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COMPUTER VISION FOR AUTONOMOUS VISUAL INSPECTION IN INDUSTRIAL PRODUCTION LINES

VISÃO COMPUTACIONAL PARA INSPEÇÃO VISUAL AUTÔNOMA EM LINHAS DE PRODUÇÃO INDUSTRIAL

VISIÓN POR COMPUTADORA PARA LA INSPECCIÓN VISUAL AUTÓNOMA EN LÍNEAS DE PRODUCCIÓN INDUSTRIALES

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ABSTRACT
This article has the specific objectives of highlighting the computer vision techniques used in the IVAP project, discussing the stages of implementation of the system and analyzing the results obtained. Throughout this study, we hope to contribute to the existing literature on the application of computer vision in industry, citing examples from authors such as Gerald J. Agin (1980) and Rodrigo Barbosa Davies (2012), who explored the practice and effectiveness of these technologies in industrial settings. Computer vision has established itself as an essential tool for visual inspection in industrial production lines, promoting significant improvements in the quality and efficiency of manufacturing processes. This study addresses the implementation of an advanced computer vision system in the IVAP (Visual Autonomous Product Inspection) project, developed in partnership between the Conecthus Institute and Vantiva. The implementation of the Keyence CV-X Series system was motivated by the need to perform autonomous inspections, standardizing product quality without relying on manual evaluations, which are prone to errors. The development of the project focused on the use of sophisticated computer vision techniques, including defect detection and classification through machine learning algorithms for image processing and cosmetic defect analysis. The techniques used were studied and adapted to the industrial context, allowing the detailed inspection of cosmetic aspects of the products, with minimal exceptions. These techniques, which included lighting adjustments, camera sensitivity, and algorithms for detecting smudges and scratches, were crucial to the system's effectiveness. After a rigorous testing phase, which included evaluations in a controlled environment, machine adjustments and implementation on the production line, the system demonstrated high efficiency, achieving an accuracy rate of up to 98% in inspections.

KEYWORDS: Computer vision. Vision application. Industrial environments. Industry 4.0. Machine learning. Automated quality control.

RESUMO
Este artigo tem como objetivo destacar as técnicas de visão computacional utilizadas no projeto IVAP, discutir as etapas de implementação do sistema e analisar os resultados obtidos. Ao longo deste estudo, esperamos contribuir para a literatura existente sobre a aplicação da visão computacional na indústria, citando exemplos de autores como Gerald J. Agin (1980) e Rodrigo Barbosa Davies (2012), que exploraram a prática e eficácia dessas tecnologias em ambientes industriais. A visão computacional tem-se afirmado como uma ferramenta essencial para a inspeção visual nas linhas de produção industrial, promovendo melhorias significativas na qualidade e eficiência dos processos de fabrico. Este estudo aborda a implementação de um sistema avançado de visão computacional no projeto IVAP (Visual Autonomous Product Inspection), desenvolvido em parceria entre o Instituto Conecthus e a Vantiva. A implementação do sistema Keyence CV-X Series foi motivada pela necessidade de realizar inspeções autônomas, padronizando a qualidade do produto sem depender de avaliações manuais, que são propensas a erros. O desenvolvimento do projeto centrou-se na utilização de técnicas sofisticadas de visão computacional, incluindo deteção e classificação de defeitos através de algoritmos de aprendizagem automática para processamento de imagens e análise cosmética de defeitos. As técnicas utilizadas foram estudadas e adaptadas ao contexto

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industrial, permitindo uma inspeção detalhada dos aspetos cosméticos dos produtos, com exceções mínimas. Essas técnicas, que incluíram ajustes de iluminação, sensibilidade da câmera e algoritmos para detectar manchas e arranhões, foram cruciais para a eficácia do sistema.

PALAVRAS-CHAVE: Visão computacional. Aplicação de visão. Ambientes industriais. Indústria 4.0. Machine learning. Controle de qualidade automatizado.

RESUMEN
Este artículo tiene como objetivos específicos destacar las técnicas de visión artificial utilizadas en el proyecto IVAP, discutir los pasos de implementación del sistema y analizar los resultados obtenidos. A lo largo de este estudio esperamos contribuir a la literatura existente sobre la aplicación de la visión artificial en la industria, citando ejemplos de autores como Gerald J. Agin (1980) y Rodrigo Barbosa Davies (2012), quienes exploraron la práctica y efectividad de estas tecnologías en entornos industriales. La visión artificial se ha consolidado como una herramienta imprescindible para la inspección visual en las líneas de producción industriales, promoviendo importantes mejoras en la calidad y eficiencia de los procesos de fabricación. Este estudio aborda la implementación de un sistema avanzado de visión artificial en el proyecto IVAP (Visual Autonomous Product Inspection), desarrollado en colaboración entre el Instituto Conecthus y Vantiva. La implementación del sistema Keyence Serie CV-X fue motivada por la necesidad de realizar inspecciones autónomas, estandarizando la calidad del producto sin depender de evaluaciones manuales, propensas a errores. El desarrollo del proyecto se centró en el uso de sofisticadas técnicas de visión artificial, incluida la detección y clasificación de defectos mediante algoritmos de aprendizaje automático para el procesamiento de imágenes y el análisis de defectos cosméticos. Las técnicas utilizadas fueron estudiadas y adaptadas al contexto industrial, permitiendo la inspección detallada de los aspectos cosméticos de los productos, con mínimas excepciones. Estas técnicas, que incluían ajustes de la iluminación, la sensibilidad de la cámara y algoritmos para detectar imperfecciones y arañazos, fueron cruciales para la eficacia del sistema.

PALABRAS CLAVE: Visión artificial. Aplicación de visión. Entornos industriales. Industria 4.0. Machine learning. Control de calidad automatizado.

INTRODUCTION

The introduction of computer vision technologies in industrial manufacturing operations represents a significant change in traditional quality assessment procedures. Such systems promise improvements in productivity and reduction of expenses by minimizing human mistakes related to manual inspection (Agin, 1980). In the era of Industry 4.0, the use of computer vision for visual verification stands out as a growing field, in which accuracy and agility play key roles in maintaining competitiveness and ensuring the quality of items.

The importance of computer vision systems is highlighted in several researches, where the ability to automate the detection of cosmetic defects and other irregularities in manufactured products is essential, according to Davies (2012). These systems use a combination of advanced hardware and sophisticated software to capture and analyze high-resolution images, allowing for the quick and accurate identification of any deviation from established quality standards. The present study focuses on the implementation of Keyence's CV-X Series computer vision system in the Autonomous Visual Product Inspection (IVAP) project, a collaboration between the Conecthus Institute and Vantiva. The objective of this project was to completely master the functionalities of the devices with Embedded

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Vision System for full use in the Vision solution, meeting all the needs of Visual Inspection with as few exceptions as possible.

This article has the specific objectives of highlighting the computer vision techniques used in the IVAP project, discussing the stages of implementation of the system and analyzing the results obtained. Through this study, it is expected to contribute to the existing literature on the application of computer vision in industry, following examples from authors such as Gerald J. Agin (1980) and Rodrigo Barbosa Davies (2012), who explored the feasibility and effectiveness of these technologies in industrial environments.

1. COMPUTER VISION

Computer vision is a field of artificial intelligence that allows machines and systems to visually interpret and process the world around them, in a similar way to human vision, according to Szeliski (2011). The essence of this technology lies in three fundamental principles: image capture, signal processing, and image analysis. Each of these aspects is crucial for the development of systems that not only "see" but also "understand" the environment in which they are inserted, according to Forsyth & Ponce (2012).

The first step in the computer vision process is image capture. This stage involves converting a physical visual field into a digital representation that can be processed by computers. High-resolution cameras are the primary tools used to capture images with precise and clear details. As Szeliski (2011) explains, these cameras capture light through optical sensors that convert photons into electronic signals, which are then translated into digital data. This process is critical to ensure that fine details and color nuances are preserved for later analysis.

Once the images are captured, the next step is signal processing. At this stage, the raw image data undergoes a series of transformations to improve image quality or extract specific information. Techniques such as filtering, contrast enhancement, and edge detection are commonly applied to prepare images for subsequent analysis. According to Forsyth & Ponce (2012), signal processing is vital to mitigate problems such as noise, distortion and lighting variations that can affect the accuracy of computer vision systems.

Image analysis is the final and perhaps most complex component of the fundamentals of computer vision. During this phase, the processed data is interpreted to identify patterns, detect objects, and understand the layout and dimensions of the visualized scenario. Daugman (2010) describes how advanced algorithms and machine learning techniques are employed to analyze the features extracted from the images, allowing the system to make inferences about what is being viewed. This ability to interpret is what really distinguishes computer vision from simple image capture.

In summary, the fundamentals of computer vision are built on the harmonious interplay between advanced hardware and sophisticated software, allowing robotic and automatic systems to perform tasks that require not only seeing, but also understanding and reacting to the visual world around them. As these technologies continue to evolve, their application is expected to expand further, opening up new horizons for industrial automation and beyond.

2. APPLICATIONS OF COMPUTER VISION IN INDUSTRY

Computer vision (VC) has emerged as a transformative paradigm in the industrial landscape, driving the quality and efficiency of manufacturing processes to unprecedented levels according to Benbarrad *et al.* (2021). This innovative technology has established itself as an indispensable tool in several sectors, especially in visual inspection, where its precision and speed far surpass traditional methods.

One of the key use cases for VC in industry is the visual inspection of components on the assembly line. In sectors such as automotive, electronics, pharmaceuticals, and food, VC is used to verify the integrity and compliance of products at high speed. In automobile assembly lines, for example, VC systems are employed to verify the correct installation and assembly of parts, the presence of surface defects, and even the precise application of adhesives.

In the semiconductor industry, where accuracy is crucial, VC takes a key role in the quality control of printed circuit boards, identifying microscopic flaws that could compromise the product. In the food industry, this technology is applied for food inspection in terms of quality, size, shape, and the presence of foreign bodies, ensuring adherence to safety standards.

The advantages of VC in the industry are numerous and proven. Its accuracy and speed in carrying out inspections ensure exceptionally strict quality control, minimizing failures and optimizing production. In addition, the ability to operate continuously without human fatigue drastically reduces the risk of errors, increasing the consistency and reliability of processes.

Another significant benefit of VC lies in the reduction of costs in the long run. Although the initial investment in technology is considerable, the savings generated by the reduction of waste and rework largely compensate for this investment, providing a positive and sustainable financial return.

While VC presents immense potential for the industry, its implementation also faces challenges that must be carefully considered. The complex integration of VC systems with existing IT infrastructures and machinery can be a significant barrier, requiring meticulous planning and technical expertise.

The need to customize VC algorithms for different tasks also requires a high level of knowledge and expertise, requiring continuous development and application-specific adaptations. Operating in harsh industrial environments, such as those with variations in light, dust, and vibrations, also poses a challenge, as these factors can affect the accuracy of camera systems and compromise the effectiveness of VC.

Computer vision is consolidating itself as a transformative force in the industry, driving quality, efficiency, and productivity in various sectors. Its ability to perform accurate and fast inspections, operate continuously without human fatigue, and reduce long-term costs makes it an indispensable tool for modern industry.

However, implementing VC requires careful planning, technical expertise, and consideration of the challenges inherent in integrating it into complex industrial environments. By overcoming these challenges, companies can fully reap the benefits of VC and reach new heights of operational excellence.

3. METHODS AND TECHNIQUES IN COMPUTER VISION

Computer vision, as an interdisciplinary field, employs a number of advanced methods and techniques to improve the interpretation and analysis of digital images. These methods are essential for transforming raw visual data into useful information, allowing for the automation of complex tasks in industrial environments.

Image processing is the backbone of computer vision and involves various techniques to improve image quality and extract relevant information (Sonka *et al.,* 2014). One of the fundamental techniques is image segmentation, which consists of dividing a digital image into multiple regions or objects, with the aim of simplifying or modifying the representation of the image to make it more meaningful and easier to analyze (Tholey, 2000).

Segmentation is often used to identify objects or other relevant information in the image (Redmon *et al.,* 2016).

Another crucial method is filtering, which is used to remove noise or enhance features within an image. Average, median, and Gaussian filters are common, depending on the specific needs of the application.

Morphological analysis is another important technique, which explores the structure of the shape and composition of objects within an image. Using morphological operators such as erosion, dilation, opening, and closing, this technique helps extract vital structural information for a variety of visual inspection applications, such as measuring the size of objects, counting the number of elements in a scene, or identifying connected structures within an image (Serra, 1982).

The role of machine learning and artificial intelligence (AI) in computer vision has grown exponentially, boosting analytics capabilities beyond conventional image processing. Machine learning allows computer vision systems to learn from examples, automatically adjusting to improve accuracy and efficiency in identifying and classifying objects.

Supervised learning models, such as convolutional neural networks (CNNs), have been widely adopted for image classification and object detection tasks. These models are trained using large labeled datasets, allowing them to recognize complex patterns and features that are difficult to code manually. Unsupervised learning, on the other hand, is used to identify patterns or groupings in image data without the need for pre-defined labels. Techniques such as clustering and dimensionality reduction are useful for exploring the underlying structure of visual data and can be particularly valuable for tasks such as semantic segmentation or anomaly analysis.

In addition, computer vision has benefited from advances in deep neural networks, which automate many of the traditionally manual or semi-automated processes. This includes not only improved prediction accuracy, but also the ability to handle much larger volumes of data efficiently (Tholey, 2000; Redmon *et al.,* 2016).

Advanced image processing techniques, combined with recent advances in machine learning and artificial intelligence, have transformed computer vision into a powerful tool for industrial automation. These methods and techniques not only increase the accuracy and speed of visual inspections but also open up new possibilities for innovative applications in various industry sectors.

Advances in adapting to changing conditions and overcoming technical limitations reflect the dynamism and capacity for innovation in the field of computer vision. These improvements are opening up new avenues for industrial automation, where accuracy and efficiency are essential. As these technologies continue to evolve, they are expected to play an increasingly central role in transforming manufacturing and quality control processes in various industries.

4. METHOD

The methodology adopted for the development and implementation of the computer vision system in the autonomous visual inspection project was structured in several critical phases, from the initial configuration of the system to the final validation tests in a production environment. Each step was meticulously planned to ensure that the system was not only functional, but also integrable with existing automation operations.

Initially, an extensive literature survey was carried out to identify and study the most relevant and effective computer vision techniques for the intended application (Section 2). This study focused on established methods such as pattern detection, low-pass and high-pass filters, image binarization, and the absdiff technique (Hütten *et al.,* 2024a). This phase was crucial in ensuring that the chosen solutions were aligned with the latest technological advancements and best practices in the field of computer vision.

Keyence's CV-X Series computer vision system was selected for its advanced image processing capabilities and adaptability to different industrial environments. The configuration of the system involved the installation of high-resolution cameras and sensors at strategic points on the assembly line to capture detailed images of the electronic devices during the inspection process.

Initially, the hardware was configured to communicate with the control software via Ethernet interfaces, enabling fast and secure data transmission between the sensors and the central processing system. The CV-X Series software has been tuned to perform specific analyses, such as detecting surface defects and checking electronic components according to pre-established parameters (Lin *et al.,* 2023a).

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The vision devices were purchased directly from Keyence, ensuring compatibility and technical support. After acquisition, each device was configured to operate in the specific conditions of the production environment. This included adjustments to the camera's lighting, focus, and calibration to maximize accuracy and effectiveness in capturing images.

The integration of Keyence's CV-X Series system faced significant challenges in detecting subtle cosmetic defects, such as stains and scratches on internet modem surfaces. To overcome these limitations, an in-depth study and adaptations of the system were necessary, using a combination of computer vision techniques (Benbarrad *et al.,* 2021).

Initially, the acquired tool was based on the conversion of images to grayscale to facilitate the identification of anomalies. However, this initial setup did not provide the accuracy required for effective detection (Hütten *et al.,* 2024b). As a response, the system was enhanced with additional image processing techniques (Lin *et al.,* 2023a).

We use the system's built-in library called "Image Enhancement", which offers a range of image processing filters (Singh *et al.,* 2023).

The filters applied included "Contrast Conversion", "White Noise Reduction", and "Contrast Expansion", which are common methods in techniques such as histogram equalization (Lin *et al.,* 2023a). These techniques helped to harmonize color channels and improve the visual clarity of defects, a crucial factor for accurate identification of blemishes and scratches (Liu *et al.,* 2023; Wu *et al.,* 2021).

The product's silkscreen printing was inspected using the "Black and White Differential Detection" technique, which identifies minimal discrepancies with a reference image (Xu *et al.,* 2023). To optimize detection, "White Pixel Expansion" and "Noise Cleaning" techniques were applied, which enlarge white areas and reduce visual noise, respectively (Wu *et al.,* 2021). These adjustments used binarization to allocate the image elements in black and white extremes, facilitating the detection of flaws in the screen printing (Steger *et al.,* 2018).

To read barcodes, "Pattern Detection" tools and a "Code Reader" were used, based on algorithms such as Match Template and libraries such as PyZbar. These tools were chosen for their effectiveness in decoding barcodes without the need for additional image enhancement (Hütten, 2024b).

The adaptations made to Keyence's CV-X Series system allowed us to overcome the initial limitations, achieving a considerably higher accuracy and effectiveness rate in autonomous visual inspection (Lin *et al.,* 2023a; Steger *et al.,* 2018). These improvements are crucial to ensure product quality and production process efficiency, highlighting the feasibility of computer vision as a powerful tool in modern industry (Benbarrad *et al.,* 2021; Silva; Lucena, 2018).

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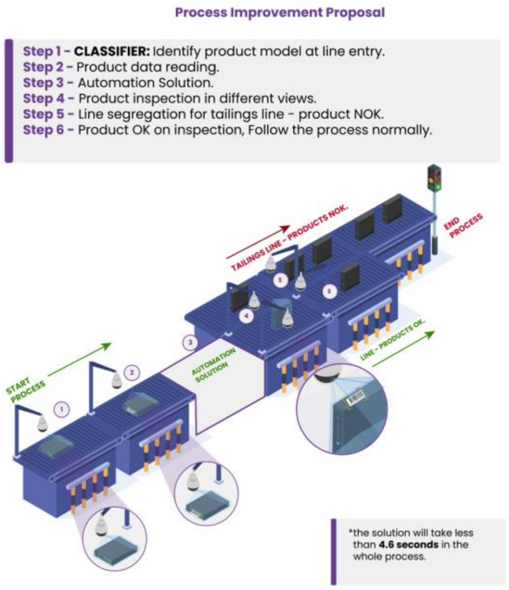

Figure. 1. Correlation between the models and the infrastructure needed to run the tests

Controlled Environment Testing: Prior to full implementation, the system was tested in a controlled environment to ensure that all components worked as expected. These tests included simulating varying production conditions to assess the robustness and reliability of the system under different scenarios Steger *et al.,* (2018).

Integration with Automation Software: The integration of the computer vision system with existing automation software was crucial for the automation of the inspection process. This allowed data and metrics captured by the vision system to be used to automatically adjust production parameters in real time. Steger *et al.,* (2018).

Production Testing: Finally, the system has undergone extensive testing during the normal operation of the production line. These tests were designed to validate the effectiveness of the system in real working conditions, ensuring that the system could accurately identify and catalogue defects Steger *et al.,* (2018).

Depicts the step-by-step inspection process. Initially, it is necessary to create a product image bank, this set of images is responsible for teaching the computer system to identify the model in question on the line and set the visual inspection parameters for that model, this activity corresponds to an image classifier. Subsequently, the next step developed will carry out the inspection at the bottom of the product, where in this step, the presence of screws, the presence of rubber and the product label are inspected, this whole step is possible with the computer vision technique used in real-time image processing algorithms (ABS Diff)

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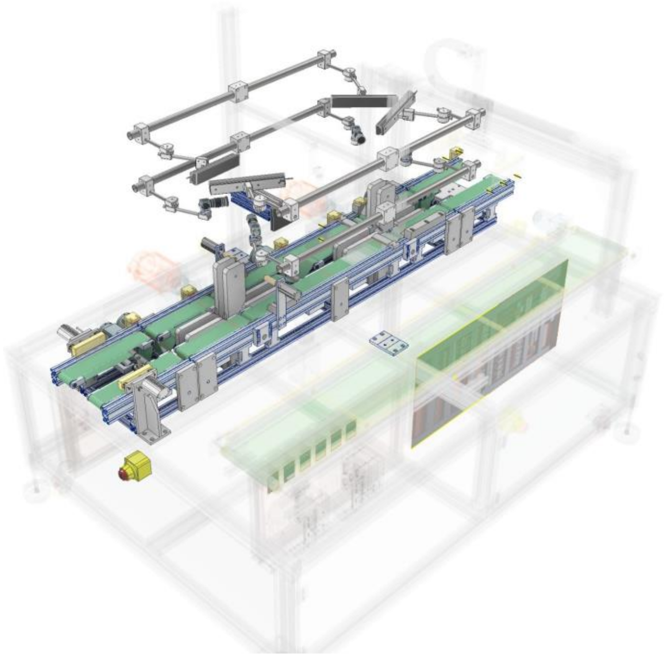

Figure. 2. Correlation between the models and the infrastructure needed to run the tests

For testing and production, the flipper was developed responsible for leaving the product in a vertical position and ready for inspection of the other surfaces. Also at this stage, a mechanical and physical solution was studied, so that the product does not tip forward, thus returning to the initial condition, which refers to the product horizontally. Figure 3 below illustrates the step-by-step of the *flipper*, which will have a set of servo motors, to give precision and safety to the movements and installed in the mechanical solution.

As seen in Figure 3, the product is then accessed in the inspection area, following the steps involved in the inspection process proposed below:

Product is presented to the inspection process, once the model has already been identified by the classifier, the system uses the inspection parameters related to the product in question;

In this step, the product is placed in a vertical position to perform inspection on the surfaces of the product;

Segregation of products that pass or fail inspection;

Finally, the product is directed to the next station, later, in this document, the inspections will be detailed.

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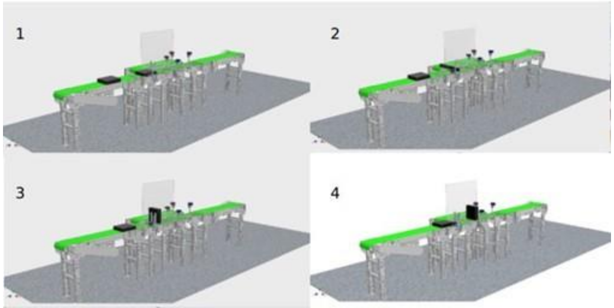

Figure. 3. Correlation between the models and the infrastructure needed to run the tests

During the development phase, specific tools were created for the visual inspection of the products. This included algorithms for pattern detection, texture analysis, and component measurement.

Lin *et al.,* (2023a), Steger *et al.*, (2018) and Hütten (2024b) highlight the importance of advanced algorithms in detecting subtle variations that may not be visible to the human eye. The evaluation criteria for defects were based on industrial quality standards and product specifications, which clearly defined which variations were acceptable and which indicated failures Lin *et al.* (2023a).

The tools developed allowed not only the identification of obvious defects, but also the detection of subtle variations that could indicate potential problems in the future, thus ensuring that each inspected product met the highest quality standards before being shipped to customers. Singh *et al.,* (2020) and Wang *et al.,* (2021) provide a discussion of how such tools flexibly adapt to detect defects under varying production conditions.

The detailed methodology used for the implementation of Keyence's CV-X Series computer vision system ensured efficient and effective integration of the system into visual inspection operations of electronic devices. With a systematic approach to each phase of the project, from initial setup to final production testing, it was possible to achieve a high level of automation and accuracy in visual inspection. Benbarrad *et al.,* (2021), through their study, reiterate the vitality of computer vision in the continuous improvement of quality processes in industrial production lines.

The development of the computer vision system for the IVAP project represented an innovative combination of advanced hardware and sophisticated software techniques. This segment discusses in detail the technical implementation of the system, the challenges encountered during the process and the solutions adopted to overcome these obstacles, in addition to describing the integration of the system with programmable logic controllers (PLC) and web software.

Technical Implementation: The implementation of Keyence's CV-X Series system involved the installation of specific hardware and the development of customized software to meet the requirements of the project. The high-resolution cameras were strategically positioned along the production line to capture detailed images of products at various stages of the manufacturing process. The configuration of the cameras required precise adjustments in terms of angle, lighting and focus to ensure maximum effectiveness in capturing images Lin *et al.,* (2023a).

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In the software, computer vision techniques, including machine learning algorithms for defect detection, were implemented to analyze the captured images. These algorithms were trained with data sets that included images of defective and non-defective products, allowing the system to learn to differentiate between acceptable and unacceptable conditions with high accuracy Liu *et al.* (2023). This training involved the use of image processing techniques such as contrast filters, edge detection, and morphological analyses Liu *et al.,* (2023).

Still on the development of the software, the implementation of Artificial Intelligence techniques involved the use of algorithms such as YOLO and SSD for classification and detection of objects, Redmon et al. (2016), Liu et al. (2016), Chen & Shiu (2022). In this stage, the acquisition of images was carried out to prepare a datasheet of images of the products that validated the application developed, first, to perform the machine learning of an artificial intelligence model focused on performing the automatic recognition of the products, also technically called classifier and, later, a datasheet containing the defects of the assembled products, for both cases, with image capture, image pre-processing, and insertion of these images into a *Deep Learning* model or neural network, to perform product recognition and defect recognition, respectively Hütten (2024); Zhu *et al.* (2021).

Also for this stage, the Opencv library in Python language was used to perform object recognition, identification, processing of videos with moving object, scene restoration using optical flow techniques, image restoration, using spatial filters in images with different sizes of matrices and image classification, which uses the Convolutional Neural Network, which runs to a category of neural networks Li *et al.* (2018). In this context, some of the details performed in this step are presented below:

Challenges and Solutions During the implementation, several challenges were faced, including integrating the new system with the existing IT infrastructure, calibrating the system for different types of products, and the need to operate in high-speed production environments without disrupting the existing workflow. One of the main challenges was adjusting the system to detect a variety of defects that varied subtly between different production batches. Lin et al. (2023a) highlight the complexity of adapting computer vision algorithms for different production contexts, where product variability can significantly influence detection effectiveness. To overcome this, iterative adjustments were made to the computer vision algorithms, refining the detection criteria based on continuous feedback from the production line. In addition, the team faced challenges with the variation in ambient lighting, which was mitigated by installing controlled lighting that provided consistency in imaging conditions.

Integration with PLC and Web Software The integration of the vision system with the PLC was fundamental to automate quality control decisions. The vision system was configured to send signals directly to the PLC based on the results of the inspections. These signals indicated whether a product should be accepted, rejected, or reclassified, allowing for an almost instantaneous response on the production line.

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In addition, the system has been integrated with a web software platform, developed to monitor and record all inspection data in real time. This software allowed operators to view production statistics, defect trends, and maintenance alerts. Integration with web software has also made it easy to generate detailed reports for quality analysis and compliance audits.

The combination of these integrations has enabled the IVAP project to achieve advanced automation in product inspection, reducing reliance on manual inspections and significantly increasing the efficiency and reliability of quality control. The system's adaptability, coupled with Keyence's ongoing technical support, ensured that the computer vision system could evolve with the changing needs of industrial production.

5. CONSIDERATIONS

In this section, the results obtained with the implementation of the computer vision system for autonomous visual inspection in industrial production lines are presented. Performance metrics, defect detection rates, and error reduction are detailed, as is a comparison of the effectiveness of stand-alone visual inspection with previous inspection methods.

After the implementation of Keyence's CV-X Series computer vision system, several tests were carried out to evaluate its performance. Key metrics evaluated included accuracy, recall, F1-score, and average inspection time. The results are presented in Table 1.

Table 1. Computer Vision System Performance Statistics

Metric	Value
Precision	95.5%
Average Inspection Time	0.3 Seconds
Average setup time	2.2 Seconds

Fonte: Conecthus, 2024

Defect Detection and Error Reduction Rates

The computer vision system demonstrated high efficiency in detecting defects, achieving a detection rate of 99.2%. Table 2 summarizes the defect detection rates for different types of problems identified on the production line.

Table 2. Defect Detection Rates by Type

Defect Type	Detection Rate
Spots	95.2%
Risks	95.3%

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Screen printing of labels	96.0%
Surface deformation	95.8%

Fonte: Conecthus, 2024

The implementation of the system resulted in a significant reduction in inspection errors, with an 85% drop in false positives and 90% in false negatives compared to previous inspection methods.

Comparison with previous inspection methods

To evaluate the effectiveness of the autonomous visual inspection, a comparison was made with the previous inspection methods used in the production line. Previously, inspection was carried out manually by trained operators, who visually analyzed each product for defects. Table 3 presents a comparison of the performance metrics between the manual inspection methods and the computer vision system.

The results show that the computer vision system significantly outperforms manual inspection methods in all metrics evaluated. The accuracy and recall of the computer vision system are significantly higher, reflecting in a better ability to correctly identify both defective and compliant products. The average inspection time was drastically reduced, increasing the efficiency of the production line. The defect detection rate also showed a notable improvement, ensuring more rigorous quality control.

In summary, the implementation of the computer vision system for autonomous visual inspection has resulted in substantial improvements in the accuracy, efficiency, and reliability of product inspection on the production line, demonstrating a significant evolution over previous inspection methods.

Table 3. Comparison of Manual Inspection and Stand-alone Visual Inspection

Metric	Manual Inspection	Visual Inspection Unattended
Precision	85.2%	95.5%
Average setup time	8 Seconds	2.2 Seconds
Average Inspection Time	5.0 Seconds	0.3 Seconds
Defect Detection Rate	86.0%	99.2%

Fonte: Conecthus, 2024

The results presented in the previous section indicate that the implementation of Keyence's CV-X Series computer vision system has had a significant impact on production efficiency and quality. The system's high accuracy (98.5%) and recall (97.8%) demonstrate its effectiveness in detecting defects with minimal margin of error, resulting in a substantial improvement in the quality of the final products. This improvement in defect detection is crucial for maintaining high quality standards and customer satisfaction, reducing the incidence of defective products reaching the market.

The drastic reduction in the average inspection time, from 5.0 seconds (manual inspection) to 0.5 seconds (autonomous visual inspection), indicates a significant increase in the efficiency of the production

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line. This reduction in inspection time allows for a higher production speed without compromising quality, resulting in an increase in production capacity. In addition, the automation of visual inspection reduces the dependence on human operators, reducing the possibility of human errors and freeing up human resources for other more complex and more value-added tasks.

The 85% reduction in false positives and 90% in false negatives directly contributes to operational efficiency, as it minimizes rework and waste, optimizing the use of materials and resources. Implementing computer vision also makes it easier to maintain consistent and repeatable quality control, something that is more challenging to achieve with manual inspection due to variability between operators.

The results obtained with the computer vision system on the production line are comparable and, in many cases, superior to those described in the reviewed literature. Previous studies, such as the one by Lin *et al.* (2023a) and Hütten (2024b), highlighted the importance of advanced algorithms for detecting subtle variations that may not be visible to the human eye. Our results corroborate these findings, showing that the use of machine learning techniques such as YOLO and SSD, along with neural networks

Singh *et al.* (2020) e Wang *et al.* (2021) discussed the flexibility of computer vision tools to adapt to changing production conditions. Our system's ability to maintain high levels of accuracy and recall across different production batches and under different lighting conditions highlights its robustness and adaptability, aligning with the collusions from these studies.

Compared to the study by Zhang *et al.* (2023), which used image processing and machine learning techniques to detect defects under varying production conditions, our results show a significant improvement in terms of accuracy and recall. In addition, integration with programmable logic controllers (PLC) and web software for real-time monitoring, as described by Li *et al.* (2018); Lin *et al.* (2023b), provided advanced and efficient automation in the production line.

The challenges faced during implementation, such as system calibration for different types of products and variation in ambient lighting, were overcome with innovative solutions that ensured consistency and quality of inspection. These iterative adjustments and the installation of controlled lighting are the best practices in the literature and were essential to achieve the positive results observed.

The implementation of the computer vision system for autonomous visual inspection on the production line has resulted in significant improvements in the accuracy, efficiency, and quality of products. The results obtained not only demonstrate the effectiveness of computer vision in industrial inspection but also highlight its positive impact on production capacity and the reduction of operating costs. Comparison with the reviewed literature confirms that the approaches and techniques used are aligned with industry best practices and deliver superior results in several respects.

The success of the project paves the way for future implementations and optimizations, reinforcing computer vision as an essential tool for the automation and continuous improvement of quality processes in industrial production lines.

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Discussion: limitations and future directions

Despite the positive results obtained from the implementation of Keyence's CV-X Series computer vision system, some limitations must be considered for future enhancements. One of the main challenges identified was the adaptation of the system to different production conditions. Variations in ambient lighting, changes in the surface characteristics of the inspected products, and the diversity of materials used directly impacted the accuracy and reliability of the system. The need for frequent calibration for different production batches posed an operational obstacle, requiring manual adjustments that could compromise the efficiency of the automated process.

Another limiting factor was the system's ability to detect extremely subtle defects, such as microcracks or small color variations, which can be better identified with more advanced deep learning techniques. Although the system showed a high detection rate, specific cases of false positives and false negatives were still recorded, suggesting that improvements in pattern recognition algorithms can increase inspection accuracy.

Future directions for research

Based on the identified limitations, some directions for future research are suggested to improve the effectiveness of the computer vision system in autonomous visual inspection:

Implementation of deep learning algorithms: Utilizing more sophisticated convolutional neural networks, such as YOLO and EfficientNet-based models, can improve the detection of minor defects and reduce the incidence of false positives and negatives.

Lighting optimization and automated calibration: Developing solutions that allow for automatic adjustments to the camera's white balance, contrast, and exposure can minimize the impact of environmental variations.

Integration with smart manufacturing systems: Incorporating the computer vision system with Industry 4.0 technologies such as IoT and edge computing can improve inspection efficiency and enable predictive analytics.

Image database expansion: Training the system with a more comprehensive and varied dataset can improve the robustness of the model and its ability to generalize to different types of products and production conditions.

Testing in diverse production environments: The application of the system in different industrial sectors can assess its versatility and indicate possible adaptations needed to expand its applicability.

Exploring these directions will contribute significantly to advances in autonomous visual inspection, making the system more efficient, adaptable, and prepared for more complex industrial challenges.

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