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Automated dimensional inspection of automotive components using computer vision through YOLO

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Abstract

This paper presents the development and deployment of an automated visual inspection system using artificial intelligence and computer vision based on the YOLOv8 algorithm, designed to replace conventional aluminum jigs for the dimensional verification of extruded tubes in a Brazilian automotive parts factory. The research followed the Design Science Research (DSR) methodology, including six stages: problem identification, objective definition, artifact development, demonstration, evaluation, and dissemination. A dataset of 800 labeled images—500 compliant and 300 non-compliant—was captured under varying conditions and annotated using Roboflow. The model was trained in a Python environment using Ultralytics' YOLOv8 with image resolution of 640×640 pixels, over multiple configurations up to 376 epochs. The best configuration (150 epochs) achieved precision of 0.97, recall of 0.969, mAP@0.5 of 0.9917, and mAP@0.5:0.95 of 0.9397, with real-time inference speed under 25 milliseconds per image. The system proved effective in detecting missing, deformed, or misaligned connectors, and accurately classifying geometric compliance. Validation by the industrial director and production manager confirmed its readiness for deployment, emphasizing gains in agility, digital traceability, and cost savings. The replacement of physical templates by AI-driven inspection systems represents a significant step toward Industry 4.0 integration, enabling increased flexibility, standardization, and sustainability in production processes. Future work will focus on augmenting dataset diversity to enhance the model's robustness against geometric and lighting variations, improving its generalization for broader industrial applications.

Keywords: Artificial Intelligence; Computer Vision; YOLO; Industry 4.0; Automatic Inspection; Physical Templates; Automotive Industry.

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1. Introduction

In the manufacturing industry, dimensional and assembly verification of components is critical to ensure product quality and process standardization. Traditionally, this verification has been performed using physical devices called jigs or gauges, especially in processes involving extruded tubes with connectors.

These jigs, usually made of aluminum, are designed to validate that the assembled tube has the correct shape, length, and fittings. Although effective, these devices have several limitations: they are specific to each part model, take up significant physical space, require time for handling and adjustments, and are expensive to manufacture and maintain.

With the advancement of artificial intelligence (AI) and computer vision technologies, new solutions have been developed to optimize quality control in the industry. Among these technologies, object detection algorithms based on convulsive neural networks (CNNs), such as YOLO (You Only Look Once), have stood out for their ability to identify and locate objects with high precision and in real-time. Adopting these solutions paves the way for replacing traditional methods with intelligent systems that are more agile, flexible, and economically viable.

This article presents the development of a technological artifact in an auto parts factory in the Brazilian automotive industry. The artifact seeks to replace the physical templates used to verify extruded tubes with an automated inspection system based on computer vision with YOLO.

The results aim to demonstrate the viability of this process with the adoption of AI without compromising the quality and reliability of the verification process. The results prove this approach's potential in Industry 4.0, promoting a significant advance in productive efficiency and technological innovation.

This research advances the academic field by demonstrating how a YOLOv8-based visual inspection system can be successfully deployed in a real industrial environment with minimal computational infrastructure. The use of the Design Science Research methodology to structure both the artifact creation and its validation in a live production setting represents a novel academic contribution. The paper also offers a full end-to-end integration from image acquisition and annotation to model deployment and industrial approval, providing a structured and replicable blueprint for researchers and practitioners.

2. Theoretical Basis

2.1. Brazilian automotive and auto parts industries

The automotive industry in Brazil plays a fundamental role in the national economy, being one of the most critical sectors for the country's industrial and technological development. Since its establishment in the 1950s, with the installation of the first foreign automakers, the sector has undergone several phases of growth, crisis, and restructuring following the global dynamics of the economy and technological innovations.

The national auto parts industry began to consolidate in the 1950s, driven both by the policy aimed at developing the automobile sector and by the support of the emerging bourgeoisie. During this same period, the primary vehicle manufacturers were established in the country, and most subsidiaries of European assemblers were established (LUEDEMANN. 2003).

According to Bonelli (2019), the automotive industry was one of the pillars of Brazil's industrialization process, contributing significantly to generating employment and income and catalyzing the development of other industrial sectors, such as auto parts, steel, and chemicals. The author highlights that, over the decades, the industry has consolidated itself as one of the main bases of the Brazilian economy, responsible for around 22% of the country's industrial GDP and more than 1.5 million direct and indirect jobs.

Auto parts industries face challenges related to competitiveness and sustainability. According to Silva and Moreira (2020), the sector needs to deal with pressures for technological innovation, such as introducing electric and hybrid vehicles and meeting demands for greater energy efficiency and reduced pollutant emissions. Public policies focused on innovation and sustainability, such as the Rota 2030 Program, are essential to ensure the Brazilian automotive industry's competitiveness on the international stage, promoting the development of cleaner and more efficient technologies.

Furthermore, the advent of Industry 4.0 has generated new opportunities and challenges for the sector. Lopes et al. (2021) emphasize that the digitalization of production, through the implementation of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and additive manufacturing, is profoundly transforming the automotive industry value chain. In Brazil, adopting these technologies is fundamental to ensuring international competitiveness and attracting new investments.

Brazil's automotive and auto parts industry is vital for economic and industrial development. However, it faces increasing technological innovation, sustainability, and global competitiveness challenges, which require continued support from public policies and greater integration with global value chains.

2.2. Verification templates: Definition and application

Gauges or conventional gauge inspection tools are widely used in evaluating visual and geometric tolerances. They usually rely on procedures described in printed tutorials that guide operators through the process and paper forms to record the results obtained. Such practice can present significant limitations for effective quality control management, as it tends to be susceptible to failures and inaccuracies, thus compromising the reliability of the operation (Davanzo et al., 2021).

According to Usamentiaga and Garcia (2021), international standards define precise methods for testing whether dimensions are within established tolerances, indicating whether they meet the required specifications. The standards describe these methods using gauges that technicians can use to check product dimensions manually. Sometimes, these methods provide different results than automated procedures because they are based on different principles.

Verification jigs are widely used in mass production processes, especially in automotive, aerospace, and metalworking sectors, where repeatability and standardization are essential. Their primary function is to provide agility in part inspection, reduce downtime, and increase efficiency in quality control.

In practice, jigs are commonly made of aluminum or steel. They are adapted to each specific type of part to be checked, which makes their use inflexible in environments with high product variability. This device requires periodic maintenance and can represent a considerable cost in its manufacture and storage, especially in production lines with many component variants.

Furthermore, physical templates do not offer digital traceability for inspections. This limitation is problematic given the current demands of Industry 4.0, which seeks integration and digitalization of production processes (Kagermann, Wahlster, and Helbig, 2013).

2.3. New technologies applied to the automotive and auto parts industries

Artificial Intelligence originated when philosophers such as R. Llull, Descartes, and Leibniz meditated on the mechanization of human thought or the case of Babbage, who dreamed of creating super-powerful images endowed with intelligence. The first steps gave rise to the formation of disciplines such as logic, philosophy, engineering, etc., which, by bringing together their knowledge derived from cybernetics considered by N. Wiener, was the first antecedent of artificial intelligence (RECUENCO & REYES, 2020).

According to Rouhiainen (2018), AI can be defined as "the ability of computers to do activities that normally require human intelligence." However, a more detailed definition would be that AI is the ability of machines to use algorithms, learn from data, and use what is learned in making decisions as a human would.

Computer vision is an area of artificial intelligence that allows computer systems to interpret and understand information extracted from images or videos in a way similar to human perception. This technology has become an essential tool for industrial automation, especially in quality inspection, fault detection, and dimensional control activities, which previously depended exclusively on human action or physical devices (SZELISKI, 2010).

In the industrial context, computer vision allows for replacing manual or mechanical processes with more agile, precise, and scalable digital solutions. Using cameras, sensors, and intelligent algorithms allows real-time production monitoring, promoting greater control and traceability of manufactured products (GONZÁLEZ; WOODS, 2018).

Among the algorithms used in computer vision, Convolutional Neural Networks (CNNs) stand out for their high capacity to recognize image patterns with robustness and precision. A CNN comprises layers that perform convolutions, automatically extracting relevant features from images. This makes these models ideal for tasks such as classification, segmentation, and object detection (GOODFELLOW; BENGIO; COURVILLE, 2016).

CNNs have been widely applied in industrial environments to replace conventional visual inspection methods. LeCun et al. (2015) state that these networks learn hierarchical data representations, reducing the need for feature engineering and increasing generalization capacity in complex environments.

The combination of computer vision and CNNs is especially advantageous for contexts that require high processing speed and reliability in detecting faults or non-conformities. As a result, intelligent systems have been implemented in production lines to reduce verification time and operating costs by Industry 4.0 guidelines.

Object detection is a central and widely studied challenge in computer vision. Over the last decade, driven by rapid advances in deep learning, researchers have devoted substantial efforts to continuously improving methods for detecting objects and performing related tasks, such as classification, localization, and segmentation, using models based on deep neural networks (Diwan et al., 2023).

With the emergence of the YOLO (You Only Look Once) model and its subsequent architectures, a significant advance in detection accuracy was observed, surpassing traditional two-stage methods in some instances. The popularity of YOLO in several applications is mainly associated with its faster inference capacity, although this often occurs at the expense of maximum accuracy in object detection (Diwan et al., 2023).

Since its inception in 2015, the YOLO architecture for object detection has evolved rapidly, culminating in the launch of YOLOv8 in January 2023. The different versions of YOLO are based on offering real-time performance combined with high accuracy, even under computational constraints. This approach has progressively intensified over the generations of the architecture, seeking to meet the growing demands for automated quality inspections in the context of defect detection on industrial surfaces — which require speed, high accuracy, and the ability to operate on edge devices with limited resources (Hussain, 2023).

3. Methodology

This study was developed based on a real case applied to an automotive company in Brazil that specializes in piping and connection systems for commercial and industrial vehicles.

To describe the methodological procedure and the methods used to develop the artifact, Design Science Research (DSR) was used; according to Peffer et al. (2007), the research process includes six main stages: identification and motivation of the problem, definition of objectives for a possible solution; design and development of the proposed solution; practical demonstration; evaluation of the results obtained; and, finally, communication of the conclusions reached.

3.1. Problem identification and motivation

In the analyzed production line, the extruded tubes are assembled with plastic or metal connectors (See Figure 1), and at the end of the assembly, they are positioned in customized aluminum jigs (See Figure 2). These jigs are used to passively verify whether the component respects the dimensions of curvature, length, diameter, and positioning of the connectors.

Fig. 1. Extruded tube with connectors. Fig. 2. Extruded tube in the jig or gauge.

In the interview with the industrial director and in the visits to the industry, it was found that the gauges or templates present some problems, such as handling when bringing them to the production line, as they are only used in the production of those types of cable. When they are not used, they are stored on shelves that take up space and increase the cost of making each gauge.

The motivation for this problem is to replace the current gauges with a technological solution based on the technologies presented in the theoretical foundation.

3.2. Defining the objectives for the solution

For replacement purposes, the success criterion was defined as the ability of the AI-based system to identify:

- The general geometric shape of the tube (contour and curvature);
- The presence and correct position of the connectors;
- Visual fault detection includes deformed, missing, or poorly fitted parts.

The objective is the development of a technological artifact in the Brazilian automobile industry that seeks to replace the physical templates used in the verification of extruded tubes with an automated inspection system based on computer vision with YOLO.

3.3. Design and development of the proposed solution

The development of the proposed solution consisted of the following tasks:

3.3.1 Image acquisition and dataset preparation

A database was built with 800 images of assembled pipes, captured under different lighting and positioning conditions, using an iPhone 15. The images were manually annotated with the Roboflow tool, indicating two classes:

- Compliant (class 1 with 500 images),
- Non-compliant (class 2 with 300 images),

The images were divided into 90% for training, 8% for validation, and 2% for testing.

3.3.2 Tools and Architecture Used

The system implementation used the Ultralytics YOLOv8 library. Training was conducted in a Python 3.10 environment using the Anaconda 24.9.2 environment manager, using the OpenCV, PyTorch, and Pandas auxiliary libraries. The training was performed on a computer with a Windows 10 operating system, Intel i7-870 CPU, 16 Gbytes of RAM, 700 Gbytes SSD storage, and NVIDIA RTX 4060 GPU (8GB).

Training parameters:

- Number of epochs: 100, 150 and 376
- Image size: 640x640 px
- Batch size: 8
- Optimizer: SGD with a learning rate of 0.01
- Early stopping: enabled after 10 epochs without mAP improvement

One of the methodological innovations of this study lies in the use of a commercially available smartphone (iPhone 15) for dataset acquisition under realistic lighting and positioning conditions, coupled with Roboflow-based annotation. The entire pipeline was implemented using the lightweight YOLOv8s model, enabling high-performance detection on standard desktop hardware (Intel i7, 16GB RAM, RTX 4060 GPU). The training used early stopping to prevent overfitting and optimized performance across limited training samples. This practical yet effective setup underscores the feasibility of deploying advanced computer vision systems without requiring large-scale infrastructure.

3.4. Practical demonstration

After training, the model was integrated into a Python program and tested with images of compliant and non-compliant products not in the original dataset. The system processed the image and provided the verification result in less than 1 second:

- "Conforming" for parts conforming to the standard,
- "Non-conforming" with visual highlighting of non-conforming elements.

The results were automatically recorded in a database for traceability and auditing.

The performance metrics adopted per class highlight explanations critical to understanding the model's performance for each class, especially in datasets with multiple object categories (Antunes et al., 2024). To measure the performance of the new AI system, the following indicators were collected:

- Accuracy - Measures how many of the detections made by the model are correct;
- Recall - Measures how many real objects the model was able to detect correctly;
- Mean Average Precision (mAP) - Average of the mean precisions (AP) obtained in all classes analyzed;
  - mAP@[0.5:0.95] - Average of the APs obtained with IoU thresholds ranging from 0.5 to 0.95 (increases the accuracy of the evaluation).
  - mAP@0.5 - The "@0.5" indicates the IoU (Intersection over Union) threshold value that defines whether detection is considered correct or not.

3.5. Evaluation of the results obtained

The effectiveness of the developed artifact was assessed through both quantitative metrics and qualitative industrial validation. Quantitative evaluation is detailed in Section 4, including precision, recall, and mean average precision (mAP) metrics across various training configurations. To ensure practical applicability, the system was presented to the industrial director and the production manager of the partnering auto parts factory, who conducted hands-on assessments of the prototype's functionality. Their feedback emphasized the model's adequacy for real-time inspection, operational ease, and potential for cost reduction, validating its readiness for industrial deployment.

3.6. Communication of conclusions reached

The findings of this research are disseminated to the academic and industrial communities through this publication, which aims to contribute to the growing body of knowledge in the field of AI-based quality inspection. By presenting a structured Design Science Research methodology and its real-world application, the study supports further exploration and adoption of smart inspection systems in manufacturing environments aligned with Industry 4.0 paradigms.

3.7. Replication Guide

To promote scientific reproducibility, we provide a detailed description of the training process using Ultralytics YOLOv8 and Roboflow. The dataset was split into 90% training, 8% validation, and 2% testing. The YOLOv8s model was trained on images of 640×640 resolution, with a batch size of 8, using SGD optimization with a learning rate of 0.01 and early stopping after 10 stagnant epochs. All scripts used in this study can be shared upon request and will be made available in an open-source repository. This pipeline enables replication of the results and adaptation for other visual inspection tasks.

4. Result and analysis

The results obtained from the experiments with different YOLOv8 models demonstrate the potential of artificial intelligence applied to the visual inspection of extruded tubes, as proposed in the theoretical foundation of this study. Four models with different numbers of training epochs were evaluated. All of them presented high performance in terms of precision, recall, and average mean precision (mAP), both at the IoU threshold of 0.5 and in the range of 0.5 to 0.95 (mAP@0.5:0.95), which represents a more rigorous assessment of the model's robustness. Table 1 summarizes the main results of the tested models:

Table 1. Results.

Model	Epochs	Precision	Recall	mAP@0.5	mAP@0.5:0.95
Model1	376	0.991	0.974	0.995	0.934
Model2	100	0.958	0.969	0.992	0.880
Model3	150	0.970	0.969	0.992	0.940

The best performance was observed in the YOLOv8 model trained for 150 epochs (model3), which achieved a precision of 0.97, recall of 0.969, mAP@0.5 of 0.9917, and mAP@0.5:0.95 of 0.9397. These indicators are significantly superior to the results obtained with traditional manual inspection methods using jigs, which, as highlighted by Davanzo et al. (2021) and Usamentiaga & Garcia (2021), are susceptible to human error, do not offer digital traceability, and do not adapt to visual variations of the parts.

We can see the results for the tubes in compliance (Figure 3a) and without compliance (Figure 3b).

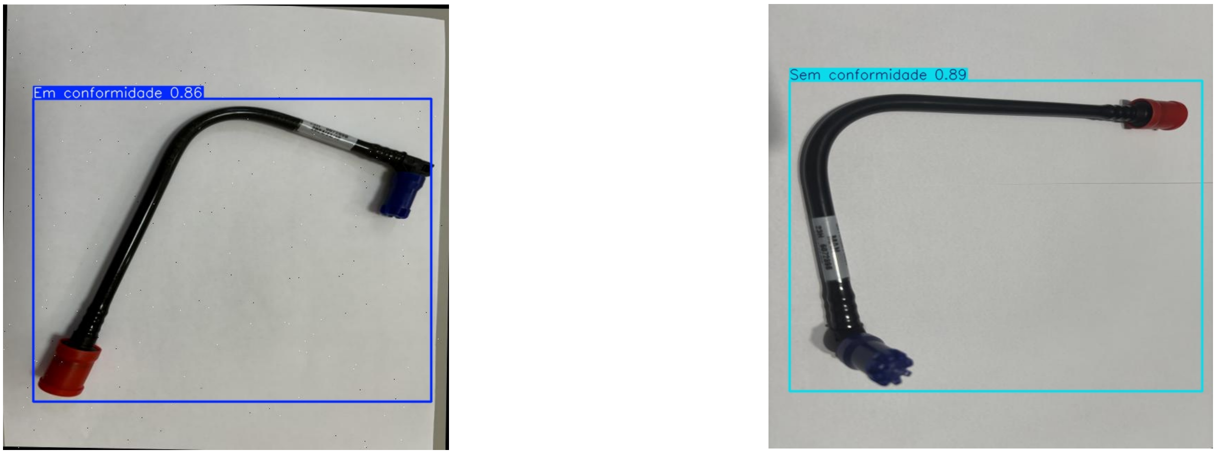

Fig. 3. (a) Compliant tube correctly assembled according to dimensional specifications. (b) Non-compliant tube showing misalignment and missing connectors.

These data reinforce the alignment with what was discussed in the theoretical foundation on the power of convulsive neural networks (CNNs) to recognize complex patterns and perform classification tasks with a high degree of reliability (Goodfellow et al., 2016; LeCun et al., 2015).

Furthermore, the application of computer vision based on YOLO, which according to Diwan et al. (2023) stands out for its speed and effectiveness, proved to be fully compatible with industrial requirements, with an average inference time of less than 25ms per image — a performance suitable for real-time inspections on the production line.

Another relevant aspect was the practical inference with new images, which were not used in the training process. The system was able to correctly detect "Compliant" parts with confidence of up to 0.96, and "Non-Compliant" parts with confidence ranging from 0.72 to 0.91. Images with significantly different geometries were not detected, which, although representing a limitation, highlights the need to increase the diversity of the dataset to improve generalization — a recurring challenge cited by Szeliski (2010) in the computer vision literature.

From a methodological point of view, the results validate the development approach adopted based on Design Science Research (Peffers et al., 2007), which guided the project from problem definition to demonstration and evaluation of the artifact. YOLOv8, combined with careful image curation and appropriate division between training, validation, and testing, effectively achieved a functional and scalable automated inspection model.

Finally, the qualitative validation of the solution was carried out on-site with two strategic professionals from the company: the industrial director and the production manager. Both attended the system demonstration, analyzed the practical results, and recognized the tool's ability to replace physical templates safely and efficiently. The industrial director highlighted the potential for savings and agility in the inspection process, while the manager emphasized the new solution's ease of use and digital traceability. This practical validation complements the quantitative results, reinforcing the proposal's applicability in the actual context of the assembly line.

5. Conclusion

This study presented the development and implementation of a system based on artificial intelligence and computer vision using the YOLO algorithm to replace traditional physical templates in the Brazilian automotive industry's visual inspection of extruded tubes. The results demonstrated that the YOLOv8 model, especially after training for 150 epochs, achieved high precision, recall, and average precision (mAP), proving its effectiveness and robustness for practical application in the industrial environment.

The qualitative validation carried out with industry professionals highlighted not only the solution's technical feasibility but also its operational and economic benefits, such as a significant reduction in inspection times, lower operating costs, and increased digital traceability of production processes.

Adopting the proposed technology reflects a significant advance toward Industry 4.0, promoting greater flexibility, productive efficiency, and sustainability. However, it is essential to highlight the importance of continuously expanding and diversifying the training database to improve further the model's generalization capacity in different industrial scenarios.

In future work, the model's accuracy should be further improved by training it with a more extensive and varied volume of images, covering different environmental conditions and part geometries. This approach will make the system even more robust and adaptable to the complexities inherent to the industrial environment.

Finally, this work not only reinforces the relevance of integration between academia and industry in the generation of innovative technological solutions but also emphasizes the constant need to humanize technology, considering its positive impact on the routines of the professionals involved and on the sustainable development of industrial operations.

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