A Deep Learning-Based Computer Vision System for Automated Screw Detection in Vehicle Wheel Boxes: Enhancing Automotive Quality Control with Industry 4.0

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Abstract. Artificial intelligence (AI) can improve the quality control in the automotive industry. Reliable inspection methods are essential in manufacturing environments, as a single defect can damage a company's reputation. This work presents a practical solution using computer vision and deep learning to detect small screws installed in the wheel boxes of vehicles on a moving assembly line. The system combines a custom image acquisition setup with preprocessing techniques to improve contrast and clarity, followed by object detection using the YOLOv8 algorithm. Synthetic data generated to train the model effectively allowed for more robust performance without relying solely on real-world samples. The system tested outcomes with a screw detection accuracy of 92%, compared to around 71% accuracy from traditional visual inspections. That result suggested that AI-based approaches can significantly enhance quality assurance processes in automotive manufacturing, particularly in fast-paced production settings.

Keywords: Quality inspection · computer vision systems · deep learning

1 Introduction

In the automotive industry, product quality is the driving force behind gaining a competitive edge. Developing technologies to detect defects during manufacturing effectively has become an essential task within this sector [1]. Product quality defects can come from various sources, including machinery failure, operational errors, or failure of existing quality control systems [2]. Such defects can impact product performance and lead to safety concerns. In this context, a single vehicle defect can damage the brand´s reputation and compromise customer loyalty, which has been built over decades.

Visual inspection performed by humans is the traditional method of quality control in the manufacturing industry [3, 4]. This approach may not be feasible for some applications and may have severe consequences in the event of failure, as it is inefficient and prone to errors due to fatigue during repetitive tasks [5, 6]. With the modern trend

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2025
O. Gervasi et al. (Eds.): ICCSA 2025, LNCS 15649, pp. 3–17, 2025.
https://doi.org/10.1007/978-3-031-96997-3_1

of Industry 4.0 technologies, computer vision systems and Artificial Intelligence (AI) are increasingly utilized in manufacturing processes for automation, enhancing quality inspection and production efficiency [7–10], as well as reducing the need for manpower by replacing visual inspection [3].

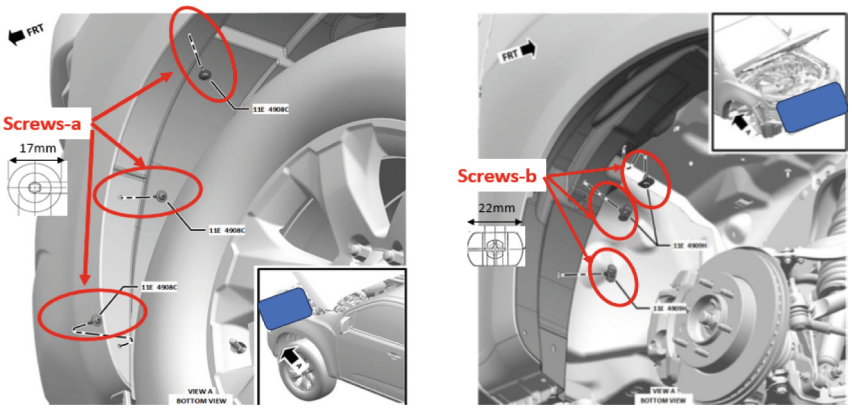
Computer vision, or machine vision technology, is commonly designed to imitate manual inspection. Computer vision is a disruptive innovation that allows computers to perceive the world through cameras and make decisions automatically based on deep learning technology [11]. However, computer vision faces significant challenges, particularly regarding quality defect detection. A purely automated solution is not necessarily the most efficient when applied to quality inspection [5]. In this context, recent vision systems increasingly use deep learning techniques to improve the accuracy and reliability of the quality inspection process [8]. According to [12], deep learning techniques have significantly improved quality control systems for detecting defects in the manufacturing industry. Thus, the major contribution of this work is to demonstrate the role of an AI-based vision systems to manufacturing quality control and deliver product with high- quality products to the end customers.

Efficient computer vision enhances the system's effectiveness by properly training machine learning models with extensive datasets. Consequently, collecting and labeling a significant amount of data presents challenges due to the high diversity of product types and the range of defects that may occur during manufacturing. A balanced dataset of classes is crucial to avoid bias in the algorithm. In this context, utilizing a synthetic dataset can be a feasible method for training AI algorithms, ensuring consistent and reliable detection and classification of defects [12]. Furthermore, synthetic data provides a vast dataset and enables the control and manipulation of various scenarios, producing realistic images.

This study aims to develop a framework for computer vision systems using deep learning to detect quality defects. Our work focuses on the intermediate section of the assembly line, where each vehicle is automatically inspected for the presence of screws in the wheel boxes as it moves along the line. Figure 1 illustrates two types of screws found in the wheel boxes, (a) screw-a and (b) screw-b. We propose a deep learning-based solution to accurately detect small screws, using synthetic data to train the algorithm for outstanding performance. The ultimate goal of this work is for this computer vision system to replace visual inspection completely.

These screws play a pivotal role in properly fixing the plastic cover on the vehicle´s wheel boxes. The plastic cover prevents debris such as rocks, mud, and water thrown by the tires from reaching sensitive components of the suspension, brake, and car body. Thus, the lack of these screws can reduce the strength and durability of that area, potentially increasing safety concerns for the customer or reducing the vehicle´s life cycle.

The remaining sections are structured as follows: Sect. 2 highlights the literature review and related work; Sect. 3 presents the proposed methodology; Sect. 4 describes the obtained results; Sect. 5 offers the discussion; and finally, Sect. 6 includes the conclusions and future research of this work.



(a) (b)

Fig. 1. Two types of screws. (a) Screw-a has a 17 mm size and (b) screw-b has a 22 mm size.

2 Literature Review and Related Work

With the concretization of Industry 4.0, the manufacturing process experiences a revolutionary level of automation in the production pipeline that incorporates Artificial Intelligence, Data Analytics, IoT, and more. Such aim is to minimize human intervention for inspection and produce products that meet high-quality standards [8]. In this context, the automation of quality inspection through computer vision and artificial intelligence has generated increasing interest among companies [5, 13, 14].

According to [15], poor product quality can lead to several negative impacts, including financial losses, environmental damage, and resource waste related to materials, personnel, and services. In response, [13] the growing popularity of investments in automated defect detection systems, which reduce labor costs and enhance the consistency and reliability of production processes. They thoroughly investigate two widely used neural network algorithms in industrial object detection systems: YOLO (You Only Look Once) and R-CNN (Region-based Convolutional Neural Network). This work emphasizes the critical role of computer vision in industrial applications, particularly for detecting defects in materials such as fabric, steel, and car rims, demonstrating its potential to improve quality control across diverse manufacturing sectors.

The quality control systems for detecting manufacturing defects have improved by implementing computer vision. However, these systems face challenges, particularly regarding the large datasets needed to train the neural network algorithm, such as YOLO. To address this issue, [12] presents an innovative method to train the AI model YOLO V5 using synthetic data, demonstrating its potential to reduce both the time and costs of data collection. The effectiveness of this method was validated through two industrial use cases: stamped parts and assembly lines. In both cases, the performance of the AI model trained on synthetic data was compared with that of models trained on real datasets. The study highlights the critical role of computational power in generating realistic synthetic images, which are essential for achieving high-quality training outcomes.

Examining related work in image preprocessing techniques, the review presented by [16] shows an interesting article that applies various image preprocessing methods, including Histogram Equalization, CLAHE (Contrast Limited Adaptive Histogram Equalization), image denoising, thresholding, binarization, and morphology transformation. In this work, the authors examined welding defects to verify that the weld spots meet the requirements using machine vision technology.

In summary, computer vision systems coupled with artificial intelligence are increasingly applied in the manufacturing industry to detect quality defects and achieve high accuracy and efficient processes. However, we could not find any papers that predominantly employ a vision system with AI able to detect small screws in the wheel boxes of moving line vehicles, which significantly increases the complexity of achieving high-accuracy performance.

3 Methodology

This section highlights the methodology used to detect and classify the presence of screws in the vehicle's wheel box on the assembly line. To achieve this, a complete computer vision framework was designed, featuring an image acquisition system and an Artificial Intelligence (AI) algorithm for detecting and classifying interesting objects with high confidence and precision, thereby enabling the removal of visual inspections currently performed by humans. Initially, this work consisted in defining the type of hardware and the appropriate setup capable of identifying with optimal quality the presence of all screws fixed in the vehicle. The next step was to develop a dataset to train and test the AI algorithm using synthetic images. Following that, image preprocessing techniques were analyzed to enhance the accuracy of the inspected objects. Finally, the system's results were evaluated using accuracy, precision, and recall. Figure 2 illustrates the proposed development flow for the automatic inspection system with a deep learning architecture.

3.1 Data Acquisition

3.1.1 Hardware

Cameras and lighting are pivotal in developing computer vision systems that detect objects. This proposed system comprises four cameras, eight lighting fixtures, and one central processing unit (CPU). Figure 3 illustrates the leading hardware used in this work.

- Lightning: Infrared light, 850 wave-length, SC75 Model, and 24V.
- Camera: Rolling Shuttle, Monochromatic, aca 3800-10gc, and Basler.
- CPU Matrox Intel core i5, 1Tb
- Cabo Ethernet

3.1.2 Set up and Commissioning of the Hardware

Initially, Process Simulate software was used to evaluate the optimal position for each camera that needed to be installed to achieve the best field of view for object detection.

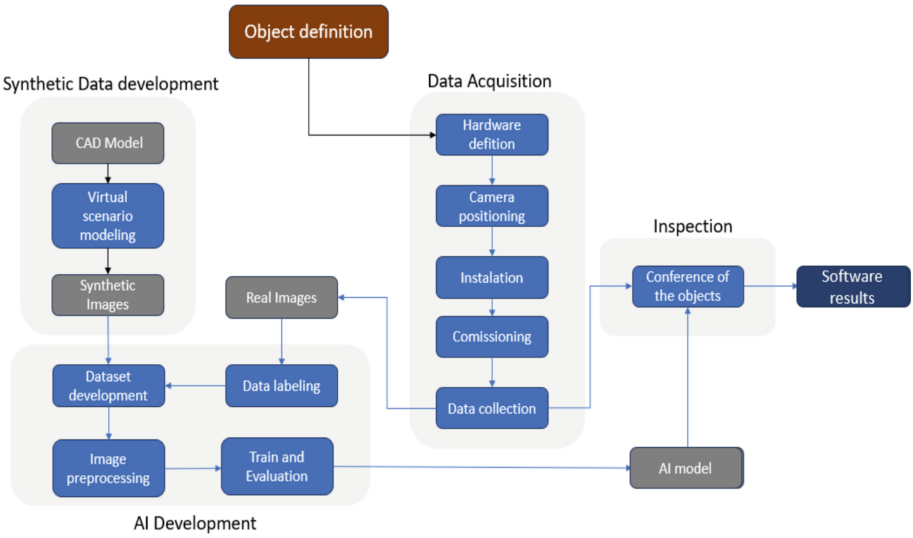


Fig. 2. Automatic Screw Inspection Process Flow



Fig. 3. Main hardware used to detect screws in the vehicle´s wheel boxes

The outcome indicated the necessity of installing two cameras on the right and two on the left sides, as shown in Fig. 4. The optimal position was the camera in "X" view, meaning that camera 1 focuses on the front face, and camera 2 focuses on the rear face. The challenges encountered in this step included adjusting four cameras to detect 27 screws distributed across four wheel boxes in difficult-access areas with varying complexity and size. Figure 5 illustrates an example of the field of view captured in a simulated environment.

3.2 Dataset Development

Real images were collected for dataset development once the data acquisition system was commissioned on the production line. According to [17], many images are required to train machine learning models. This work generated synthetic data to train and validate the proposed artificial neural network in this context.

Firstly, the dataset was developed based on synthetic images generated from CAD (Computer-Aided Design) models. Blender software was utilized for modeling and rendering 3D images. Furthermore, Blender was able to add texture and color and adjust

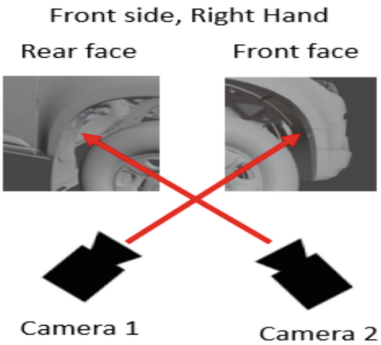


Fig. 4. Position "X" of the cameras. Example of the front part of the Vehicle

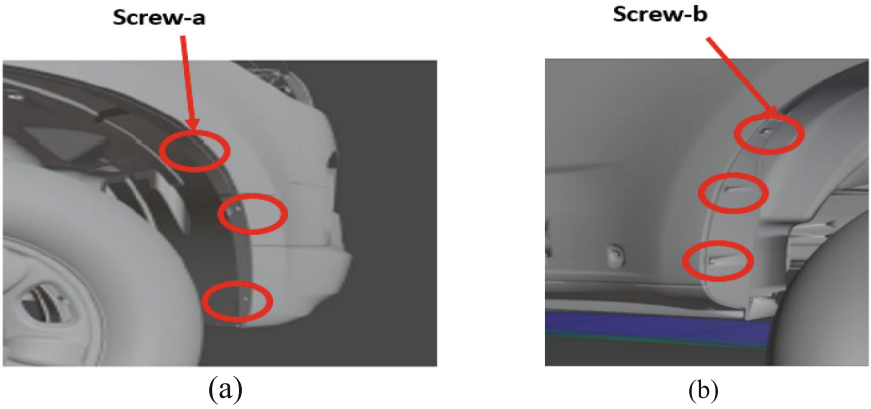


Fig. 5. Two types of screws are fixed in the right/front of the wheel boxes. (a) screw-a positioned in the front face and (b) screw-b positioned in the rear face.

lighting and sharpness, allowing realistic images to be created in a virtual environment. Once the part was modeled, user-friendly integration of Python and PyTorch with Blender automated the development of synthetic data. In addition, real images were captured through the image acquisition system installed in the production line, contributing to the dataset for training and improving the software performance. Figure 6 highlights the comparison of synthetic images (a) and real images (b).

The test dataset was developed using real images collected through the data acquisition system and manually labeled by software developers. Table 1 shows the number of images used to train the algorithm. These images refer to the presence of screw-a and screw-b. Table 2 presents the number of images used to test the AI algorithm. The lower number of screw-b is justified by the number of screws fixed in the vehicle.

3.3 AI Development

One of the characteristics of Deep Learning models is the necessity of representative data for training. In this work, AI development is based on a hybrid dataset for training

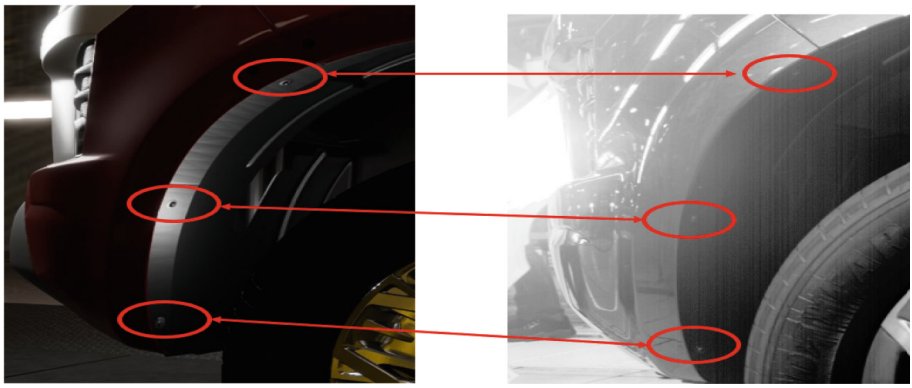


Fig. 6. Comparison of synthetic image and real image. The red cycles highlight the screws in the left/front side wheel box. (a) synthetic image and (b) real image.

Table 1. Number of images used to train the AI algorithm.

Dataset	Number of Image by class	
	Screw-a	Screw-b
Synthetic (S)	15389	15767
Real (R)	3262	3105
Hybrid (S + R)	18651	18872

Table 2. Number of images used to test the AI algorithm.

Dataset	Number of Image by class	
	Screw-a	Screw-b
Real (R)	1830	294

and real images for testing, as shown in Table 1. Considering that YOLO is widely recognized for its speed and precision in computer vision tasks [18], we adopted YOLO V8 and tested YOLO V5 and V10 versions. Regarding image preprocessing techniques, CLAHE and Histogram Equalization (HE) were evaluated to enhance the quality of the images and thus obtain better performance.

YOLO (You Only Look Once)

YOLO stands out among single-stage detectors due to its simple architecture, high accuracy, and fast inference speed [19]. Figure 7 illustrates a generic YOLO architecture.

This work prioritized the YOLO V8 due to its improvements in accuracy and processing speed [1, 25], which are essential for our proposed solution's requirement of

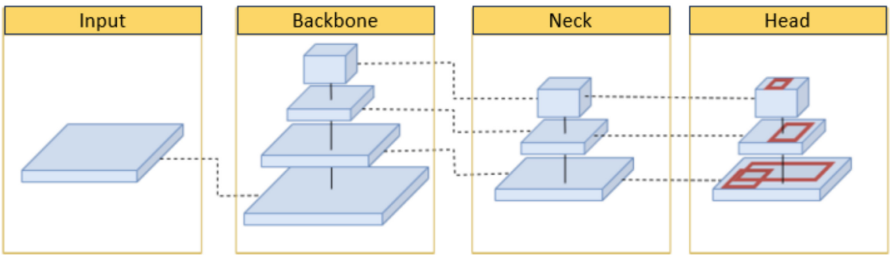


Fig. 7. Generic YOLO architecture.

real-time inspection. This model contains various parameters that can be modified and explored to optimize according to purposes. Table 3 presents some parameters used to develop our AI algorithm, as well as the corresponding parameters for YOLO V5 and YOLO V10. In this test, the dataset consisted of 5000 images, which included only synthetic data.

Table 3. Some parameters used to evaluate the AI algorithm

Parameters	YOLO V5	YOLO 8	YOLO 10
Number of neural layers	22 layers	75 layers	50 layers
Input image size	640 × 640 pixels	960 × 960 pixels	960 × 960 pixels
Initial layer activation function	ReLu	Simoid + SiLu	Simoid + SiLu
End layer activation function	Softmax	Softmax	Softmax

3.4 Image Preprocessing Techniques

Image preprocessing is a pivotal stage in computer vision systems, used to prepare raw images and ensure better results for the next step [20]. This stage aims to solve or minimize inference-related issues, such as noise and lack of image representation [21]. In our work, the CLAHE and HE techniques were evaluated to improve image quality.

According to [22], the HE technique is a method of image preprocessing that enhances the contrast of images. Meanwhile, CLAHE is a variant of HE that aids in preserving an image's local contrast features dynamically. Figure 8 showcases three distinct images: (a) the original image without preprocessing, (b) the image processed with the CLAHE technique, and (c) the image processed with the HE technique. This comparison allows us to evaluate the effectiveness of the preprocessing techniques in enhancing the algorithm's overall performance.

3.5 Performance Metrics

The performance metrics commonly used to evaluate vision systems are accuracy, precision, and recall [2, 8]. A confusion matrix was employed to evaluate our AI algorithm, as



(a) (b) (c)

Fig. 8. Comparison of images without preprocessing technique (a), and images using preprocessing techniques (b) and (c).

presented in Table 3. The observed classes identified by the system included the presence of screws, with the ultimate goal set at achieving 95% accuracy. This target is based on level 4 of the FMEA (Failure Mode Effect and Analysis) occurrence table.

Accuracy (Acc):

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}} \tag{1}$$

Precision (PPV):

$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall (TPR):

$$\text{TPR} = 1 - \text{FN} \tag{3}$$

TP = True Positive; TN = True Negative; P = Positive; N = Negative; FP = False Positive; FN = False Negative

The AI classification results were evaluated using the Confusion Matrix based on the model in Table 4. This method was chosen for its simplicity, which aligns with the approach taken by [23].

Furthermore, the results of the proposed framework for computer vision systems were compared with visual inspection. This comparison demonstrates how important automatic vision is to guarantee product quality in the manufacturing process.

4 Results

This section embraces the results that led to the implementation of computer vision systems for detecting small screws in vehicle wheel boxes. Notably, YOLO V8 outperformed both YOLO V5 and YOLO V10 in all metrics, as shown in Table 5. Although YOLO V10 is the latest version, it did not perform better than the previous version in this evaluation.

Table 4. Confusion Matrix to evaluate AI algorithm.

		Predicted class	
		Class 1	Class 2
Annotated class	Class 1	TP	FN
	Class 2	FP	TN

Table 5. Results of the comparison between YOLO V5, V8 and V10.

	YOLO V5	YOLO V8	YOLO V10
Accuracy	73%	87%	42%
Precision	76%	92%	51%
Recall	73%	91%	51%

Table 6 details the results of image preprocessing techniques using CLAHE and HE. Both techniques focus on improving image quality by reducing noise and enhancing sharpness in the original images [14]. However, we have seen the HE's favorable improvements in contrast and sharpness achieved by demonstrating better outcomes than CLAHE.

For AI model evaluation, a dataset of 2,124 real images was used to test the model. The objective was to validate the effectiveness of this model in detecting the presence of 27 screws in the vehicle wheel boxes. Table 7 presents the number of real images from screw-a and screw-b. The lower amount of screw-b is justified by the number of screws fixed in the vehicle.

Table 6. Results of the image preprocessing techniques.

	Original Image	CLAHE	HE
Accuracy	89%	92%	94%
Precision	90%	93%	94%
Recall	94%	97%	98%

Table 7. Number of real images from screw-a and screw-b to AI test.

Classes	Number of Images by class
Screw-a	1830
Screw-b	294

The classification results were evaluated using the confusion matrix, chosen for its practicality and simplicity, according to the approach outlined in [23]. The results of this analysis, including annotated and predicted images, are presented in Table 8 and the Overall performance in Table 9.

Table 8. Results of the AI evaluation using Confusion Matrix.

		Predicted		
		Screw-a	Screw-b	background
Annotated	Screw-a	1798	3	92
	Screw-b	4	283	49
	background	28	8	0

Table 9. Summary of the AI performance

Overall Performance:	
Accuracy	92%
Precision	93%
Recall	99%

The confusion matrix analysis using real images reveals that, from the 1893 images tested, the system correctly predicted 1798 as screw-a, only three as screw-b, and 92 images were considered as background (images identified by the system as screw-a, but there were no screw-a annotations). In another tested class comprising 336 images, the system correctly recognized 283 images as screw-b, only four predicted as screw-a, and 49 as background. In summary, the AI algorithm´s overall performance results in 92% accuracy, 93% precision, and 99% recall.

5 Discussion

This work demonstrated the development and implementation of an AI-powered computer vision system capable of achieving 92% accuracy in identifying the presence of screws in the vehicle's wheel boxes on a moving assembly line. This level of performance enables automated inspection to surpass traditional manual visual inspection methods, significantly enhancing detection rates and preventing customer dissatisfaction caused by product quality issues. Furthermore, the automated inspection system aligns with Level 8 of the FMEA, underscoring its reliability and effectiveness. Such advancements are critical for manufacturers seeking a competitive edge in today's demanding market.

According to Prabhu et al. [14], HE minimizes image distortion and noise. In this study, HE was applied during the image preprocessing stage and compared with CLAHE to evaluate alternative techniques for image enhancement. The results demonstrated that

HE outperformed CLAHE in screw detection tasks, primarily due to its superior ability to process low-contrast images, particularly in complex backgrounds and small areas, as supported by [24].

An extensive and recent search in the electronic databases revealed no prior research addressing the inspection of small screws fixed in vehicle wheel boxes using computer vision systems integrated with AI technology. Consequently, this study fills a critical gap in the field, offering valuable insights for manufacturers seeking to enhance product quality control and optimize production processes.

The proposed AI model's performance demonstrated outstanding results, with all metrics exceeding 90%. Compared to traditional visual inspection methods, which achieve an efficiency of 71%, the system significantly improves quality control accuracy to 92%. This improvement highlights the significant practical implications of AI-driven solutions for the manufacturing industry. It showcases their potential to revolutionize conventional inspection practices, reduce error rates, and ensure process stability and customer satisfaction, consistent with findings reported in [2]. Such innovations are particularly impactful in applications where human vision is limited and high precision is essential, such as detecting missing screws in vehicles.

Furthermore, synthetic data is pivotal in accelerating AI model training, as highlighted in [12]. In this study, the YOLO V8 algorithm was predominantly trained on a synthetic dataset, delivering consistent and precise results. This approach demonstrates that the use of synthetic data is a strategy to reduce data collection time while increasing the volume and diversity of training datasets, as noted in [5].These advances highlight the potential of AI-based systems to provide scalable, efficient, and highly accurate quality inspection solutions in industrial settings.

Our research aligns with and complements the [13], showcasing practical applications of the YOLO V8 algorithm for quality inspection of wheel box´s screws. This addresses the challenge of detecting small components in areas with a limited field of view while also providing real-time results. As mentioned, synthetic data played a pivotal role in this research, enabling efficient training of the proposed algorithm. This is based on the work of [12], who introduced this method to train the YOLO V5 with real and synthetic images.

On the other hand, the present work provides a comprehensive development of the vision system, encompassing all stages—from dataset creation for training to testing the YOLO V8 algorithm. Furthermore, YOLO V5 and YOLO V10 were also evaluated to determine the best version of the algorithm for screw inspection in wheel boxes using synthetic data, further distinguishing from existing research. Finally, the HE technique was crucial to improve the raw image of the screws and enhance the performance of the vision system. This differs from the approach of [16], who used the CLAHE technique to improve the defective weld images in their research.

6 Conclusion and Future Works

This work shows how AI-based vision systems contribute to manufacturing quality control in the automotive industry. Automated solutions replacing manual visual inspection may improve product quality, optimizing efficiency and reliability in manufacturing.

As accuracy and consistency are critical in the automotive industry, these systems can help detect defects in complex assemblies, which improves production lines´ safety and performance.

In the context of Industry 4.0, advanced technologies, such as deep learning integrated with computer vision, have proven reliable for reducing costs, saving time, and increasing operational efficiency. Although the results presented in this paper focus specifically on detecting screws in wheel housings, future research should include the analysis of objects with different shapes, sizes, compositions, and textures. Such expansion would validate the adaptability of these systems for other industrial applications beyond the automotive sector.

Future studies exploring this type of Industry 4.0 perspective could occur to further integrate these tools towards Lean Manufacturing in the context of Quality 4.0. The synergy of these approaches would enable a more comprehensive exploration of emerging concepts and technologies, thereby supporting the development of innovative computational capabilities for the manufacturing industry. These computational capabilities would specifically help the automotive industry, notably in terms of quality optimization and customization of the production chain.

Acknowledgment. The authors are grateful to FAPESP (Fundação de Amparo à Pesquisa do Pesquisa do Estado de São Paulo, Brazil; grant: 2020/09850-0) for the financial support.

Disclosure of Interests. The authors have no competing interests to declare relevant to this article's content.

References

1. Jung, D.Y., Oh, Y.J., Kim, N.H.: A study on GAN-based car body part defect detection process and comparative analysis of YOLO v7 and YOLO v8 object detection performance. Eletronics (2024). https://doi.org/10.3390/electronics13132598
2. Jamal M., Faisal S., Kusumaningrum D.S., Rohana T.: Application of Yolo V8 for product defect detection in manufacturing companies. Journal Sistem Informasi dan Ilmu Komputer Prima. Vol. 8. N. 1 (2024)
3. Ren, Z., Fang, F., Yan, N., Wu, Y.: State of the art in defect detection based on machine vision. International Journal of Precision Engineering and Manufacturing -Green Technology (2022). https://doi.org/10.1007/s40684-021-00343-6
4. Hachem, C.E., Perrot, G., Paivin, L., Couturier, R.: Automation of quality control in the automotive industry using deep learning algorithms. IEEE Xplore (2021). https://doi.org/10.1109/ICCCR49711.2021.9349273
5. Torto, I.R., Campaniço, A.T., Pereira, A., Teixeira, L.F., Filipe, V.: Automatic quality inspection in the automotive industry: a hierarchical approach using simulated data. IEEE 8th International Conference on Industrial Engineering and Application (2021). https://doi.org/10.1109/ICIEA52957.2021.9436742
6. Rahimi, A., Anvaripour, M., Hayat, K.: Object detection using deep learning in a manufacturing plant to improve manual inspection. IEEE International Conference on Prognostics and Health Management (2021). https://doi.org/10.1109/ICPHM51084.2021.9486529

7. Abukhait J.: Dust Detection on Solar Panels: A computer vision approach. Ingénierie des Sistemes d´information. Vol. 29. N. 2 (2024)
8. Asif, S., Akmal, M.U., Koval, L., Knollmeyer, S., Mathias, S.G., Grossmann, D.: Supervised anomaly detection for production line images using data augmentation and convolutional neural network. IEEE 29th International Conference on Engineering Technologies and Factory Automation (2024). https://doi.org/10.1109/ETFA61755.2024.10710718
9. Avola, D., et al.: Real-time deep learning method for automated detection and localization of structural defects in manufactured products. Computer & Industrial Engineering (2022). https://doi.org/10.1016/j.cie.2022.108512
10. Chouchene, A., Carvalho, A., Lima, T.M., Santos, F.C., Osório, G.J.: Artificial intelligence for product quality inspection toward smart industries. IEEE Xplore (2020). https://doi.org/10.1109/ICITM48982.2020.9080396
11. Reyna, M., Delgado, G., Akundi, A., Luna, S., Chumacero, E.: Product digital quality inspection using machine vision systems – a categorical review. 17th Annual System of Systems Engineering Conference (2022)
12. Werda, M.S., Taibi, H., Kouiss, K., Chebak, A.: Generation of synthetic data for deep learning in manufacturing quality control systems. IEEE 22nd Mediterranean Electrotechnical Conference (2024). https://doi.org/10.1109/MELECON56669.2024.10608616
13. Tang, T., Sun, K., Zhao, D., Lu, Y., Jiang, J., Chen, H.: Industrial defect detection through computer vision: a survey. IEEE 7th International Conference on Data Science in Cyberspace (2022). https://doi.org/10.1109/DSC55868.2022.00091
14. Prabhu, A., Sangeeta, K.V., Likhitha, S., Lakshmi, S.: Application of computer vision for defect detection in fruits: a review. IEEE Xplore (2021). https://doi.org/10.1109/CONIT51480.2021.9498393
15. Azamfirei, V., Psarommatis, F., Lagrosen, Y.: Application of automation for in-line quality inspection, a zero-defect manufacturing approach. Journal of Manufacturing Systems (2023). https://doi.org/10.1016/j.jmsy.2022.12.010
16. Yun, G., Oh, S., Shin, S.: Image preprocessing method in radiographic inspection for automatic detection of ship welding defects. Applied Science (2022). https://doi.org/10.3390/app12010123
17. Shahrabadi, S., Castila, Y., Guevara, M., Magalhães, L.G., Gonzalez, D., Adão, T.: Defect detection in the textile industry using image-based machine learning methods: a brief review. Journal of Physics Conference Series (2021). https://doi.org/10.1088/1742-6596/2224/1/012010
18. Usamentiaga, R., Lema, D.G., Pedrayes, O.D., Garcia, D.F.: Automated surface defect detection in metals: a comparative review of object detection and semantic segmentation using deep learning. IEEE Transactions on Industry Applications (2022). https://doi.org/10.1109/TIA.2022.3151560
19. Geetha, A.S., Alif, M.R., Hussain, M., Allen, P.: Comparative analysis of YOLOv8 and YOLOv10 in vehicle detection: performance metrics and model efficacy. Vehicles (2024). https://doi.org/10.3390/vehicles6030065
20. Ebayyeh, A.R.M.A., Mousavi, A.: A review and analysis of automatic optical inspection and quality monitoring methods in electronics industry. IEEE Access (2020). https://doi.org/10.1109/ACCESS.2020.3029127
21. Luo, Q., et al.: Automated visual defect classification for flat steel surface: a survey. IEEE Transactions on Instrumentation and Measurement (2020). https://doi.org/10.1109/TIM.2020.3030167
22. Mustafa, W.A., Kader, M.M.M.A.: A review of histogram equalization techniques in image enhancement application. Journal of Physics (2018). https://doi.org/10.1088/1742-6596/1019/1/012026

23. Malacca, P., Rocha, L.F., Gomes, D., Silva, J., Veiga, G.: Online inspection system based on machine learning techniques: real case study of fabric textures classification for the automotive industry. Journal of Intelligent Manufacturing (2019)
24. Kalyani, J., Chakraborty, M.: Contrast enhancement of MRI images using histogram equalization techniques. International Conference on Computer, Electrical & Communication Engineering (2020). https://doi.org/10.1109/ICCECE48148.2020.9223088
25. Ravichandran, M., Laxmikant, K., Muthu, A.: Efficient vehicle detection and classification using YOLO v8 for real-time applications. Global Conference on Information Technologies and Communication (2023). https://doi.org/10.1109/GCITC60406.2023.10426587