INDUSTRIAL COMPUTER VISION FOR AUTOMOTIVE QUALITY CONTROL

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Abstract: Maintaining consistent product quality is a key challenge in automotive manufacturing, where high production volumes and product variability place significant demands on inspection processes. Industrial computer vision (ICV) offers an effective approach for automating visual quality control using modern image processing and deep learning techniques. This paper presents a case study of an ICV system deployed at Škoda Auto for automated inspection of automotive door components on a pre-assembly production line. The system integrates industrial cameras, edge processing devices, and neural network models trained on annotated production datasets. The paper describes the system architecture, dataset preparation, model training, and integration with production monitoring tools. The deployed system inspects several million components annually and demonstrates reliable defect detection performance under real manufacturing conditions. The study highlights the practical benefits of industrial computer vision for large-scale automotive quality control and outlines future development directions including digital twin integration and predictive analytics.

Key words: *ICV, quality inspection, neural networks, digital twin, automotive manufacturing, machine learning*

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1. Introduction

1.1 Digitalization of Manufacturing and Industry 4.0

In recent years, industrial production has undergone a significant transformation driven by the digitalization of manufacturing processes and the implementation of the Industry 4.0 paradigm, which integrates cyber-physical systems, the industrial internet of things (IIoT), and advanced data analytics into manufacturing environments [7, 10]. These developments are leading to the emergence of so-called smart

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factories, where production equipment, information systems, and analytical tools are interconnected within a unified digital ecosystem that enables autonomous control of manufacturing processes and real-time optimization of production operations [9].

A key prerequisite for the effective functioning of such systems is the ability to rapidly and reliably acquire and interpret data from the production environment. In this context, industrial computer vision (ICV) technologies play an increasingly important role, as they enable automated processing of visual information and its use for monitoring production processes, detecting anomalies, and performing quality inspection of manufactured products [11]. ICV is an interdisciplinary field that combines image processing techniques, machine learning methods, and artificial intelligence in order to enable machines to interpret visual data in a manner similar to human perception [20].

In industrial applications, ICV systems are widely used to automate visual inspection, identify manufacturing defects, and monitor key parameters of production processes. Modern image processing algorithms and deep learning techniques allow large volumes of visual data to be analysed in real time, providing operators and control systems with relevant information about the current state of production [4, 14]. As a result, these technologies contribute to improved stability of manufacturing processes, reduction of defective products, and decreased reliance on manual quality inspection procedures [16, 23].

In the automotive industry, which is among the most technologically advanced manufacturing sectors, the demand for automated quality inspection is particularly significant. Production processes in this sector are characterized by high product complexity, a large number of component variants, and strict requirements for the quality and reliability of final products [3]. The implementation of ICV systems therefore represents an important step toward the digital transformation of manufacturing processes and enables manufacturers to respond effectively to increasing demands for quality, productivity, and production flexibility [2].

1.2 Application of ICV in Industrial Quality Inspection

In recent years, ICV technologies have become one of the key tools for automating quality inspection in industrial manufacturing. The use of camera systems combined with image processing algorithms enables the automatic analysis of visual product characteristics and the identification of deviations from the required manufacturing parameters [4]. Such systems are capable of detecting a wide range of manufacturing defects, including surface imperfections, geometric deviations, or missing components, with high speed and repeatability [15]. As a result, they can significantly contribute to the stabilization of manufacturing processes and to the reduction of variability in production outcomes [22].

In modern manufacturing environments, ICV technologies are frequently integrated with machine learning methods and deep neural networks, enabling automated classification and detection of complex visual patterns. Convolutional neural networks (CNNs) have proven to be particularly effective for the analysis of image data and the detection of manufacturing defects across various industrial applications [4, 6]. These methods allow models to learn representations of visual features directly from training data and achieve higher accuracy than traditional algorithms based on manually designed feature extraction rules [8].

The implementation of ICV systems also provides significant operational benefits. Automated inspection enables quality control to be performed in real time directly on production lines, which reduces response time when defects are detected and limits the propagation of defective products within the manufacturing process [5]. At the same time, such systems generate large volumes of production data that can be further utilized for analytical tasks, such as the optimization of manufacturing parameters or the implementation of predictive quality management strategies [21].

1.3 Limitations of Traditional Quality Inspection Methods

Despite the rapid development of automated inspection technologies, a significant portion of quality control operations in many manufacturing environments still relies on manual visual inspection performed by human operators. Historically, this approach has been one of the most widely used methods of quality control, as human inspectors are capable of flexibly responding to different product variants and identifying complex visual anomalies [17]. However, manual inspection exhibits several limitations, particularly in terms of consistency and repeatability of results, which may be influenced by the individual experience of the operator or by the current working conditions in the production environment [23].

A major issue associated with manual inspection is the influence of human factors, such as fatigue, reduced attention, or time pressure in high-volume production environments. These factors may lead either to missed detection of manufacturing defects or to the incorrect rejection of defect-free products [18]. In large-scale manufacturing environments, even a relatively small error rate can result in significant economic losses, particularly if defects are detected only in later stages of the production process or even by the end customer [23].

Another limitation of traditional quality inspection methods lies in their limited ability to systematically collect and analyse data about the manufacturing process. While manual inspection provides only partial information about individual inspected products, modern automated inspection systems enable continuous acquisition of production data and its subsequent analysis using advanced analytical techniques [21]. These data can then be used to identify root causes of defects and to support long-term improvements of manufacturing processes.

1.4 Emergence of Artificial Intelligence and Deep Learning in Industrial Inspection

In recent years, industrial visual inspection has undergone a significant transformation driven by the rapid development of artificial intelligence and deep learning methods. While traditional ICV approaches were often based on manually designed rules and handcrafted feature extraction techniques, modern deep learning methods enable models to automatically learn feature representations directly from training data [8]. In particular, convolutional neural networks (CNNs) have become a dominant tool for image analysis and for detecting complex visual patterns that may indicate manufacturing defects or deviations in production processes [6].

One of the key advantages of deep learning methods is their ability to process large volumes of image data and identify subtle visual differences between defect-free and defective products. As a result, these models can achieve high accuracy in classification, detection, and segmentation tasks across a wide range of industrial applications, including automotive manufacturing [15, 13]. When combined with modern computing platforms and specialized hardware accelerators, such as GPUs and edge computing devices, these algorithms can be deployed directly in production environments to perform real-time image analysis and defect detection [5].

The integration of artificial intelligence methods into quality inspection systems also opens new possibilities for more advanced manufacturing process management. Automated visual inspection systems can generate large volumes of production data, which can be further analysed using advanced data analytics and machine learning techniques. Such data-driven approaches enable predictive quality control, identification of root causes of manufacturing defects, and continuous optimization of production parameters [21]. Consequently, these technologies not only improve defect detection capabilities but also contribute to a deeper understanding of manufacturing processes and to systematic quality improvement in digitally integrated production environments [10].

Ensuring consistent product quality represents one of the fundamental prerequisites for customer satisfaction and the long-term competitiveness of manufacturers in the automotive industry. However, as manufacturing processes become increasingly complex and the number of component variants continues to grow, traditional manual quality inspection methods encounter significant limitations in terms of scalability, consistency, and reliability in defect detection. As a result, automated inspection systems based on ICV and artificial intelligence methods are gaining importance, enabling quality control to be performed directly within the production process while maintaining a high level of repeatability in inspection results.

Despite the growing number of studies focusing on the application of ICV in industrial manufacturing, only a limited number of publications describe the real-world deployment of such systems in fully operational automotive production environments. Existing research often concentrates primarily on the development of algorithms or on experimental validation using laboratory datasets, whereas the practical aspects of implementing these technologies in real manufacturing processes are addressed only marginally. This paper therefore presents a case study of the implementation of an industrial computer vision system for quality inspection in automotive manufacturing at Škoda Auto.

2. Related Work

Early research in automated visual inspection was primarily based on classical image processing techniques such as thresholding, edge detection, and texture analysis. These approaches were widely applied in surface defect detection due to their relatively low computational requirements and straightforward implementation.

Xie [22] provides a comprehensive overview of traditional surface defect detection techniques based on texture analysis and statistical image processing methods. Although these approaches achieved satisfactory results under controlled conditions, their performance often decreases in real industrial environments characterized by varying illumination conditions, different material properties, and product geometries.

With the development of machine vision hardware and increasing computational capabilities, more advanced computer vision techniques have gradually been introduced into industrial inspection systems. Modern machine vision systems typically combine industrial cameras, controlled lighting environments, and specialized algorithms for analysing captured images. These systems enable automated inspection of products and the detection of various types of defects such as scratches, cracks, surface irregularities, or missing components. Steger et al. [19] describe a broad range of machine vision algorithms used for industrial inspection tasks, including geometric inspection, object recognition, and defect detection in manufacturing environments.

A significant advancement in industrial visual inspection has been driven by the introduction of machine learning and deep learning techniques. Instead of relying on handcrafted features, machine learning methods enable models to learn relevant representations directly from training data. In particular, convolutional neural networks (CNNs) have become one of the most widely adopted approaches for image-based inspection tasks. The pioneering work of Krizhevsky et al. [6], which demonstrated the effectiveness of deep convolutional neural networks for large-scale image classification, significantly influenced subsequent research in computer vision and industrial inspection systems.

Deep learning techniques have since been successfully applied to defect detection in manufacturing environments. Ren et al. [15] proposed a generic deep-learning-based framework for automated surface inspection capable of detecting multiple types of defects with high accuracy. In addition, the comprehensive study by LeCun et al. [8] highlighted the broader impact of deep learning methods in computer vision applications, demonstrating their ability to learn hierarchical visual representations directly from data.

Further research has shown that convolutional neural networks can achieve high accuracy in a variety of image analysis tasks. Rawat and Wang [12] provide a comprehensive overview of deep convolutional neural networks and their applications in image classification and visual recognition tasks, emphasizing their relevance for automated inspection systems in industrial environments.

Recent developments in manufacturing research have also focused on the integration of machine learning techniques within broader data-driven production systems. Wuest et al. [21] discuss the potential of machine learning methods for improving manufacturing processes, including applications in quality monitoring, predictive maintenance, and automated defect detection.

Despite these advances, the practical deployment of computer vision systems in real industrial production environments remains challenging. Many studies focus primarily on algorithm development or evaluation using laboratory datasets, while fewer works address the implementation of inspection systems in operational manufacturing environments. Bergmann et al. [1] addressed this challenge by introducing the MVTec AD dataset, which provides real-world industrial image data for anomaly detection research and enables more realistic evaluation of automated inspection algorithms.

Overall, existing research demonstrates the significant potential of computer vision and deep learning technologies for automated defect detection and quality inspection in manufacturing. However, relatively few studies describe the deployment of such systems in full-scale automotive production environments. This highlights the need for practical case studies that document the implementation of industrial computer vision systems and evaluate their performance under real manufacturing conditions.

3. Proposed Method and System Architecture

The proposed industrial computer vision (ICV) system is designed for automated quality inspection of automotive door components within a production line environment. The system is deployed at the door pre-assembly station, where it is used to identify visual defects and verify the correct assembly of individual components. The main objective of the system is to automate selected inspection operations that were previously performed through manual visual inspection by operators. Automated inspection improves repeatability, reduces the risk of undetected defects, and ensures traceability of inspection results within the production process. The proposed solution combines industrial cameras, image processing algorithms, and deep learning models for the detection and classification of manufacturing defects. The architecture of the system enables automatic processing of visual data directly during the production process and its subsequent analysis using neural networks.

Fig. 1 shows an example of manual visual inspection during the final assembly of passenger vehicles in an automotive production line. Operators visually inspect vehicle body surfaces and assembly components to identify potential defects and verify product quality.

Fig. 1 *Example of manual visual inspection during the final assembly.*

3.1 System Architecture

The architecture of the proposed inspection system is designed as a modular processing pipeline consisting of several functional components responsible for image acquisition, preprocessing, neural network analysis, and visualization of inspection results.

The implemented system combines EDGE devices and smart cameras, controlled by a supervisory software layer. Each inspection station is equipped with industrial cameras from AXIS (models F9114 and F2115 – Full HD, 2 MP) and lighting systems from AMV (models MTXF and HILI). These devices capture images of inspected components and transmit them to the processing unit, where the captured data are analysed using computer vision algorithms and deep learning models.

In the initial phase, the system architecture is implemented as a local inspection solution operating independently from the surrounding production infrastructure. In this configuration, image data captured by industrial cameras are processed locally by the inspection node. The resulting classification outputs (OK/NOK) are displayed directly on the monitoring workstation of the inspection station. At this stage, the system operates as an independent inspection unit and is not connected to the control infrastructure of the production line. Fig. 2 shows the local architecture of the industrial computer vision inspection system operating as an independent processing node without integration into external manufacturing systems.

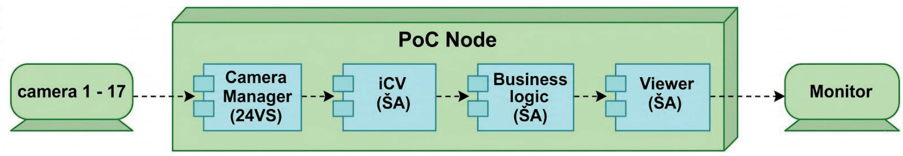

Fig. 2 *Local architecture of the industrial computer vision inspection system.*

The inspection workflow follows a standard computer vision pipeline consisting of image acquisition, preprocessing, neural network analysis, decision logic, and data storage. The overall processing flow of the system is illustrated in Fig. 3.

In this configuration, multiple cameras capture images of inspected components on the production line. A camera management module controls the acquisition of image data and transfers them to the industrial computer vision module responsible for neural network inference. The inspection results are then processed by the business logic component and displayed through a visualization interface for the operator.

Due to the wide range of vehicle models and component variants, the system supports dynamic inspection routines that adapt to the specific configuration of the inspected vehicle, such as the trim level or installed components. Flexible data handling and fault classification are therefore essential for reliable operation of the inspection system.

The system also includes a database of annotated training images, which is continuously expanded during system operation. This dataset supports further

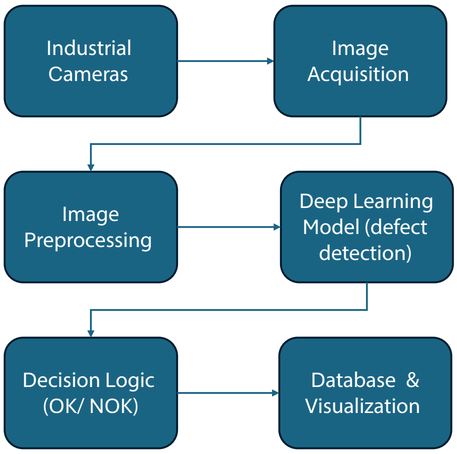

Fig. 3 *Block diagram of the automated inspection pipeline used in the industrial computer vision system.*

improvement of the deep learning models and enables detailed analysis of detected defects and their potential root causes.

After the validation of the concept, the system architecture can be extended toward integration with manufacturing and quality management systems. The overall system architecture integrates the production line inspection infrastructure with data processing services located in the central data environment. The architecture supports communication between production equipment, inspection cameras, and higher-level manufacturing information systems (Fig. 4).

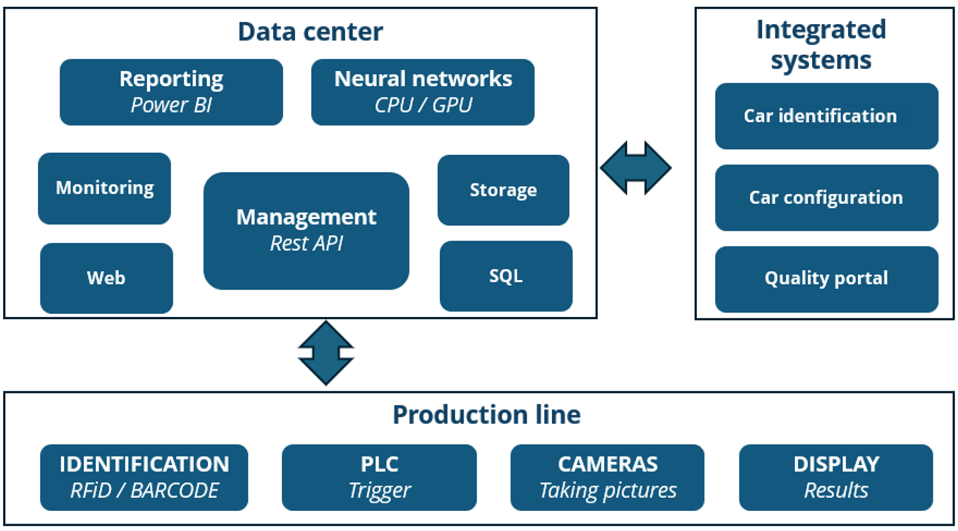

Fig. 4 *System architecture integrating production line inspection devices with centralized data processing and manufacturing information systems.*

This extended architecture enables automatic recording of inspection results within quality monitoring systems and supports additional functionalities such as production monitoring and traceability of inspected components (Fig. 5).

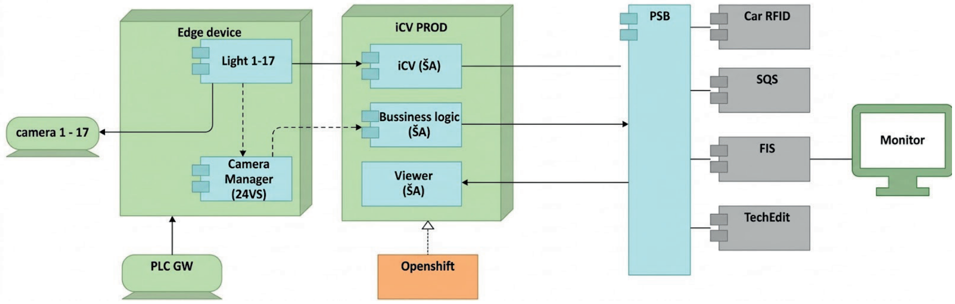

Fig. 5 *Integration of the camera-based inspection system with surrounding manufacturing and quality management infrastructure.*

In the integrated configuration, the inspection system communicates with surrounding production and quality management systems. Inspection results are stored in a centralized database and can be visualized through internal analytical tools used by production operators and supervisors. This integration enables long-term monitoring of product quality and supports data-driven decision-making within the manufacturing process.

3.2 Image Acquisition and Pre-processing

Images of inspected components are captured using industrial smart cameras installed at predefined positions along the door pre-assembly station. The placement of cameras is designed to ensure optimal visibility of the critical inspection areas of automotive door components while minimizing the influence of environmental factors such as reflections, shadows, or occlusions caused by moving operators and assembly tools.

Each inspection cycle begins with image acquisition triggered by the arrival of a component at the inspection position. The captured images are transmitted to the processing unit where several preprocessing operations are applied before the data are analysed by the neural network model.

The preprocessing stage typically includes several operations such as region-of-interest extraction, normalization of image intensity, and resizing of the image input to match the neural network requirements. These operations ensure stable and consistent input data for the machine learning model and reduce the influence of noise and environmental variability in the production environment.

The identification of regions of interest (ROI) focuses the analysis on relevant parts of the inspected component and removes unnecessary background information, thereby improving the robustness and performance of the defect detection model.

3.3 Deep Learning Model for Defect Detection

The detection of visual defects is performed using a deep learning model based on the convolutional neural network (CNN). This type of architecture is particularly suitable for industrial image analysis because it enables automatic extraction of hierarchical visual features directly from training data [6].

The model is trained using an annotated dataset containing images of both defect-free and defective components collected during system operation. Each image is labelled according to the type of defect present or the absence of defects.

Examples of potential defects include incorrect assembly of components, missing parts, or visible surface imperfections.

During the training phase, the neural network learns to identify characteristic visual patterns associated with different defect categories. Once trained, the model is deployed within the inspection pipeline where it performs inference on newly captured images in near real-time. Similar approaches have been successfully applied for automated defect detection in manufacturing environments [4].

3.4 Decision Logic and Inspection Output

The outputs generated by the neural network are processed by a decision module that determines the final inspection result. This module evaluates classification probabilities produced by the model and applies predefined decision thresholds to determine whether a defect has been detected.

The inspection system distinguishes between two primary states:

- OK – the inspected component meets quality requirements and can proceed further in the production process,
- NOK – a potential defect has been detected, and the component may require additional inspection or removal from the production flow.

The decision logic may also incorporate contextual production information such as vehicle configuration or production parameters in order to dynamically adapt inspection routines.

Inspection results are recorded in the system database and made available for further analysis and visualization through internal monitoring tools used by production operators and quality engineers.

3.5 System Integration and Data Management

Following the successful validation of the inspection concept, the system architecture can be extended to support integration with manufacturing and quality management systems. In this configuration, inspection results are automatically recorded within production databases and quality monitoring platforms (see illustrative example in Fig. 6).

Centralized data storage enables long-term monitoring of production quality and provides valuable input for statistical analysis and process optimization. The accumulated dataset of annotated inspection images can also be used for continuous improvement of the deep learning model.

Fig. 6 *Deployment of the inspection system on the automotive assembly line during pilot testing.*

Integration with manufacturing information systems allows inspection results to be associated with specific vehicles or production batches, which supports traceability and root cause analysis of detected defects.

The modular design of the system architecture enables gradual expansion of the inspection solution and integration with additional industrial systems in accordance with the principles of Industry 4.0 and data-driven manufacturing.

4. Dataset Preparation

The performance of deep learning models used in industrial inspection systems strongly depends on the quality, diversity, and representativeness of the datasets used during training and validation. In automotive manufacturing environments, where extremely high reliability is required, careful preparation of datasets is essential to ensure robust defect detection and minimize the risk of false classifications.

The dataset used in this study was collected directly from the production environment of an automotive door pre-assembly line. Image data were acquired during pilot deployment of the inspection system and stored in a centralized database for further processing and annotation. The collected dataset therefore reflects real production conditions, including variations in product configurations, assembly conditions, and environmental factors.

4.1 Data Collection

The image dataset was obtained from the inspection stations installed at the door pre-assembly line. During the production process, industrial cameras capture images of selected areas of the door assembly where potential defects may occur. These images are transferred to the inspection system where they are analysed by the computer vision pipeline described in Section 3.

The collected images represent both normal production conditions and simulated defect scenarios introduced during the testing phase of the inspection system. The dataset therefore includes examples of defect-free components (OK states) as well as defective components (NOK states). The use of production data ensures that the training dataset captures the variability present in real manufacturing environments, including differences in component appearance, lighting conditions, and assembly configurations.

4.2 Defect Categories and Annotation

The collected images were annotated by quality engineers and domain experts responsible for the inspection process. Each image was labelled according to the presence or absence of specific defect types that may occur during the door pre-assembly process.

Typical defect categories include missing components, incorrectly positioned elements, surface defects, or mechanical damage of parts. These annotations form the basis for supervised training of the neural network model. The defect categories used during the training process are summarized in Tab. I.

Defect Category	Description	Example
Missing component	Required component is not present in the assembly	Missing clip, screw or connector
Incorrect component position	Component is assembled but positioned incorrectly	Misaligned cable or bracket
Surface defect	Visible damage or surface imperfection	Scratch, deformation
Assembly inconsistency	Incorrect combination of installed components	Wrong trim configuration
Component damage	Mechanical damage of a part	Broken plastic element

Tab. I *Defect categories used for training the inspection model.*

Visual examples of defect categories used for model training are shown in Fig. 7. These examples represent practical instances of defects observed during real production and illustrate how the inspection system identifies visual anomalies in specific components. While Tab. I defines defect categories in a structured and abstract manner for the purpose of model training, Fig. 7 presents their real-world manifestations as captured by the inspection system.

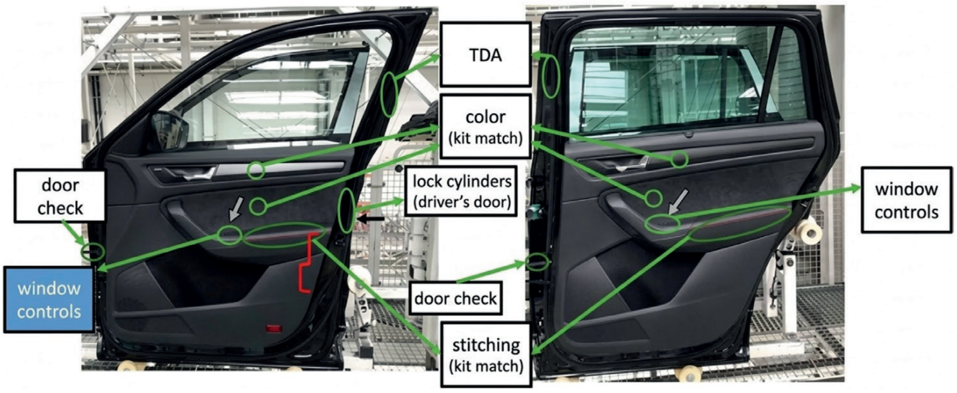

Fig. 7 *Examples of defect categories used for training the deep learning model.*

4.3 Region of Interest Definition

To improve the robustness and computational efficiency of the inspection process, the analysis is limited to predefined regions of interest (ROI) corresponding to critical areas of the inspected components. The ROI selection ensures that the neural network processes only relevant parts of the captured images while ignoring background information that is not relevant for defect detection.

The ROI regions were defined based on expert knowledge of the inspected components and the typical locations where defects may occur during the assembly process. This approach reduces computational complexity and improves the stability of the inspection algorithm.

The defined ROI regions used during the dataset preparation process are the following 8 areas (17 possible defects and 47 possible states), as detailed below:

1. Window control switch (so-called “piano”),
2. Reflector,
3. Sunshades,
4. Hinge area,
5. Speakers,
   (a) upper,
   (b) lower,
6. Lock area,
7. Mirror screw,
8. Glass sealing.

4.4 Training and Validation Dataset Preparation

The performance of the neural network model strongly depends on the quality and representativeness of the training data. For this reason, a training dataset containing at least 1,000 image samples was prepared. Among these samples, at least 100 examples represent NOK states, corresponding to simulated defect scenarios introduced during the initial testing phase.In addition to the training dataset, an independent validation dataset was prepared to evaluate the generalization capability of the trained model. The validation dataset also contains at least 1,000 samples, including at least 50 samples representing defective components. This dataset was created using an independent defect simulation process to ensure that the evaluation is not biased by the training data.

To ensure reliable inspection performance, the dataset includes representative samples of different product variants, including variations in component appearance, trim levels, and colour configurations. This variability is essential to ensure that the model performs reliably across the wide range of production conditions encountered in automotive manufacturing.

During system operation, the dataset can be continuously expanded with new image samples collected from the production process. These images may be further annotated and incorporated into subsequent training cycles, enabling gradual improvement of the inspection model.

5. Experimental Setup and System Deployment

This section describes the training procedure and evaluation workflow used for the proposed industrial computer vision system. The goal of the experimental setup was to train a neural network capable of detecting visual defects in automotive door components under real manufacturing conditions.

To address the defect detection problem, an appropriate neural network architecture must first be selected. This includes determining the number of layers, the number of neurons in individual layers, and the choice of activation functions. The input data for the model consist of images captured by the inspection system described in Section 3.

At the initial stage of training, the parameters of the neural network are randomly initialized. The network is then iteratively optimized using the annotated dataset described in Section 4. During this process, the model gradually learns to identify visual patterns associated with both defect-free and defective components.

5.1 Industrial Inspection Use Case

The industrial computer vision system was deployed on the door pre-assembly lines at Škoda Auto, where it performs automated inspection of selected door components during the assembly process. The inspection system focuses on critical areas of the door panel where assembly errors, missing components, or visual defects may occur.

At the ML1 production line, approximately 5 million parts are inspected annually, with around 3,000 detected defects. The ML2 production line processes approximately 2.5 million inspected components per year, with roughly 1,200 detected defects. These numbers demonstrate the large-scale deployment of the inspection system and highlight the importance of automated inspection in high-volume automotive manufacturing.

The inspection tasks include verification of component presence, correct assembly of interior elements, and detection of visible defects on the door panel structure. Typical inspection points on the door panel are illustrated in Fig. 8, which highlights selected use cases of the inspection system.

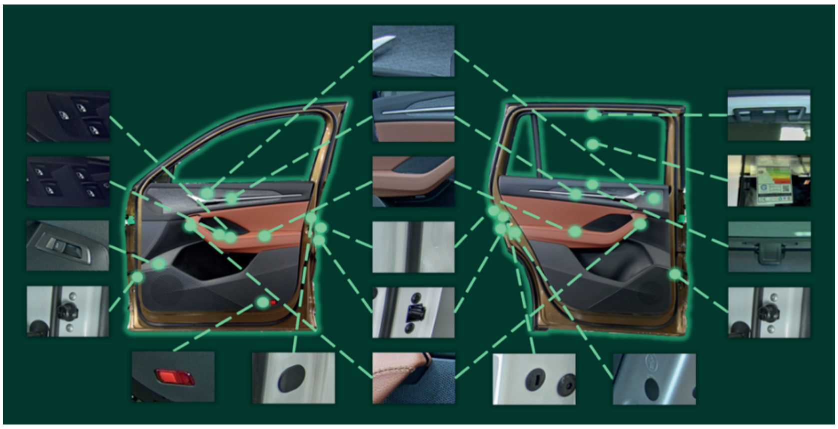

Fig. 8 *Door panels of Kodiaq II including examples of inspected areas and controlled use cases.*

The highlighted regions indicate typical inspection points used by the industrial computer vision system. These areas correspond to components such as control buttons, connectors, fasteners, and interior trim elements that must be verified during the assembly process. By focusing on these predefined inspection locations, the system can efficiently detect assembly inconsistencies and visual defects during production.

5.2 Neural Network Model

To prevent overfitting during training, the training dataset is internally divided into training and validation subsets, where the majority of samples are used for model optimization and a smaller portion is reserved for validation during the training process. These include:

- image normalization,
- data augmentation,
- dropout regularization.

The neural network model is implemented using modern deep learning frameworks, including PyTorch and TensorFlow, which provide efficient tools for training and deploying neural network models.

5.3 Detection and Classification Process

Neural networks used for visual inspection tasks can generally be categorized into three main groups:

- classification networks, which assign an input image to a predefined class,
- object detection networks, which identify objects within an image using bounding boxes,
- segmentation networks, which provide pixel-level identification of objects within the image.

For defect detection tasks in industrial inspection systems, object detection and segmentation methods are often used because they allow precise localization of defects within the inspected component. Examples of object annotations used during model training are illustrated in Fig. 9.

Fig. 9 *Example of labeled defect regions using bounding boxes.*

In more advanced scenarios, segmentation models can be used to identify defect regions at the pixel level. Instead of bounding boxes, segmentation models use polygons to define the exact shape of detected objects.

Examples of polygon-based annotations used in segmentation models are shown in Fig. 10.

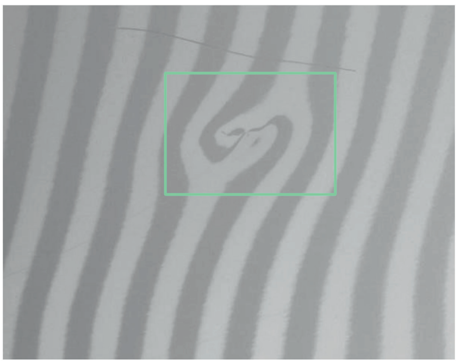

Fig. 10 *Example of polygon annotations used in segmentation-based neural networks.*

To reduce the amount of training data required, transfer learning techniques may be used. In this approach, the neural network is initialized using weights pre-trained on large datasets such as ImageNet, COCO, or Pascal VOC.

Model performance during training is evaluated using standard computer vision metrics such as:

- intersection over union (IoU),
- mean average precision (mAP),
- training and validation loss.

These metrics provide quantitative measures of the model's ability to detect and classify defects in the inspection images.

5.4 Inference Phase

After the training phase is completed, the trained neural network model is deployed within the inspection system and used for inference during real-time production operation. During inference, new images captured by the inspection cameras are first pre-processed using the methods described in Section 3.2. The processed images are then passed to the neural network model, which produces predictions regarding the presence of potential defects.

The output of the model typically includes:

- predicted class labels,
- bounding box coordinates,
- confidence scores associated with each prediction.

These outputs are visualized in the inspection system interface, where detected defects are displayed as overlays on the captured images. The inspection results are simultaneously stored in the system database and may be exported for further analysis and quality monitoring.

6. Discussion

The presented industrial computer vision system demonstrates the practical applicability of deep learning-based inspection methods in large-scale automotive manufacturing environments. The system has been deployed on door pre-assembly lines at Škoda Auto, where it performs automated inspection of selected door components during the assembly process.

The performance of the inspection system is continuously monitored using internal analytics dashboards implemented in Microsoft Power BI. These dashboards provide real-time visualization of key performance indicators, including the total number of inspected components, alert frequency, detection success rate, occurrence of false positives, and distribution of detected defect types across different vehicle models.

Operational data collected during pilot deployment indicate that the inspection system achieves an overall inspection accuracy approaching 99.99%. Although this value depends on the specific inspection scenario and dataset characteristics, it demonstrates that industrial computer vision systems can achieve highly reliable performance when properly trained and integrated into the production process.

Compared to traditional manual visual inspection, the proposed industrial computer vision approach significantly reduces operator dependency and enables standardized evaluation of inspected components. Manual inspection processes are inherently influenced by fatigue, subjectivity, and varying working conditions, whereas automated inspection systems provide consistent and repeatable evaluation criteria.

Unlike traditional rule-based vision systems, neural network-based approaches are able to adapt to variability in lighting conditions, material appearance, and component geometry. This adaptability is particularly important in automotive manufacturing environments where numerous product variants and visual configurations must be inspected within the same production line.

The deployment described in this study demonstrates that a well-curated dataset combined with clearly defined inspection logic can lead to reliable defect detection even in complex manufacturing scenarios. Continuous data collection during production also enables gradual improvement of the inspection model as additional defect examples become available.

Despite these advantages, several limitations must be considered when deploying industrial computer vision systems in real production environments. One of the main challenges is the requirement for sufficiently large and accurately annotated datasets used for model training. Preparing such datasets may require substantial effort from domain experts, particularly when new product variants or defect categories are introduced.

Another important consideration is the need for continuous model maintenance. As manufacturing processes evolve and new components are introduced, the inspection model must be periodically updated to maintain reliable performance. Human oversight therefore remains an important component of the inspection workflow, especially for evaluating edge cases and validating training data.

Integration of the inspection system with production control infrastructure also plays a crucial role in maximizing the benefits of automated inspection. By linking the inspection system with production databases and quality monitoring platforms, detected defects can be analysed more quickly and corrective actions can be implemented more efficiently. Such feedback loops improve response time and support faster defect resolution within the manufacturing process [21].

Overall, the presented case study illustrates that industrial computer vision systems can significantly enhance quality control processes in automotive manufacturing when supported by high-quality datasets and proper system integration.

6.1 Future Work

Future research will focus on further integration of industrial computer vision systems with digital manufacturing environments. In particular, tighter coupling between inspection systems and digital twin models of production processes could enable real-time monitoring and simulation of manufacturing operations [10].

Another promising direction involves the use of transfer learning techniques to reduce training time when new components or product variants are introduced into the production process. Such approaches could significantly accelerate deployment of inspection models for new manufacturing scenarios.

Future work will also investigate predictive analytics methods that analyse historical inspection data in order to identify emerging defect patterns and anticipate potential quality issues before they occur. These predictive capabilities could support proactive quality management and improved process optimization.

Finally, further development will explore multimodal inspection approaches that combine multiple sensing modalities, such as ultraviolet (UV), infrared (IR), and 3D imaging. Integrating these complementary data sources may further increase detection robustness and enable identification of defects that are difficult to detect using conventional RGB imaging.

7. Conclusion

This paper presented an industrial computer vision system designed for automated quality inspection of automotive door components in a production environment. The proposed approach combines deep learning-based visual analysis with a modular inspection architecture integrated into the manufacturing process.

The deployment of the system in a real automotive production line demonstrated that machine learning-based inspection can significantly improve the consistency and reliability of defect detection compared to traditional visual inspection methods. By leveraging annotated datasets and adaptive neural network models, the system is capable of handling variability in component appearance and manufacturing conditions.

Although industrial computer vision has already shown clear benefits in automotive quality control, future development will likely focus on deeper integration with digital twin technologies, adaptive learning mechanisms, and predictive analytics. Improvements in data quality, annotation efficiency, and computational performance will further enhance detection accuracy and responsiveness of inspection systems.

The main contribution of this work lies in the real-world deployment and validation of an industrial computer vision system under full-scale automotive production conditions, where the system is evaluated on large-scale production data and integrated directly into the manufacturing process. In addition to demonstrating high detection reliability, the paper provides practical insights into system architecture, dataset preparation, and integration with production and quality management systems.

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All figures for which no external source is cited are based on internal materials and documentation of Škoda Auto.

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