Automatic visual inspection in automotive assembly lines: a techno-economic assessment for the configuration check of exterior components

Michele Ronchi*, Mauro Gamberi*, Cristian Cafarella*, Alice Caporale* and Francesco Gabriele Galizia*

** Department of Industrial Engineering, Alma Mater Studiorum - University of Bologna, Viale del Risorgimento 2, 40136 - Bologna – Italy (michele.ronchi8@unibo.it, mauro.gamberi@unibo.it, cristian.cafarella2@unibo.it, alice.caporale2@unibo.it, francesco.galizia@unibo.it)*

Abstract: In the automotive industry, the demand for more customised products requires highly flexible production systems. Consequently, human operators, often responsible for assembly tasks and quality inspections in vehicle assembly lines, face increasing complexity resulting from the elevated number of product versions. This complexity heightens the risk of non-conformity in the products is rising, making defect detection before delivering the final product to the customer more challenging. This scenario presents a strategic opportunity for applying Computer Vision (CV) in visual inspections. However, more contributions in the literature are needed to attest to the feasibility of such automatic systems in automotive assembly lines. This paper conducts a technical-economic assessment of the application of CV to the configuration conformity control of car exterior components. It first presents an analysis of available ready-to-use solutions on the market. Subsequently, it proposes a cost-effective solution for the quality inspection under investigation.

Keywords: Automatic quality control, Computer Vision, Assembly, Configuration conformity, Defect detection

1. Introduction

Industrial activities are essential for human progress and development but have caused significant environmental impacts. Therefore, it is imperative to improve the efficiency and effectiveness of production systems to meet the resource and service needs of current and future generations without compromising the health of ecosystems (Bortolini et al. 2023a; Bortolini et al. 2023b; Cafarella et al. 2024). The automotive industry is currently undergoing significant transformations, such as the electrification of vehicles and the advent of autonomous driving (Wittmann 2017; Brenner and Herrmann 2018; Casper and Sundin 2021; Bortolini 2022). Moreover, in response to consumers' increasing demand for personalised vehicles, manufacturers are expanding their range of products with several options and features (Alford et al. 2000). These evolving product trends push production systems towards greater flexibility to deal with all product variants (Wittmann 2017; Bortolini et al. 2024). However, the risk of non-conformities, defined as deviations from specified standards or requirements, escalates with the complexity of the product (Hinckley and Barkan 1995). This is due to the multitude of components and configurations involved, which can lead to errors during the manufacturing process. One of the primary defects that can be generated is assembling a component in a colour, design or material version that does not conform to the customer's order.

There are three primary causes of defects related to the incorrect configuration of assembled components:

- errors in the supply chain, e.g. the insertion of a component in a container whose identification label requires a different version;
- errors in internal logistics, e.g. a component is delivered from the warehouse to the assembly line station in the wrong configuration;
- errors in the assembly line, e.g. the operator takes a component from the racks at the edge of the line that does not conform to the customer's order.

As discussed by Montgomery (2009), quality assurance is the set of activities that ensures the quality levels of products and services are appropriately maintained and that supplier and customer quality issues are properly resolved. These practices are crucial to prevent the delivery of faulty products to customers, which can generate significant negative economic impact. The internal costs of quality, encompassing all expenses incurred in performing inspections and dealing with any internally identified defects, are easily calculable. In contrast, the external costs of quality, which arise when the errors made by companies directly impact the customer, are often challenging to quantify (Campanella 1999). As proposed by Snieska et al. (2013), typical external quality costs usually include such costs as:

- complaints investigation;

- costs of returned products and services;
- costs of defect product repair, change at customer's;
- cost of warranty service;
- discounts due to nonconformance of products and services;
- fines for breach of ecological and other laws;
- costs of lost customers' goodwill;
- costs of lost image.

Brand loyalty plays a pivotal role in the automotive sector, and the customer's perception of lower product quality results in reduced sales (Saritas and Penez 2017; Sánchez-Iglesias et al. 2024).

Traditionally, the majority of inspections in the automotive industry are performed by humans (Chouchene et al. 2022; Tjolleng et al. 2023). While human inspectors play a crucial role in maintaining quality standards, their performance can fluctuate due to factors such as fatigue, distraction, or inconsistency in judgment (Kolus et al. 2018; Tjolleng et al. 2023). This variability can lead to inconsistent inspection results and potentially overlooked non-conformities.

In this context, the application of CV for automating visual inspections in manufacturing systems represents an opportunity to enhance quality assurance and improve the efficiency of quality processes. Convolutional Neural Networks (CNNs), the most significant deep learning schemes used in computer vision problems, have shown considerable promise (Voulodimos et al. 2018; Bhatt et al. 2021). Despite the growing interest and promising results in the literature on the application of Artificial Intelligence (AI) in image analysis, there is still a lack of case studies attesting to the applicability of CV to vehicle assembly lines. Furthermore, while image acquisition can be conducted using various technological solutions, to the best of the authors' knowledge, no contributions support manufacturers in choosing the most suitable alternative for their reality.

The aim of this paper is to propose a Computer Vision System (CVS) responsible for the visual inspection of external car components at the end of an assembly line. It also presents the techno-economic assessments conducted for the design of the system.

The remainder of this paper is organised as follows: Section 2 reviews the literature concerning the application of CV in the field of automotive production, while Section 3 describes the key decision factors and the proposed system for automatic visual inspection for the investigated case study. Section 4 concludes the paper with final remarks and future research opportunities.

2. Related work

Most of the contributions in the literature concerning the application of CV in the automotive sector focus on the quality control of paint and car body surfaces. Kieselbach et al. (2019) highlight the growing customer attention on the appearance of cars, necessitating meticulous inspection of every vehicle body in automotive paint shops. Previously, in the analysed case, study skilled workers visually inspected each car body to detect and repair occurring paint defects. However, the human inspection process lacks the capacity to consistently and objectively identify and evaluate these defects over an extended period. To address this issue, they present the development and validation of an algorithm for a surface inspection system. This system improves the accuracy of detecting paint defects through an image processing system. A specific lighting system and cameras in fixed positions are used for image acquisition. Molina et al. (2017) propose a novel approach using deflectometry and vision-based technologies in order to check paint defects also on surfaces that are not flat. The image acquisition is carried out by 23 monochrome cameras in a light-controlled tunnel. The quality control system is applied at a Mercedes-Benz production site in Spain, and defect analysis is performed in 15 seconds. Zhou et al. (2019) propose a system for managing surface defects, such as dents and scratches. The images are acquired through fixed cameras and a lighting system. The collected results demonstrate that the automatic inspection system can achieve accuracies of 95.6% in dent defects and 97.1% in scratch defects.

Müller et al. (2014) suggest the utilisation of cobots for repetitive and less ergonomic inspection task. The authors design a cobot-based system for the localisation of water leaks in the vehicles after the water leak test. The robot is mounted on a linear track and guided alongside the assembly object. A thermographic camera takes pictures of the car's interior and processes the images to detect wet spots. The CVS can detect tiny drops and give relevant feedback for reworks.

Dalle Mura and Dini (2021) propose a system for automated gap and flush control between car body panels. Measurements are collected from images taken by a camera-equipped cobot. Then, the necessary modifications are developed, and the instructions are shown to a human operator via an Augmented Reality headset.

Chouchene et al. (2020) apply the CV to check the presence of specific components in the front bumpers and on the car's sides. The inspection would take a long time for a human operator, who would have to consult documents each time showing the intended configuration of each component.

3. Description of the Computer Vision System

This section aims to propose a CVS for automating the conformity check of a car's exterior components at the end of the assembly line. These inspections, in fact, are time-demanding and require a trained operator, especially for highly customisable vehicles. Moreover, any non-conforming product delivered to the customer can damage the company's image and incur additional costs for fixing the defects. The proposed system aims to reduce human error, increase efficiency, and maintain high quality control standards.

3.1 Hardware solutions analysis

Three categories of hardware solutions are identified for image acquisition, based on similar application cases and market analysis: hand-held devices (HHDs) such as smartphones and tablets, fixed-position cameras and camera-handling cobots.

The analysis of the identified technological solutions is based on the following factors:

- Precision: the repeatability of image acquisition. It involves aspects such as the stability of the imaging sensor, the control of environmental conditions, and the repeatability of the positioning system.
- Scalability: the ease with which the CVS can be extended to further visual inspections, whether similar to those already considered or totally different.
- Flexibility: the level of adaptability of the system to changes in the workstation, assembly line or product.
- Integrability: the ease with which a solution can be incorporated into the existing production process. It includes the compatibility of the solution with existing machinery, workflows and human operators in the same area, the time required for installation and setup, and the potential impact on production speed.
- Investment costs: the initial financial outlay required to implement the CVS.
- Operating costs: the costs incurred annually to maintain the automatic inspection system in function. They include the cost of energy for the power supply, maintenance and repair costs of components, and the cost of human resources required for the operation.

HHDs are easy to implement in an assembly line as they do not create structural constraints and require minimal expenditure. Furthermore, the total freedom of positioning in image acquisition allows for variations in the working environment and checks to be put in place. However, HHDs are not autonomous in framing the region of interest and necessarily require human resources for this purpose. As a result, precision is very low, and operating costs are considerable. Despite these drawbacks, HHDs offer a quick and easy solution for smaller operations or for initial implementation stages.

Cameras in fixed positions avoid these issues by independently maintaining standardised image acquisition conditions. Their rigid design, however, makes them unsuitable for frequent reconfigurations of the production processes. Fixed cameras offer a high degree of precision and consistency, making them ideal for operations where the production process remains relatively unchanged over time.

Using cobots provides a hybrid alternative between the previous two, combining their advantages: the positioning of the image capture point is variable and easily modifiable while preserving high accuracy. The trade-offs to be paid for these benefits are significantly higher costs for the initial investment and greater complexity in integrating the CVS within the working area, given the larger physical encumbrance and possible interactions with human operators performing their tasks in the identical location. They are indeed designed to operate safely in the same areas occupied by humans, but their respective tasks and movements must not conflict. However, the flexibility and adaptability of cobots make them a promising solution for dynamic and evolving production environments.

Table 1 schematically summarises the analysis of hardware solutions.

Table 1: analysis of the available technological solutions

	HHDs	Fixed cameras	Cobots
Precision	↑	↑↑↑	↑↑
Scalability	↑↑↑	↑	↑↑
Flexibility	↑↑↑	↑	↑↑
Integrability	↑↑	↑↑	↑
Investment costs	↑	↑↑	↑↑↑
Operating costs	↑↑↑	↑	↑

3.2 Economic assessment of the identified solutions

The most commonly used indicator among companies for evaluating investments is the Payback Period (PBP), which measures the time required for an investment's cash flows to equal its initial cost. This indicator provides a straightforward way to assess the risk and liquidity of an investment by calculating the period within which the project's initial investment is recovered. Companies favour the PBP method because it is simple to compute and easy to understand, making it a practical tool for preliminary investment screening. The criterion for acceptance or rejection is a benchmark set by the company, often based on its risk tolerance, investment strategy, and financial goals. A common value used as benchmark PBP for this type of investments is around three years. If the PBP is less than or equal to this benchmark, the company will accept the project; otherwise, it will reject it.

For calculating the PBP, it is necessary to estimate the cash flows in the years following the investment. The cash flow in year j CF_j is obtained by subtracting the project-related costs to be incurred in that year C_j from the savings expected in that year S_j, as shown Eq. 1.

$$CF_j = S_j - C_j \qquad (1)$$

The operating costs associated with a CVS can be estimated by considering three components: maintenance costs (including regular servicing, repairs, and replacement of parts as needed), energy costs (electricity to power the system), and human resources costs (related to the necessary human operators for the system to function). Similarly, the annual savings can be divided into three components: reduced labor costs (achieved by automating inspections and thereby reducing the need for human inspectors), internal quality savings (related to immediate detection of non-conformities leading to less expensive reworks and wastes), and external quality savings (resulting from fewer returns from customers and brand empowerment).

While the PBP method is useful, it has limitations. It ignores cash flows that occur after the payback period, potentially overlooking the overall profitability of a project. As a result, companies often use the PBP method in conjunction with other financial metrics, such as Net Present Value (NPV) or Internal Rate of Return (IRR), to make more informed investment decisions.

3.3 Case study: proposed system design

The evaluation criteria presented are used to design a CVS for controlling the configuration of vehicle external components in an industrial case study of an automotive producer characterised by low production volumes.

The technological solution that is identified as most suitable for the automatic visual inspection of the exterior components of cars and that is proposed in this paper employs fixed cameras. In fact, this design allows for a contained initial investment and does not require human operators in the system. The lack of flexibility of the CVS is an acceptable constraint for this specific use case since it is assumed to be applied at the end of the assembly line, therefore, in an area not particularly subject to change.

Furthermore, fixed cameras are the only hardware solution capable of having a PBP of less than three years, as capital expenditure weighs heavily on cobots, while HDDs have high operating costs related to the inclusion of human operators in the system. Figure 1 shows the proportion of initial investment and average cash flow to compare the three alternatives.

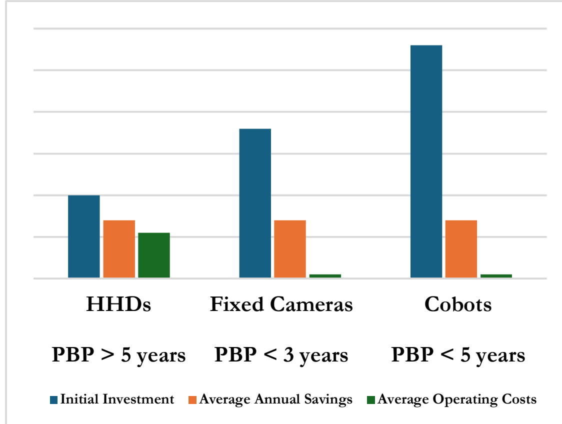

Figure 1: comparison of the three alternatives based on the economic evaluation

A diagram of the proposed CVS is shown in Figure 2. It involves the use of eight cameras in a fixed position:

- 1 camera framing the front of the car to check components such as bonnet, front bumper and licence plate;
- 1 camera framing the rear of the car to check components such as spoilers, rear bumper and muffler;
- 6 cameras positioned laterally (3 on each side) to cover the entire vehicle and to check components such as wheel arches, rims and door covers.

Reflective surfaces characterise cars, while assembly lines generally allow sunlight to enter. For this reason, every camera must be equipped with a direct and coaxial lighting system. The lighting must enable images to be captured at constant conditions over time and not be disturbed by external light.

The collected images are used as input to CNN. Prior to this, they may be subjected to pre-processing in order to improve the performance of the CVS. The image pre-processing can include steps such as noise reduction and contrast enhancement. Another input to the CVS is the desired configuration of each component in the customer order. Enterprise Resource Planning (ERP) or Manufacturing Execution System (MES) systems must also be connected to the CVS for this purpose. The CNN has the task of extracting features from the images and, based on these, determining which class the component belongs to, where each class represents a configuration. After that, CVS compares the configuration identified with the one requested by the customer. The results of the conformity checks of all external components and collected images are transferred to the company information system. In case of any discrepancies, the CVS can alert the quality control team for further inspection and to fix the defect.

Moreover, the system can provide valuable insights into the manufacturing process by identifying common errors.

Engineers can then use data to improve the overall production process.

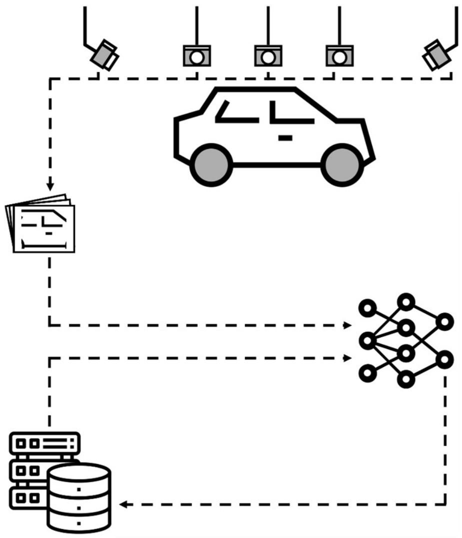

Figure 2: a schematic of the proposed CVS for the configuration check of car's exterior components

4. Conclusion and future developments

The high customisation of products that characterises the automotive sector is a risk factor in the generation of defects in production systems. For this reason, it is essential to put in place a planning of activities to pursue quality assurance. Operators are subject to human factors, which can compromise their performance and make the inspection process unreliable. AI represents an opportunity to automate visual inspections by processing images depicting the areas to be inspected. However, there is a small number of contributions in the literature presenting application cases of CV to vehicle assembly lines.

This paper proposes a cost-effective solution for the inspection of external car components. It identifies the key factors and cost and saving components typical for this type of project for choosing the most suitable hardware design. Afterwards, the identified criteria are applied to a case study in the automotive sector to select the most suitable solution. The final solution described involves the use of fixed cameras, which enable high image acquisition and analysis performance while keeping CVS costs moderate. The PBP of the proposed solution is less than three years, indicating a promising return on investment.

Moreover, the proposed system has the potential to significantly reduce the rate of non-conformities, thereby enhancing the overall quality of the product. This, in turn, could lead to increased customer satisfaction and brand loyalty, which are crucial in the highly competitive automotive sector.

Despite its potential, this paper acknowledges its limitations. It focuses on preliminary assessments of the choice of technology for CVS, without including its implementation in the industrial context. Additionally, it examines a specific type of inspection, in contrast to the multiple typical cases in assembly lines, which could benefit from automation. These limitations provide avenues for future research and development.

For future research, it is proposed to implement the CVS in a real case to evaluate its performance both in terms of the time required for control and the accuracy of feedback. This real-world application will provide valuable insights into the practical challenges and benefits of implementing such a system.

A further possible future research direction is the development of a methodology for identifying the most suitable technological solution for different application cases. Such a methodology would be a valuable tool for manufacturers seeking to implement automated visual inspection systems in their production lines. This could pave the way for more widespread adoption of automated inspection systems across the industry.

Acknowledgements

The PhD scholarship of Michele Ronchi is financed by the EU - NextGenerationEU with funds made available by the National Recovery and Resilience Plan (NRRP) Mission 4, Component 2, Investment 3.3 (MD 352/2022).

The PhD scholarship of Cristian Cafarella is financed by the "Programma Operativo Nazionale Ricerca e Innovazione 2014–2020" (CCI 2014IT16M2OP005), FSE REACT-EU resources, Action IV.4 "PhDs and research contracts on innovation topics" and Action IV.5 "PhDs on green topics", DOT1303432-1, CUP: J35F21003210006.

References

Alford, D., Sackett, P., & Nelder, G. (2000). Mass customization - an automotive perspective. *International Journal of production economics*, 65(1), 99-110.

Bhatt, D., Patel, C., Talsania, H., Patel, J., Vaghela, R., Pandya, S., ... & Ghayvat, H. (2021). CNN variants for computer vision: History, architecture, application, challenges and future scope. *Electronics*, 10(20), 2470.

Bortolini, M., Cafarella, C., Galizia, F.G., Gamberi, M., Mora, C., Ventura, V.: The potential of Industry 4.0 toward smart grids: opportunities and challenges. In: Proceedings of the XXVII Summer School "Francesco Turco", pp. 1–7. AIDI - Italian Association of Industrial Operations Professors, Rome (2022).

Bortolini, M., Cafarella, C., Galizia, F.G., Gamberi, M. (2023a). Energy System Optimization Modelling and Electrical Grid Management: The Case of Italy. In: Galizia, F.G., Bortolini, M. (eds) Production Processes and Product Evolution in the Age of Disruption. CARV 2023. Lecture Notes in Mechanical Engineering. Springer, Cham.

Bortolini, M., Galizia, F.G., Gamberi, M., Mora, C., Naldi, L.D., Regattieri, A., Ronchi, M.: Interaction between Lean and Green Supply Chain Management: experiences from the automotive sector. In: Proceedings of the XXVIII Summer School "Francesco Turco", pp. 1–7. AIDI - Italian Association of Industrial Operations Professors, Rome (2023b).

Bortolini, M., Cafarella, C., Galizia, F.G., Gamberi, M., Naldi, L.D. (2024). A Clustering-Based Algorithm for Product Platform Design in the Mass Customization Era. In: Scholz, S.G., Howlett, R.J., Setchi, R. (eds) Sustainable Design and Manufacturing 2023. SDM 2023. Smart Innovation, Systems and Technologies, vol 377. Springer, Singapore.

Brenner, W., & Herrmann, A. (2018). An overview of technology, benefits and impact of automated and autonomous driving on the automotive industry. *Digital marketplaces unleashed*, 427-442.

Cafarella, C., Bortolini, M., Gabellini, M., Galizia, F.G., Ventura, V. (2024). Energy Network Optimization Model for Supporting Generation Expansion Planning and Grid Design. In: Scholz, S.G., Howlett, R.J., Setchi, R. (eds) Sustainable Design and Manufacturing 2023. SDM 2023. Smart Innovation, Systems and Technologies, vol 377. Springer, Singapore.

Campanella, J. (1999). Principles of quality costs: Principles, implementation, and use. In *ASQ World Conference on Quality and Improvement Proceedings* (p. 507). American Society for Quality.

Casper, R., & Sundin, E. (2021). Electrification in the automotive industry: effects in remanufacturing. *Journal of Remanufacturing*, 11, 121-136.

Chouchene, A., Carvalho, A., Lima, T. M., Charrua-Santos, F., Osório, G. J., & Barhoumi, W. (2020, February). Artificial intelligence for product quality inspection toward smart industries: quality control of vehicle non-conformities. In *2020 9th international conference on industrial technology and management (ICITM)* (pp. 127-131). IEEE.

Chouchene, A., Ventura Carvalho, A., Charrua-Santos, F., & Barhoumi, W. (2022). Augmented reality-based framework supporting visual inspection for automotive industry. *Applied System Innovation*, 5(3), 48.

Dalle Mura, M., & Dini, G. (2021). An augmented reality approach for supporting panel alignment in car body assembly. *Journal of Manufacturing Systems*, 59, 251-260.

Hinckley, C. M., & Barkan, P. (1995). The role of variation, mistakes, and complexity in producing nonconformities. *Journal of Quality Technology*, 27(3), 242-249.

Kieselbach, K. K., Nöthen, M., & Heuer, H. (2019). Development of a visual inspection system and the corresponding algorithm for the detection and subsequent classification of paint defects on car bodies in the automotive industry. *Journal of Coatings Technology and Research*, 16, 1033-1042.

Kolus, A., Wells, R., & Neumann, P. (2018). Production quality and human factors engineering: A systematic review and theoretical framework. *Applied ergonomics*, 73, 55-89.

Molina, J., Solanes, J. E., Arnal, L., & Tornero, J. (2017). On the detection of defects on specular car body surfaces. *Robotics and Computer-Integrated Manufacturing*, 48, 263-278.

Montgomery, D. C. (2009). Statistical quality control (Vol. 7). New York: Wiley.

Müller, R., Vette, M., & Scholer, M. (2014). Inspector robot–a new collaborative testing system designed for the automotive final assembly line. *Assembly Automation*, 34(4), 370-378.

Sánchez-Iglesias, N., García-Madariaga, J., & Jerez, M. (2024). The impact of financial performance and corporate reputation on customer purchases: the role of stakeholders and brand value in the automotive sector. *Marketing Intelligence & Planning*, 42(1), 23-39.

Saritas, A., & Penez, S. (2017). Factors of Purchasing Decision and Measuring Brand Loyalty: An Empirical Study of Automotive Sector. *Journal of Marketing & Management*, 8(1).

Snieska, V., Daunoriene, A., & Zekeviciene, A. (2013). Hidden costs in the evaluation of quality failure costs. *Engineering Economics*, 24(3), 176-186.

Spring, M., & Dalrymple, J. F. (2000). Product customisation and manufacturing strategy. *International Journal of Operations & Production Management*, 20(4), 441-467.

Tjolleng, A., Chang, J., Park, J., Lee, W., Cha, M., Park, J., & Jung, K. (2023). Development of a human-friendly visual inspection method for painted vehicle bodies. *Applied Ergonomics*, 106, 103911.

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. *Computational intelligence and neuroscience*, 2018.

Wittmann, J. (2017). Electrification and digitalization as disruptive trends: new perspectives for the automotive industry?. *Phantom ex machina: Digital disruption's role in business model transformation*, 137-159.

Zhou, Q., Chen, R., Huang, B., Liu, C., Yu, J., & Yu, X. (2019). An automatic surface defect inspection system for automobiles using machine vision methods. *Sensors*, 19(3), 644.