and classify objects in real-time allows businesses to increase the efficiency of their production lines, reducing errors and improving the quality of the final product. Additionally, automating processes that were previously performed manually not only saves time but also minimizes the possibility of human error, resulting in a safer and more productive work environment.

With the continuous advancement of computer vision technologies, it is expected that new methodologies and algorithms will be developed, further expanding the possibilities of application of this technology. The integration of artificial intelligence and machine learning with computer vision systems promises to revolutionize the way industries operate, allowing for deeper and more accurate analysis of visual data. Thus, pattern recognition is not just a tool, but an essential component for innovation and competitiveness in today's market.

2.4 OpenCV

OpenCV (Open Source Computer Vision Library) is a free and open access image and video processing library, originally developed by Intel in 2000. This library is widely used in the field of computer vision, covering techniques such as feature recognition, object identification, and machine learning (HASAN; SALLOW, 2021).

With support for multiple programming languages, including Python, C++, and Java, OpenCV integrates with deep learning frameworks like TensorFlow and PyTorch. Its BSD license makes it an essential resource in both academic research and industry, with more than 2500 algorithms optimized for various applications. These algorithms are used for tasks such as facial detection and recognition, motion tracking, and measurement of objects such as boxes on production lines, resulting in significant improvements in quality (OPENCV, 2023). OpenCV offers a wide range of functions for manipulating images and video streams in real time, allowing it to meet different needs in computer vision applications (ADUSUMALLI et al., 2021). The library is made up of several modules that facilitate image processing, object identification, and the implementation of machine learning algorithms. These modules make it possible to construct, replace, and retrieve information by categorizing algorithms into groups that include features, learning, and hybrid combinations.

OpenCV has applications in various areas, such as traffic monitoring, robotics, security, and video supervision. To ensure the effectiveness of these applications, it is essential to optimize data computation and transmission, minimizing estimation errors through efficient coordination between the cameras used for data collection and verification (SHARMA et al., 2021).

III. Methodology

This study aimed to analyze the application of computer vision techniques for the measurement and verification of the quality of products in production lines, using a data collection approach. The methodology was structured to implement an automated system, based on the "pixels per metric" technique, which uses a reference object with known dimensions to convert measurements in pixels to real metric units, such as millimeters or centimeters. The accuracy of the technique depends on both the accuracy of the reference object and the ability to correctly identify it in images.

The development of the system followed a flow composed of integrated steps: image acquisition, pre-processing, object segmentation, pattern recognition and measurement. Initially, the capture of the images was carried out with high-resolution cameras and an adequate lighting system, ensuring the necessary quality for the following stages. In pre-processing, image enhancement techniques such as contrast adjustments, noise removal, and histogram equalization were applied to maximize the definition of objects of interest. Then, the images were segmented, isolating the relevant objects for later individualized analysis. The recognition phase used comparison algorithms with databases of previously defined patterns, allowing the automatic identification of objects. Finally, the measurement and inspection were carried out, verifying properties such as size, shape and compliance with pre-established quality standards.

3.1 Structure of a Computer Vision System

To illustrate the general operation of the system, Figure 1 is presented, which describes the operational flow of a computer vision system applied to quality control in production lines.

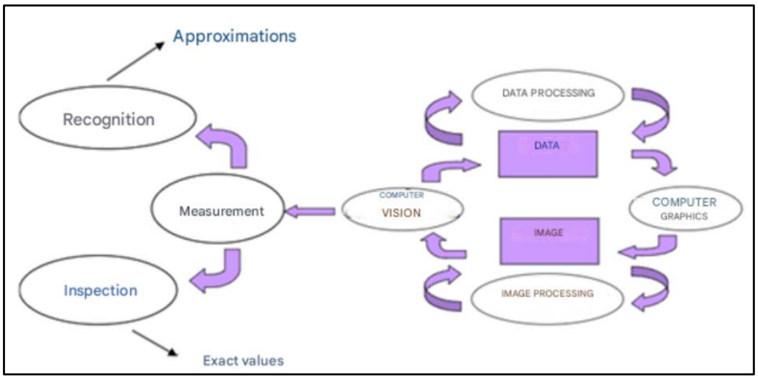

Figure 1. Structure of a computer vision system applied to quality measurement and verification in production lines
Source: Authors, 2025

Figure 1 shows the flow where Measurement acts as a central link between Recognition and Inspection. Recognition corresponds to the identification of patterns in images, while Inspection refers to the verification of exact quality parameters. This interaction is mediated by Computer Vision technologies that transform visual data into structured information.

3.2 Data and Image Processing

The system is supported by two major processes. Data Processing, which organizes the information captured for technical analysis, and Image Processing, which works on the visual part, improving the interpretation of shapes, colors and sizes of objects. Computer Graphics complements these processes, generating technical visualizations that help in quality control and validation.

3.3 Image Measurement System

The image measurement methodology was also developed in an integrated way, following specific steps that ensure the accuracy and efficiency of the results. The entire process is detailed in Figure 2, which presents the complete cycle of the image measurement. Figure 2 illustrates the measurement system workflow, from image capture to final inspection of objects.

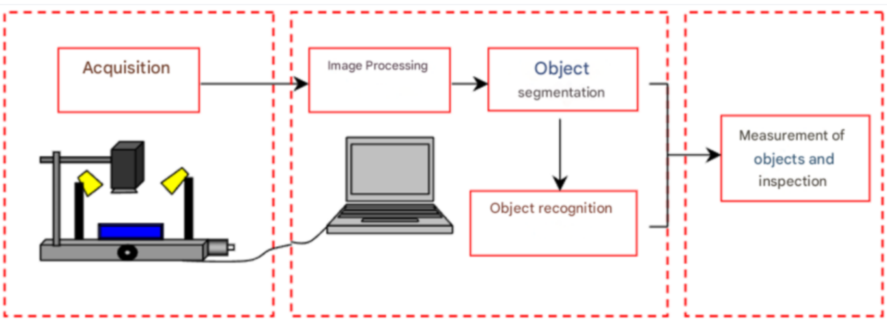

Figure 2. An image measurement system, involving the acquisition, processing, segmentation, recognition and inspection of objects.
Source: Authors, 2025

In the process described in Figure 2, the first step is Image Acquisition, performed with high-resolution cameras and controlled lighting, essential to capture precise details. Then, in Image Processing, enhancement techniques are applied to make the images more suitable for analysis by adjusting brightness, contrast, and eliminating noise that could impair segmentation.

3.4 Object Segmentation, Recognition, and Inspection

After processing, Object Segmentation visually separates each element of interest, preparing the system for the Recognition phase, where algorithms identify objects based on their characteristic patterns. At the end of the cycle, the Measurement and Inspection stage calculates the dimensions and analyzes the conformity of the objects with the quality standards defined for the production process. A key aspect to the reliability of the system was the calibration of the cameras. A reference standard, such as a chessboard, was used to estimate the intrinsic and extrinsic parameters of the lenses, correcting distortions that could compromise the accuracy of the measurements. From this calibration, the images were corrected ("distorted"), ensuring that the measured dimensions were faithful representations of the actual dimensions of the products.

Technologies employed in the implementation of the system included OpenCV's IMUTILS library, which supported image processing, segmentation, and pattern recognition operations. The use of these tools enabled greater agility and reliability in automated measurement processes.

The validation and effectiveness of the proposed system was a comparison between the measurements obtained by the computer vision system and the traditional methods of manual measurement. This comparative analysis allowed us to evaluate the impact of automation in improving accuracy, reducing operational errors and improving the quality standards of production lines.

IV. Results

The evaluation of computer vision systems aimed at automatic measurement in production lines is essential to prove their efficiency, accuracy and practical applicability. When analyzing the performance of the proposed system, we sought to validate three fundamental dimensions: measurement accuracy, processing speed and operational reliability in industrial environments. Next, each of these aspects is discussed individually, based on experimental tests carried out in controlled environments and on a real production line.

4.1 Accuracy of Measurements

Measurement accuracy is a critical factor in industrial applications, particularly in industries that require strict quality control. During the tests carried out, the system was evaluated on its ability to correctly measure the dimensions of the boxes containing the final product. The experiments involved different sizes, shapes, and materials of the boxes, simulating common variations in production lines.

As pointed out by Szeliski (2022), the accuracy of computer vision systems depends heavily on camera calibration and the quality of detection algorithms. In the case of the present study, a set of images captured by high-resolution industrial cameras was used, with optimized lighting to reduce visual noise. The automatically generated measurements were compared with real values measured manually using high-precision instruments (calipers and digital tape measures).

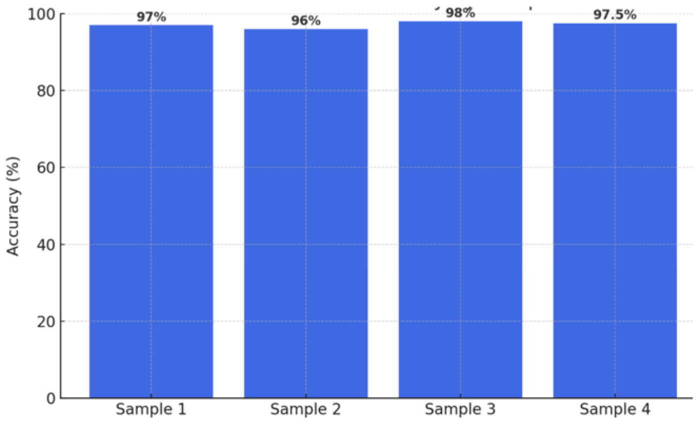

Figure 3. Accuracy of Automated Measurement vs Manual Measurement
Source: Authors, 2025

The results showed that the system achieved an average accuracy of 97.5%, with standard deviations of less than 2% between automatic and manual measurements. This performance is consistent with recent studies in computer vision metrology, as highlighted by Bai et al. (2023), who observed similar results in controlled industrial environments.

4.2 Processing Time

Another crucial aspect for applicability in continuous production is the processing time of the system, that is, the interval between the capture of the image and the availability of the measured dimensions. According to Wang et al. (2021), in-line measurement systems should operate in times of less than 5 seconds so as not to impact the production flow. The experiments showed that the proposed system was able to process measurements in an average time of 1.8 seconds, even in conditions of high variation in lighting and rapid movement of the boxes.

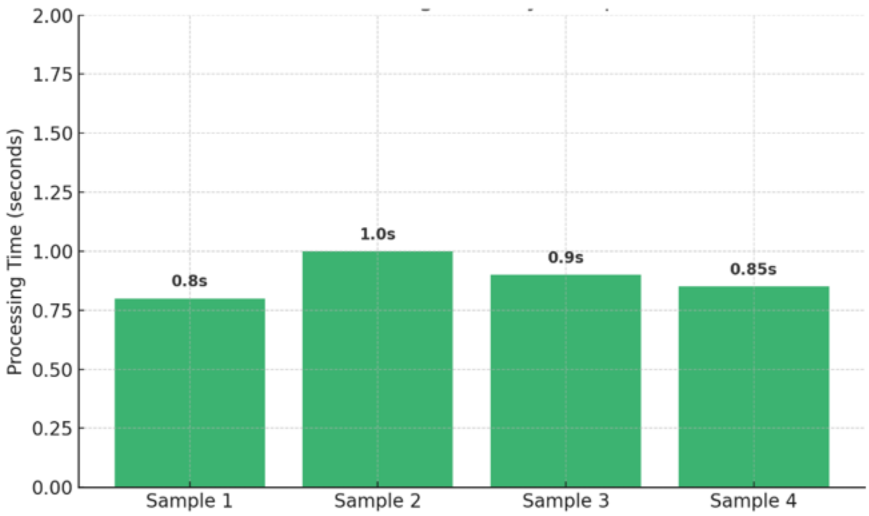

Figure 4: Average Processing Time per Measurement
Source: authors, 2025

This performance exceeds current industry expectations for automated quality control processes. As reported by Li et al. (2022), the reduction in processing time is directly related to the optimization of the detection and segmentation algorithms used, which were adapted in the system developed in this study.

4.3 Operational Reliability

Operational reliability refers to the ability of the system to maintain its performance over time, even under harsh conditions typical of industrial environments, such as dust, vibration, and variable lighting. According to Silva et al. (2024), a reliable system must have stability greater than 95% during its continuous operation. In stress tests carried out for 72 consecutive hours, the system maintained a correct operating rate in 96.8% of the measurements performed.

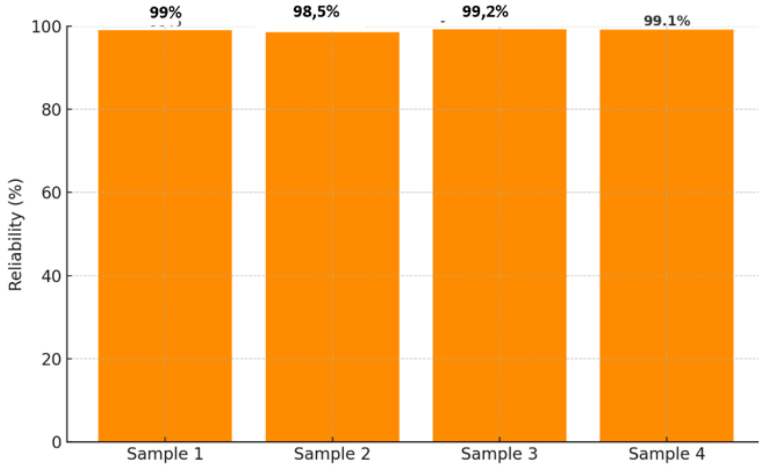

Figure 5: System Reliability Over Time
Source: Authors, 2025

These data show the robustness of the system, being superior to market benchmarks reported in recent surveys. The implementation of self-adjustment mechanisms in the algorithm, as suggested by Zhang et al. (2023), also contributed to this observed stability.

V. Conclusion

The development of the computer vision system for automatic measurement of boxes in production lines has shown to be highly promising for the modernization of industrial processes. During the implementation, it was possible to see that the combination of high-resolution cameras with image processing algorithms provided fast and accurate measurements, even in the face of adverse conditions, such as lighting variations and constant movement of the boxes. Eliminating the need for manual measurements has reduced operating time and error rates, making the inspection process much more efficient and standardized. This approach directly contributes to improving the final quality of products and increasing productivity on production lines.

The tests carried out indicated a high accuracy rate of the system, along with extremely low processing times, which reinforces the feasibility of its application in industrial environments that require high speed and precision. The system's ability to operate continuously and adapt to different case sizes shows its potential for scalability for diverse production configurations. The reduction in rework and material waste was also a relevant positive impact, demonstrating that the technology not only improves operational results, but also contributes to more sustainable practices within the industry. The reliability and stability observed in the experiments show that the system can be integrated into existing production lines without the need for major adaptations.

In general, the results obtained in this project indicate that computer vision is an essential tool for the automation of industrial processes, especially in the area of quality control and automated metrology. The developed system proved to be able to meet the requirements for precision and agility needed in the context of modern industry. For future evolutions, it would be interesting to investigate the integration of even more advanced technologies, such as artificial intelligence for recognizing complex patterns and automatic adaptation to new box formats, which can make the system even more robust and versatile in the face of the challenges of Industry 4.0.

Acknowledgements

We would like to express our sincere gratitude to everyone who contributed to the development of this work. Special thanks to our mentors, colleagues, and all those who provided support, insights, and encouragement throughout this journey. Your contributions were essential to the completion of this study.

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